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On Emerging Asia-Pacific Equity Markets from the Perspective of the Dynamics of Mean and Volatility Spillovers

Li Xu
Florida International University, eugenexu@yahoo.com

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FLORIDA INTERNATIONAL UNIVERSITY

Miami, Florida

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by

Li Xu

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To: Dean John F. Stack
Steven J. Green School of International and Public Affairs

This dissertation, written by Li Xu, and entitled On Emerging Asia-Pacific Equity Markets from the Perspective of the Dynamics of Mean and Volatility Spillovers, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

Brice V. Dupoyet

Sheng Guo

Kai Huang

Cem Karayalcin

Prasad V. Bidarkota, Major Professor

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The dissertation of Li Xu is approved.

Dean John F. Stack
Steven J. Green School of International and Public Affairs

Dean Lakshmi N. Reddi
University Graduate School

Florida International University, 2015

DEDICATION

This dissertation is dedicated to my parents and grandparents.

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ABSTRACT OF THE DISSERTATION

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Li Xu

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Miami, Florida

Professor Prasad V. Bidarkota, Major Professor

This dissertation investigates the dynamics of mean and volatility spillovers from the U.S. and three large (regional) Asia-Pacific stock markets to ten small (local) ones from June 2008 to May 2013.

After a brief introduction to the main purposes and contributions of my research in Chapter 1, I examine the impact of lagged American and regional returns on the local markets in Chapter 2. By building up a univariate autoregressive model and treating lagged U.S. and regional returns as exogenous variables, I find that the local markets have statistically significant exposure to lagged returns of their own and the U.S. market only. The empirical results suggest that lagged American returns have exerted considerable mean spillover impact upon most of the local markets, whereas the large Asia-Pacific markets involved in this study have few such impacts.

I study the linkage between the U.S. market and each of the regional markets in Chapter 3 by employing two specifications of the bivariate GARCH process—the BEKK and general dynamic covariance (DC) models—to capture common features of equity return data. Based on the results of carefully constructed diagnostic tests, the BEKK model is demonstrated to be more appropriate for the U.S.–China and U.S.–Japan cases, and the dynamic covariance model for the U.S.–Australia case.

In Chapter 4, I discuss time-varying correlation of a local market with the U.S. market and with each regional market by proposing three Markov-switching shock spillover

models. A comparison of model performance is drawn based on a series of model selection criteria. In fourteen cases, the local market is found to be more sensitive to regional shocks. Disturbances from two regional markets account for a higher proportion of local variance than those of U.S. origin. I conclude that the regional center, although having little mean spillover effect upon the local markets, has become increasingly influential in volatility transmission. Possible extended studies in the future as well as main findings in the preceding chapters are summarized in Chapter 5.

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CHAPTER 1

Introduction

Accompanying global economic integration are record levels of financial interaction among the world's economies. In spite of many merits of financial integration such as unrestricted flows of capital, labor and information within a region, one of the most obvious demerits is financial contagion. Owing to growing interdependence in international equity markets, an economic or financial event effects a change in stock returns and price volatility not merely in the country where the event occurs but in foreign markets as well. This dissertation attempts to quantify the degree to which return volatility of ten stock markets in the Asia-Pacific region is affected by innovations originating in a larger market in the same area as well as in the U.S. market during and after the 2007–2009 global financial crisis.

Unlike past crises, such as the 1997–1998 Asian financial crisis, the 1998 Russian crisis and the 1999 Brazilian crisis, the 2007–2009 global financial crisis originated in the largest and most influential economy, the U.S. market, and was spreading all over the world. This crisis, therefore, provides a unique natural experiment for investigating the dynamic inter-relationships amongst global stock markets, as empirical studies of transmission of return shocks from one market to another are essential in international portfolio management.

The dynamics of those interrelationships between the financial markets in Greater China Region[1] (mainland China and Hong Kong Special Administrative Region) and other Asian stock markets is a noteworthy issue of economic and financial research not only because the integration of the mainland Chinese economy with the rest of the world is asymmetric but also because the economic systems and institutional features within this area are inherently different. Specifically speaking, the real economy of Mainland China has integrated,

[1] Although 'Greater China' or 'Greater China Region' usually includes mainland China, Hong Kong, Macau and Taiwan, the term is confined to referring to mainland China and Hong Kong only in this study.

to a considerable extent, with those of developed countries, while the Mainland Chinese financial market is tightly controlled and shuts the door on foreign investors.[2] The equity market in Hong Kong, on the contrary, has been very open to foreign investors and playing an active role in attracting international investment. The special economic and political relations between mainland China and Hong Kong provide an excellent setting for current empirical research.

This study intends to delineate a dynamic pattern of co-movement, during the process of financial integration of mainland China and Hong Kong, between the Greater Chinese market and the smaller others in Asia. The ’smaller others’ covered in this study are the equity markets of India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Sri Lanka, Taiwan, Thailand and Vietnam. These markets are often referred to as ’local markets’ in the international finance literature, for a large market can have considerable influence over them but not vice versa.[3] In order to have a complete view of the volatility spillover amongst the Asian equity markets, I also conduct similar analysis concerning two mature markets—Japan and Australia. These two are well qualified as regional sources of fluctuations in share prices, since both Tokyo Stock Exchange and Australian Securities Exchange are top stock exchanges in terms of market capitalisation in the Asia-Pacific area (ranked first and fourth, respectively). Table 1.1 displays the largest domestic equity market capitalisations in the Asia-Pacific region in June 2012. I let each of the three largest Asia-Pacific stock markets—the Australian, the Greater Chinese and the Japanese markets—be a proxy for the regional market[4] and compare their respective mean and volatility spillover effects on

[2]The Chinese government has recently allowed international investors to trade directly in Chinese bonds and stocks via approved banks and financial institutions based in London through an agreement with the United Kingdom.

[3]International Finance Corporation (IFC) classifies India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan and Thailand as emerging markets. Sri Lanka and Vietnam are covered by the Russell Frontier Index (RFI).

[4]In the international finance literature, a stock market is often referred to as a ’regional market’ if it is large enough to influence the neighboring markets, though it may even be able to have a global

the local markets with those of the U.S. market as a proxy for the global market. Hence, with each local market combined with three regional market proxies, there are thirty cases in total to be studied. Such an international comparison, I believe, will lead me to draw a fair conclusion.

Table 1.1: Market Capitalisation of Top Stock Exchanges in Asia-Pacific Area (June 2012)

Stock Exchange	*Ranking in Asia*	*Worldwide Ranking*	*Market Capitalisation (US$ billion)*
Tokyo Stock Exchange (TSE)	1	3	3384.87
Shanghai Stock Exchange (SSE)	2	6	2410.87
Hong Kong Exchanges (HKEx)	3	7	2375.85
Australian Securities Exchange (ASX)	4	9	1215.60
Shenzhen Stock Exchange (SZSE)	5	11	1149.18
Bombay Stock Exchange (BSE)	6	13	1101.87
Korea Exchange (KRX)	7	15	1024.63

Source: World Federation of Exchanges (2012).

Understanding the effect of volatility transmission amongst the Asian equity markets is paramount to institutional investors and policy makers. First of all, this study provides those derivatives developers or hedging strategists interested in this area with an insight on the development of price volatility in relevant markets. Secondly, with the conditional correlations between the Greater Chinese and other Asian markets being time-varying, the weights for a portfolio of assets from those markets have to be adjusted accordingly for the purpose of optimizing asset allocation. From the perspective of portfolio management, portfolio diversification will become less justified if conditional correlations have strengthened over time. The financial regulators in the Asia-Pacific countries, on the other hand, can benefit from this paper as well since they may improve their knowledge of the dynamic patterns of new information from a regional market as well as the U.S. market. Such knowledge is indispensable for accurate assessment of the effect of shocks from abroad on the local economy and rapid development of policies and procedures to minimize the risk of economic downturn.

impact.

There is an extensive literature on contemporaneous cross correlation over stock market indices. Although the list of the empirical studies on volatility spillovers and financial interdependence amongst global stock markets is rapidly growing, the following papers serve to illustrate the existing literature. Originally, analysis of cross-market correlation and transmission of information exclusively focuses on developed markets. Hamao et al. [1990] employ univariate generalized autoregressive conditional heteroskedasticity (henceforth, GARCH) models to compare mean and volatility spillovers amongst the Japanese, U.K. and U.S. markets before and after the 1987 crash. They find the effect of volatility transmission very strong after October 1987 but not significant at all in the pre-crash period. Koutmos and Booth [1995] examine price and volatility transmission amongst the same three markets as in Hamao et al. [1990] by explicitly modelling asymmetries with the multivariate exponential GARCH (henceforth, EGARCH) specification and find evidence strongly in favor of asymmetric volatility spillovers from one market to the other two. They conclude that since October 1987 the U.K. and U.S. markets have become increasingly sensitive to disturbances from Japan. Analysing the effect of volatility spillovers between the London and New York stock markets, Susmel and Engle [1994] argue that such effect is short-term and modest.

With emerging markets capturing more and more attention from international investors, empirical studies have been conducted on the volatility of these markets since the second half of the 1990s. Pioneering the research in this field, Bekaert and Harvey [1997] present a model, which allows time-varying world factors to affect both expected returns and conditional variances in a local market, and discover that the twenty emerging markets covered by their study generally become more correlated with the rest of the world after some liberalisation policies take effect, although liberalisation does not add to market volatility. Beirne et al. [2009] investigate volatility spillovers from mature markets to forty one regional and local emerging ones during turbulences in mature markets. According to their study, during the period September 1993–March 2008, conditional correlations between developing and mature markets rise when the latter are disturbed, and meanwhile, although conditional variances of both emerging and developed markets increase, mature markets turn comparatively more volatile. On the contrary, Chambet and Gibson [2008] report that there is a dramatic decrease, albeit not time-invariant, in the level of financial integration of most emerging markets with advanced ones during the financial crises of the 1990s.

Following a series of reforms to their capital markets, co-movement of the emerging markets in Asia with the world's major financial markets in equity returns and price volatility has been brought up for discussion in academia recently. Kim and Rogers [1995] quantify the mean and variance spillovers from the Standard and Poor's 500 and Nikkei 225 to the Korea Composite Stock Price Index (KOSPI) by estimating univariate GARCH models. Their study reveals that the effect of such spillovers has been magnified since the Korean capital market became liberalized in January 1992. Tai [2007] confirms the similar findings for India, Malaysia, the Philippines and Thailand that all four markets have completely integrated with other capital markets since their official liberalization. Extending Bekaert and Harvey [1997]'s work by adding disturbances of Japanese origin, Ng [2000] shows evidence of pronounced volatility spillovers from Japan as a regional center as well as the United States to six Pacific-Basin markets. Miyakoshi [2003] also studies return and volatility spillovers between Japan and seven smaller equity markets in Asia with the U.S. market innovations being exogenous, finding that there is mutual volatility transmission amongst the Japanese and other Asian stock markets whereas only mean spillovers exist between the U.S. market and the studied smaller Asian markets. Nguyen et al. [2007], on the other hand, concentrate their research on financial interdependence not only between mature markets such as Europe or the United States and emerging Asia but within those Asian markets as well, demonstrating that those markets in trouble during the 1997 crisis become significantly more interrelated with each other but in the meantime correlations with the U.S. and European markets maintain the same level.

Considering that China is a major trading partner of most of Asia-Pacific countries, there is no doubt that the country's gradually loosened capital controls have influenced the neighboring markets both economically and financially. The current literature, however, is relatively thin on the topic of the Chinese market volatility and the correlation between the Chinese and other emerging markets in the Asia-Pacific region. Linkages amongst the three markets in the Greater Chinese area, owing to strong business and economic ties among mainland China, Hong Kong and Taiwan, have been recorded in the literature. It is worthwhile to point out that the few studies conducted on this issue have yet to reach a unanimous conclusion. According to Groenewold et al. [2004], there exists a strong contemporaneous relationship between two Mainland Chinese markets—the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), which are isolated from their neighboring markets in Hong Kong and Taiwan. The cointegration test results in Cheng and Glascock [2005] show that although the two mainland Chinese markets are not cointegrated with either the Hong Kong or Taiwanese market there exist significant non-linear relationships amongst these markets. Johansson and Ljungwall [2009], however, find significant interdependencies amongst the three markets in the Greater China region. Similarly, Ho and Zhang [2012] examine the dynamics of the volatility in the Greater China area by applying a multivariate framework. Incorporating the features pertaining to asymmetries, persistence and time-varying correlations, their study indicates that SZSE and SSE are positively correlated with one another whereas weakly related with the Hong Kong and the Taiwanese markets.

Traditionally, Hong Kong serves as a major transfer station for international capital inflows to mainland China such as syndicated loans and foreign direct investment and the lion's share of China's exports. Cheung et al. [2003] argue that since before it was handed over to China in 1997 Hong Kong has accelerated financial and real integration with mainland China in regard to international finance and trade. An increasing number of Mainland Chinese corporations recently listed on the Hong Kong Stock Exchange have also promoted financial integration between these two Greater Chinese markets. Ranked sixth and seventh worldwide in terms of market capitalisation, respectively, the Shanghai and the Hong Kong equity markets play an important role in the world financial markets. As a result, the interrelationship of the highly integrated Greater Chinese stock markets and the rest of the Asia-Pacific markets will definitely become a hot topic amongst financial practitioners. Further research is therefore needed to expand the knowledge especially of time-varying correlation between the equity markets in Mainland China and Hong Kong as a whole and other Asian emerging markets. A recent paper by Zhou et al. [2012] sheds some light on this issue. Based on the method proposed by Diebold and Yilmaz [2012], they measure the directional volatility spillovers between the Chinese and world stock markets and find that (I) volatility of the Chinese market had a significantly positive net spillover effect on other markets from 2005 to 2009; (II) the interrelationships amongst the mainland Chinese, the Hong Kong and the Taiwanese market appear to be highly significant, implying further financial integration in the Greater China region; (III) volatility transmission is more prominent amongst the Chinese and other Asian markets than amongst the Chinese and the western markets, which indicates strong correlations amongst the Asian equity markets.

The main contribution of this dissertation to the current literature resides in the following three aspects. First of all, my study spans a five-year period, during which the latest financial crisis peaked, then eased and finally ended. This extensive coverage leads to an in-depth analysis of the dynamics of information spillover for an emerging Asia-Pacific market throughout the crisis period and a detailed comparison of the market's response to external influences during the crisis and post-crisis periods. Secondly, I focus on the mean and volatility spillover effects of the Chinese market, which has not been carefully studied to date. With strengthened economic ties between mainland China and the rest of Asia, it is reasonable to anticipate a growing financial interdependence within the Asia-Pacific area. Last but not least, my research adds to the comparative economics literature since I draw a comparison between regional and U.S. risk factors in terms of the extent to which these factors have affected a local Asian market on both mean and volatility levels. In addition, through quantifying regional shock spillover intensities and calculating proportions of local variance explained by regional risk factors, I perform a comprehensive analysis of the similarities and distinctions amongst the dynamics of volatility spillovers from each proxy for the regional center to a certain local market.

The remainder of this dissertation is structured as follows. In the second chapter, I examine the mean spillover effects upon the ten local markets of the three regional center proxies and of the U.S. market. The next two chapters concentrate on the impact of volatility transmission. I first study in detail the linkages between the U.S. market and each of the regional markets in Chapter 3 and then discuss time-varying correlations of a local market with the U.S. market and with each regional center proxy in Chapter 4. The final chapter summarizes possible extended studies in the future as well as main findings in the preceding chapters.

CHAPTER 2

Mean Spillovers from U.S. and Large Asia-Pacific Markets

Integration of global markets has been increasing, as is highlighted by the impact of previous financial crises. One of the implications of strong co-movement between markets is significant mean spillover effect. In this chapter, the purpose of study is to search for evidence of interrelationships amongst the ten local markets, the presumed regional center and the U.S. market. Specifically, I address the following question—which of the local, regional and U.S. factors dominates the other two in terms of mean spillovers to a small market in the Asia-Pacific area during and after the 2007–2009 financial crash? I employ a univariate autoregressive (henceforth, AR) model to quantify the mean spillover effect the U.S. and the regional markets have upon the ten local markets, taking into account four different presumptions about the proxy for the regional center. This chapter is organized as follows. The first section offers an introduction to the current literature on financial contagion and interdependence in emerging Asia. Sections 2.2 and 2.3 discuss in detail the data and methodology employed, respectively. Section 2.4 summarizes the results of estimation and discusses their implications. Concluding remarks are offered in section 2.5.

2.1 Review of Literature on Asian Stock Market Co-movement

Recent studies of equity market co-movements in the Asia-Pacific region have reported mixed findings. Some researchers argue that Hong Kong is the most influential stock market in Asia (Dekker et al. [2001] and Masih and Masih [1999]). Utilizing an error correction model to investigate long-term interrelation amongst the stock markets of the United States, Japan and ten less developed Asian countries and areas, Yang et al. [2003], however, contend that Singapore is a leading Asian market during the entire covered period including the 1997–1998 Asian financial crisis whereas Hong Kong is found not so influential as previously believed in the same period of time. A tertiary point of view is that Hong Kong and Singapore are equally influential. For instance, Huyghebaert and Wang [2010] argue that both Hong Kong and Singaporean markets affect other Asia-Pacific markets to a large extent after the 1997 Asian stock market crash.

In some cases, empirical results of such studies even contradict one another. So far several possible scenarios have been documented in regard to the relationship of a small Asia-Pacific market with a large one such as Japan and with the U.S. market. Adopting a vector autoregressive (henceforth, VAR) approach and considering the period January 1987–May 1998, Dekker et al. [2001] found evidence that in the period between the two crashes of 1987 and 1997 the U.S. market has a substantial impact upon eight markets in the Asia-Pacific region whereas the Japanese market is rather isolated from emerging Asia. In contrast, applying the International Capital Asset Pricing Model (ICAPM) to their data spanning January 1991 to December 2005, Chi et al. [2006] analyzed the level of integration of ten Asia-Pacific emerging markets with the U.S. and Japanese markets during the pre-crisis, crisis and post-crisis sub-periods to have a better understanding of the 1997–1998 Asian financial crisis. They argue that those markets are financially more integrated with Japan than the United States. Awokuse et al. [2009] examined the dynamic pattern of the interdependence among the markets of selected Asian countries and the Japanese, U.K. and U.S. markets by the use of the inductive causation algorithm as well as method of rolling co-integration. According to them, both Japanese and U.S. markets have made quite an impact on those emerging Asian markets since the 1997–1998 crisis. Miyakoshi [2003] carried out in-depth research on both mean and volatility spillovers between a less developed Asian equity market and each of the Japanese and U.S. markets. For those seven countries and areas covered by his study (Hong Kong, Indonesia, Malaysia, Singapore, South Korea, Taiwan and Thailand), he argues, the Japanese market exerts a great influence on their market volatility, whereas the U.S. market does on their market returns.

A few more recent studies focus on interactions among Asian markets during the 2007–2008 U.S. sub-prime mortgage crisis. Among them, Lean and Ghosh [2010] compared the degree of financial integration between Malaysia and each of the world's three largest economies. Their research reveals that Malaysia is more integrated with China than with Japan and the United States. They reach the conclusion that regional integration is becoming more significant relative to global integration for the Malaysian market. Carefully studying both short-term and long-term linkages among six major stock exchanges in East Asia as well as their interrelationships with the U.S. exchanges with VAR models, Wang [2014] contends that East Asian stock markets have strengthened the linkages among themselves and become less responsive to U.S. shocks. Tam [2014] utilized a spatial-temporal model with an error correction specification and the implied impulse response functions in order to conduct spatial analysis of the shock transmission mechanism among eleven Asia-Pacific markets. She argues that (1) Japan maintains its regional leadership position as a dominant driver of market linkages; (2) cross-border financial linkages are increasing between China and other Asian economies in the wake of the 2007–2008 crisis; (3) despite being endogeneous and isolated from its Asian neighbors in general, the Australian market has recently become increasingly responsive to market news from China and Japan.

2.2 Description of Stock Return Data

Compiled by Morgan Stanley Capital International (henceforth, MSCI), the daily price level composite indices are U.S. dollar denoted and market capitalisation weighted, and cover the period from 2 June 2008 until 3 May 2013. The MSCI Global Equity Indices apply a consistent index construction and maintenance methodology, which allows for meaningful global perspectives and cross-regional comparisons. For the Greater Chinese market, I employ the MSCI Zhonghua Index, which belongs to the MSCI China Markets Index Family, as it provides exhaustive coverage of the large- and mid-cap segments in the mainland Chinese and Hong Kong markets and captures the market-value-weighted return of the following constituents: China B shares, China H shares, Red chips, P chips, and Hong Kong shares.[1] The rest of the chosen MSCI indices fall into three categories: MSCI Developed Markets (Australia, Japan and the United States), MSCI Emerging Markets (India, Indonesia, Malaysia, the Philippines, South Korea, Taiwan and Thailand), and MSCI Frontier Markets (Pakistan, Sri Lanka and Vietnam). Figures 2.1–2.2 display the daily values of the aforementioned indices during the covered period. The shaded area indicates the most recent recession period reported by the National Bureau of Economic Research (henceforth, NBER).

The daily return of each market, $DR_{i,t}$, is constructed from the corresponding price level data in the following way:

$$DR_{i,t} = \ln p_{i,t} - \ln p_{i,t-1}, \tag{2.1}$$

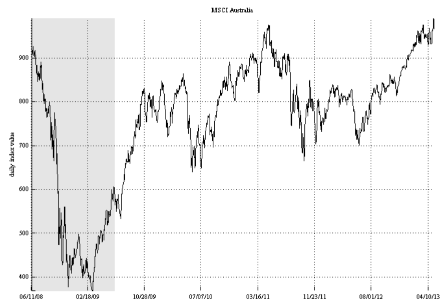
where $p_{i,t}$ is the closing price of market i's index at time t. The annualized daily return, $R_{i,t}$, then derives from multiplying the logarithmic return by 252, the average number of trading days in a year

$$R_{i,t} = DR_{i,t} \times 252. \tag{2.2}$$

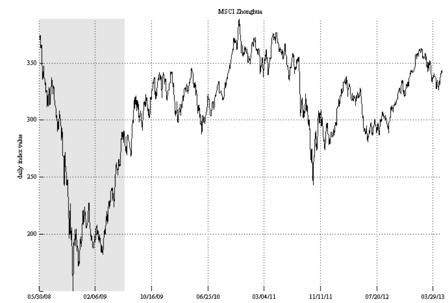
Table 2.1 presents statistical characteristics of the annualized daily return of the fourteen stock markets under study. On average, the annualized daily returns of the ten emerging markets are higher and slightly more volatile than those of the three developed markets, which is consistent with the findings in Bekaert and Harvey [1997]. Over the entire sam-

[1] China B shares are listed on the Shanghai and Shenzhen Stock Exchanges and traded in foreign currencies in contrast to China A shares, which are domestically listed and traded only in Chinese yuan. The stocks issued by companies incorporated in mainland China and traded on the Hong Kong Stock Exchange are termed China H shares. Red chips and P chips refer to the Hong Kong-listed stocks of companies incorporated outside but based in mainland China; red-chip companies are government-controlled while P-chip corporations are privately owned.

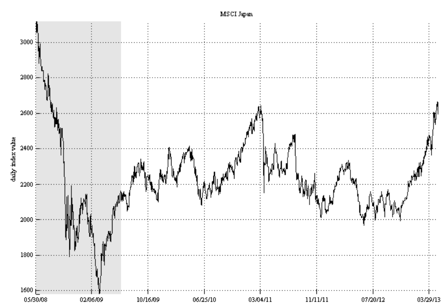
Figure 2.1: Daily Values of MSCI Australia, Japan, U.S. and Zhonghua



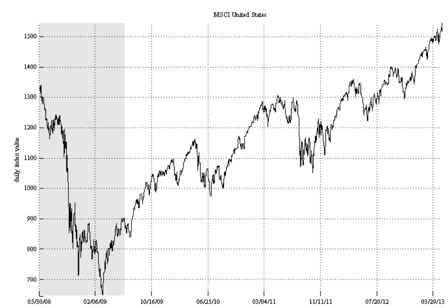
(a) Australia



(b) Greater China



(c) Japan

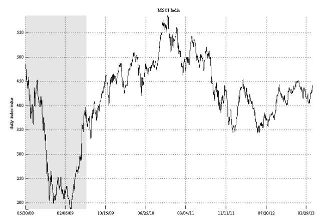


(d) The United States

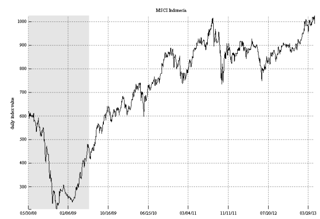
ple period, the standard deviations for all of the markets range from 2.610 (Malaysia) to 5.982 (South Korea). The mean returns for seven out of the ten emerging and frontier equity markets in Asia are positive—amongst these seven markets, five (Indonesia, Malaysia, the Philippines, Sri Lanka and Thailand) yield higher returns but exhibit lower volatility compared with either Australia or the United States. The Jarque-Bera test and Engle's Lagrange multiplier test[2] are performed to check for normality and autoregressive conditional heteroskedasticity (henceforth, ARCH), respectively. The results of the ARCH(5) test show that each smaller market, without exception, is conditionally heteroskedastic at the 1% level of significance. Calculated up to the fifth-order autocorrelation, the Ljung-Box *Q*-statistics

[2] Table 2.1 reports the results of Engle's Lagrange multiplier test when lagged U.S. and Chinese market returns are included in the first regression as control variables. The same test is repeated under the other three presumptions about the proxy for the regional market. These results are presented in Table A.5 in Appendices of Chapter 2.

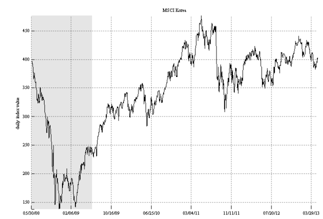
Figure 2.2: Daily MSCI Index Values of Ten Small Asia-Pacific Stock Markets



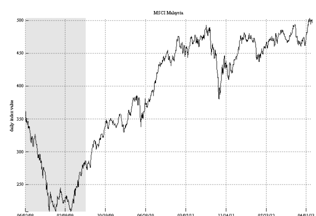
(a) India



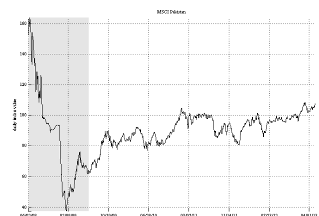
(b) Indonesia



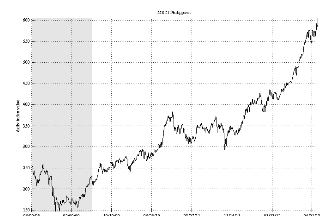
(c) Korea



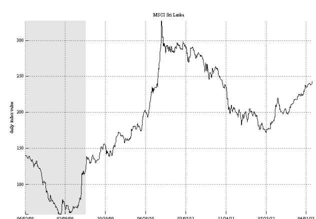
(d) Malaysia



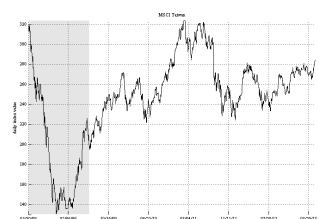
(e) Pakistan



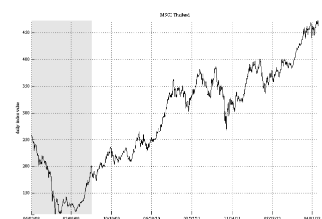
(f) The Philippines



(g) Sri Lanka



(h) Taiwan



(i) Thailand

(j) Vietnam

indicate significant autocorrelation in the return series for most of the markets. The Jarque-Bera test statistics reject the null hypothesis at the 1% level, suggesting that all of the return series may be non-normally distributed, i.e. either the coefficient of skewness or excess kurtosis or both being non-zero.

Table 2.1: Descriptive Statistics for Annualized Daily Return of Fourteen Stock Markets

The annualized daily stock market returns are computed in U.S. dollars according to (2.1) and (2.2) with the related MSCI composite indices. Jointly testing $E\left[\frac{(R_{i,t}-\mu_i)^3}{\sigma_i^3} - s_i\right] = 0$ and $E\left[\frac{(R_{i,t}-\mu_i)^4}{\sigma_i^4} - 3 - ek_i\right] = 0$ with and without serial correlation adjustment gives the Wald test statistics labelled 'HAC' and 'Robust', respectively, which asymptotically follow a $\chi^2(2)$ distribution. The coefficients of skewness and excess kurtosis along with their standard errors are also derived from the above test. P-values are given in square brackets while heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively.

							Test Statistics				
							GMM				
Market	*Mean*	*Min.*	*Max.*	*Std. Dev.*	*Skewness*	*Excess Kurtosis*	*HAC*	*Robust*	*Jarque-Bera*[a]	*Ljung-Box*[b]	*LM ARCH*[c]
Australia	0.008	−40.257	22.196	5.215	−0.841	7.158	1.333	5.069	$2.877\times10^{3*}$	12.521†	-
					(0.728)	(6.370)	[0.514]	[0.079]	[<0.001]	[0.028]	
China	−0.015	−32.087	30.397	4.586	−0.017	7.126	1.525	6.217†	$2.719\times10^{3*}$	9.540	-
					(0.174)	(5.930)	[0.467]	[0.045]	[<0.001]	[0.089]	
Japan	−0.032	−23.973	28.898	3.930	−0.087	6.433	1.694	6.189†	$2.217\times10^{3*}$	35.296*	-
					(0.148)	(5.185)	[0.429]	[0.045]	[<0.001]	[<0.001]	
India	−0.020	−30.344	49.106	5.111	0.426	9.057	2.826	3.645	$4.431\times10^{3*}$	5.160	45.948*
					(0.747)	(6.869)	[0.243]	[0.162]	[<0.001]	[0.397]	[<0.001]
Indonesia	0.092	−36.730	37.906	5.105	−0.273	8.467	2.842	5.956	$3.854\times10^{3*}$	30.854*	132.493*
					(0.677)	(5.035)	[0.242]	[0.051]	[<0.001]	[<0.001]	[<0.001]
Malaysia	0.062	−11.136	13.977	2.610	0.008	2.615	2.282	9.707*	365.963*	20.213*	141.834*
					(0.195)	(1.732)	[0.319]	[0.008]	[<0.001]	[0.001]	[<0.001]
Pakistan	−0.068	−32.403	21.746	4.103	−0.614	5.583	2.335	3.219	$1.749\times10^{3*}$	92.803*	180.288*
					(0.642)	(4.041)	[0.311]	[0.200]	[<0.001]	[<0.001]	[<0.001]
Philippines	0.161	−36.525	20.018	4.046	−0.711	7.752	1.354	2.301	$3.323\times10^{3*}$	31.185*	73.383*
					(0.614)	(6.706)	[0.508]	[0.317]	[<0.001]	[<0.001]	[<0.001]
South Korea	0.004	−52.094	62.966	5.982	−0.091	16.757	1.587	3.748	$1.504\times10^{4*}$	7.843	129.613*
					(0.593)	(14.397)	[0.452]	[0.154]	[<0.001]	[0.165]	[<0.001]
Sri Lanka	0.108	−17.850	41.898	3.721	1.994	21.508	1.490	2.426	$2.560\times10^{4*}$	115.716*	235.506*
					(1.739)	(17.944)	[0.475]	[0.297]	[<0.001]	[<0.001]	[<0.001]

(***Continued on next page***)

Table 2.1 - Continued from previous page

Market	*Mean*	*Min.*	*Max.*	*Std. Dev.*	*Skewness*	*Excess Kurtosis*	*Test Statistics* GMM *HAC*	GMM *Robust*	*Jarque-Bera*[a]	*Ljung-Box*[b]	*LM ARCH*[c]
Taiwan	−0.019	−16.316	20.744	4.028	−0.104	2.692	3.743	11.750*	390.183*	13.703†	124.725*
					(0.202)	(1.487)	[0.154]	[0.003]	[<0.001]	[0.018]	[<0.001]
Thailand	0.113	−36.730	24.529	4.601	−0.552	6.889	1.457	4.279	2.604×10^{3}*	7.768	264.590*
					(0.540)	(5.849)	[0.483]	[0.118]	[<0.001]	[0.170]	[<0.001]
United States	0.029	−23.975	27.826	4.050	−0.310	7.954	2.722	9.562*	3.408×10^{3}*	25.180*	-
					(0.271)	(5.388)	[0.257]	[0.008]	[<0.001]	[<0.001]	
Vietnam	0.005	−17.619	12.209	4.634	−0.136	0.578	1.195	3.338	21.820*	73.576*	119.459*
					(0.153)	(0.646)	[0.550]	[0.188]	[<0.001]	[<0.001]	[<0.001]

[a] Under the null hypothesis that both skewness and excess kurtosis of the sample data equal zero, the Jarque-Bera test statisitcs is asymptotically subject to the $\chi^2(2)$ distribution.

[b] The Ljung-Box $Q(5)$ statistic is asymptotically $\chi^2(5)$ distributed if there is no autocorrelation (of order 1, 2,..., 5) in the series of market returns.

[c] The LM ARCH(5) test checks whether the residuals from an ordinary least-squares (OLS) regression of a small market's return at time t on one-period lagged Chinese and U.S. market returns exhibit autoregressive conditional heteroskedasticity. The test statistic is obtained by running one more OLS regression on the lagged residuals up to the fifth order and multiplying the coefficient of determination by the sample size. Under the null hypothesis of no ARCH effects, the test statistic follows a $\chi^2(5)$ distribution.

Proposed originally by Richardson and Smith [1993], a generalized method of moments (henceforth, GMM)–based test for normality of equity returns is also carried out. The following orthogonality conditions are estimated for market i:

$$E\left(R_{i,t}-\mu_i\right)=0, \tag{2.3a}$$

$$E\left[\left(R_{i,t}-\mu_i\right)^2-\sigma_i^2\right]=0, \tag{2.3b}$$

$$E\left[\frac{\left(R_{i,t}-\mu_i\right)^3}{\sigma_i^3}-s_i\right]=0, \tag{2.3c}$$

$$E\left[\frac{\left(R_{i,t}-\mu_i\right)^4}{\sigma_i^4}-3-ek_i\right]=0, \tag{2.3d}$$

where μ_i stands for the mean return of market i, σ_i^2 the variance, s_i the skewness and ek_i the excess kurtosis. Since the Ljung-Box *Q*-statistics suggest the presence of autocorrelation in the return series, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent by the use of the Parzen kernel with the lag order selected by Newey and West [1994]'s optimal lag-selection algorithm. The same system is estimated without serial correlation adjustment as well. Reported in the columns labelled 'HAC' and 'Robust' in Table 2.1 are the results of a Wald test with and without correction of serial correlation, respectively. Under the null that the coefficients of skewness and excess kurtosis are both zero, the Wald statistic is asymptotically $\chi^2(2)$ distributed. Within the GMM framework, the heteroskedasticity and autocorrelation consistent (henceforth, HAC) standard errors of skewness and excess kurtosis show that none of the return series is skewed or leptokurtic at the 1% level of significance—the Indonesian and Taiwanese market returns are leptokurtic at the 10% level though.[3] The Wald test suggests that the null hypothesis of uncondi-

[3] In the case of serial correlation's not being adjusted, leptokurticity is found to be present in the three developed markets as well as in four out of the ten emerging markets (Greater China, Indonesia, Malaysia and Taiwan) at the 5% significance level. At that same level, none of the coefficients of skewness is significant for all fourteen stock markets.

tional normality, when the variance-covariance matrix of the parameters is HAC, cannot be rejected at conventional significance levels in all of the equity markets concerned. The ’Robust’ statistics, however, confirm that the null can be rejected in Malaysia, Taiwan and the United States at the 1% level and in Greater China and Japan at the 5% level when the variance-covariance matrix corrects for heteroskedasticity only. The results of the GMM–Wald test contrast markedly with those of the Jarque-Bera test, which produces evidence against the null hypothesis at the 1% level for all of the markets, indicating that the latter is much more powerful in most cases.

In order to explore whether the ten small Asia-Pacific markets are correlated with the three large ones and the U.S. market in a changing pattern, I divide the degree of the Australian/Greater Chinese/Japanese/U.S. market volatility into three categories—low, moderate and high. The correlations fit into the ’low’ group during those days when the squared returns of a large market fall within one standard deviation away from their average. If the squared returns of the same large market fall outside two standard deviations away from their average in some periods, the corresponding correlations are placed into the ’high’ category. The ’moderate’ group consists of the rest of correlations. Displayed in Table 2.2, the results of the correlation analysis show that the linkage generally grows stronger between the Australian/Greater Chinese/Japanese/U.S. market and a small Asia-Pacific market when the former becomes increasingly volatile. It is worth pointing out that the Japanese and the U.S. market are very weakly correlated by the degree of U.S. market volatility (the absolute value of the correlation coefficient is less than 10% in each category). In addition, it should also be noted that three emerging markets, Pakistan, Sri Lanka and Vietnam, are negatively correlated with the U.S. market during the highly volatile periods of the latter.

Table 2.2: Correlations Amongst Fourteen Asia-Pacific Equity Markets

Market	*Correlation with Australia*			*Correlation with China*			*Correlation with Japan*			*Correlation with U.S.*		
	low[a]	*moderate*[b]	*high*[c]	*low*	*moderate*	*high*	*low*	*moderate*	*high*	*low*	*moderate*	*high*
Australia	1.000	1.000	1.000	0.590	0.832	0.845	0.436	0.729	0.816	0.252	0.348	0.485
China	0.601	0.821	0.914	1.000	1.000	1.000	0.417	0.537	0.781	0.206	0.288	0.523
Japan	0.476	0.705	0.791	0.381	0.656	0.828	1.000	1.000	1.000	−0.022	0.017	0.072
India	0.421	0.743	0.828	0.483	0.792	0.778	0.182	0.204	0.396	0.230	0.495	0.790
Indonesia	0.433	0.703	0.829	0.515	0.770	0.800	0.267	0.501	0.668	0.114	0.392	0.140
Malaysia	0.536	0.801	0.874	0.547	0.844	0.748	0.355	0.625	0.731	0.115	0.307	0.321
Pakistan	0.040	0.302	0.306	0.080	0.337	0.218	0.126	−0.112	0.194	−0.004	0.042	−0.092
Philippines	0.422	0.705	0.858	0.425	0.679	0.872	0.329	0.740	0.697	0.042	0.028	0.157
South Korea	0.609	0.738	0.791	0.646	0.692	0.787	0.496	0.635	0.667	0.148	0.237	0.454
Sri Lanka	0.074	0.027	0.413	0.053	0.255	0.267	0.042	−0.013	0.382	0.022	−0.136	−0.072
Taiwan	0.575	0.813	0.795	0.610	0.761	0.837	0.463	0.557	0.704	0.144	0.341	0.197
Thailand	0.445	0.695	0.795	0.524	0.717	0.877	0.287	0.440	0.608	0.160	0.506	0.598
United States	0.287	0.489	0.387	0.143	0.273	0.643	0.012	0.243	−0.096	1.000	1.000	1.000
Vietnam	0.203	0.175	0.619	0.126	0.308	0.350	0.156	0.666	0.614	0.028	−0.037	−0.164

$\text{distance}_{i,t} = \left|\frac{R_{i,t}-\mu_i}{\sigma_i}\right|$, $i \in$ {AU, CN, JP, US} measures how far the annualized daily return deviates from its average in terms of its standard deviation.

[a] The '*low*' category contains the correlations during these periods when $\text{distance}_{i,t} < 1$.

[b] If $1 \leq \text{distance}_{i,t} \leq 2$ for some periods, the correlations belong to the '*moderate*' category.

[c] Days of high market volatility refer to those when $\text{distance}_{i,t} > 2$ in the correlation analysis.

2.3 Methodology

I adopt a methodology similar to the one in Miyakoshi [2003] and in Beirne et al. [2009]. Miyakoshi [2003] treated the U.S. return as an exogenous variable in both of the mean and variance equations of a VAR–EGARCH model for Japan and an emerging market in Asia. Beirne et al. [2009] constructed a VAR model of returns in mature, regional emerging and local emerging markets and utilized a tri-variate BEKK specialisation in their variance equation. The AR(1)–GARCH(1,1) model employed in this chapter, however, is different from theirs in both mean and variance equations. The regional return is treated as an exogenous variable in the mean equation whereas it is an endogenous variable in both Miyakoshi [2003] and Beirne et al. [2009]. I apply a univariate GARCH(1,1) process instead of a multivariate one in the variance equation, because the main focus of interest in this chapter is the mean spillover effect the U.S. and three regional markets have upon the ten local markets.

Let $R_{m,t}$ and $R_{j,t}$ denote the annualized daily return in the U.S. dollar, computed according to (2.2), on the composite stock index of local market $m \in${ID, IN, KR, LK, MY, PK, PH, TW, TH, VN} and regional market $j \in${AU, CN, JP}, respectively. The model has the following form:

$$R_{m,t} = \alpha_0 + \alpha_1 R_{m,t-1} + \alpha_2 R_{US,t-1} + \alpha_3 R_{j,t-1} + \varepsilon_{m,t}, \tag{2.4a}$$

$$\varepsilon_{m,t} | \mathcal{F}_{m,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,t}\right), \tag{2.4b}$$

$$\sigma^2_{m,t} = \beta_0 + \beta_1 \varepsilon^2_{m,t-1} + \beta_2 \sigma^2_{m,t-1} \text{(symmetric model)}, \tag{2.4c}$$

$$\sigma^2_{m,t} = \beta_0 + \beta_1 \varepsilon^2_{m,t-1} + \beta_2 \sigma^2_{m,t-1} + \beta_3 \varepsilon^2_{m,t-1} I\left(\varepsilon_{m,t-1} < 0\right) \text{(asymmetric model)}, \tag{2.4d}$$

where $\mathcal{F}_{m,t-1}$ is the information set at time $t-1$ specific to local market m. The expected return for country m is assumed to be decomposable into three components. The local portion of the expected stock return of market m at time t is determined by the market's one-period lagged return: $\alpha_0 + \alpha_1 R_{m,t-1}$. Similarly, the U.S. and regional portions are dependent on the one-period lagged equity returns of the U.S. market, $\alpha_2 R_{US,t-1}$, and those of regional market j, $\alpha_3 R_{j,t-1}$, respectively. However, the unexpected portion of country m's returns is driven by purely idiosyncratic shocks, $\varepsilon_{m,t}$, which are assumed to be subject to the normal distribution with zero mean. The conditional local variance, $\sigma^2_{m,t} = E\left(\varepsilon^2_{m,t}|\mathcal{F}_{m,t-1}\right)$, is assumed to evolve in accordance with the GARCH (1,1) process in (2.4c) and (2.4d).

The asymmetric GARCH model is an extension of its symmetric counterpart, taking into account the finding repeatedly recorded in the literature that a market turns more volatile subsequent to a negative shock in comparison with a positive one of the same magnitude. A possible explanation for this phenomenon is that negative market news further increases the financial leverage of firms in emerging markets, most of which are already highly debt-financed, inducing a higher volatility at the market level. In order to incorporate market asymmetries in volatility of stock returns of local market m, I include in equation (2.4d) the term, $\varepsilon^2_{m,t-1} I\left(\varepsilon_{m,t-1} < 0\right)$, in which the indicator function $\boldsymbol{I}$ takes the value of 1 when $\varepsilon_{m,t-1}$ is negative and 0 otherwise. Glosten et al. [1993] (henceforth, GJR) first proposed modelling the leverage effect for a univariate GARCH process in this way. The Monte Carlo simulation results in Engle and Ng [1993] show that the GJR–GARCH model accommodates market asymmetries better than any other asymmetric GARCH model.

In the above model, I assume only one regional market. Alternatively, the impact of all three regional market proxies on a local market may be accommodated:

$$R_{m,t} = \alpha_0 + \alpha_1 R_{m,t-1} + \alpha_2 R_{US,t-1} + \alpha_3 R_{AU,t-1} + \alpha_4 R_{CN,t-1} + \alpha_5 R_{JP,t-1} + \varepsilon_{m,t}, \tag{2.5a}$$

$$\varepsilon_{m,t}|\mathcal{F}_{m,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,t}\right), \tag{2.5b}$$

$$\sigma^2_{m,t} = \beta_0 + \beta_1 \varepsilon^2_{m,t-1} + \beta_2 \sigma^2_{m,t-1} (\text{symmetric model}), \tag{2.5c}$$

$$\sigma^2_{m,t} = \beta_0 + \beta_1 \varepsilon^2_{m,t-1} + \beta_2 \sigma^2_{m,t-1} + \beta_3 \varepsilon^2_{m,t-1} I\left(\varepsilon_{m,t-1} < 0\right) (\text{asymmetric model}). \tag{2.5d}$$

In this case, the regional portion is determined by the one-period lagged returns of all three countries' market returns: $\alpha_3 R_{AU,\,t-1} + \alpha_4 R_{CN,\,t-1} + \alpha_5 R_{JP,\,t-1}$.

I assume that conditional on the previous information set, $\mathcal{F}_{m,\,t-1}$, the idiosyncratic shock, $\varepsilon_{m,\,t}$, of local market m has zero mean:

$$E\left(\varepsilon_{m,\,t}|\mathcal{F}_{m,\,t-1}\right) = 0. \tag{2.6}$$

It is therefore implied that

$$E\left(\varepsilon_{m,\,t}R_{US,\,t-1}|\mathcal{F}_{m,\,t-1}\right) = 0, \tag{2.7a}$$

$$E\left(\varepsilon_{m,\,t}R_{j,\,t-1}|\mathcal{F}_{m,\,t-1}\right) = 0, \tag{2.7b}$$

$$E\left(\varepsilon_{m,\,t}R_{m,\,t-1}|\mathcal{F}_{m,\,t-1}\right) = 0. \tag{2.7c}$$

The conditional density of the local innovation is assumed to be Gaussian and the log-likelihood function to be optimized, therefore, has the following form:

$$\mathcal{L}\left(\boldsymbol{\theta}\right) = \sum_{t=1}^{T} l\left(\varepsilon_{m,\,t}|\mathcal{F}_{m,\,t-1};\boldsymbol{\theta}\right) = -\frac{1}{2}\left[T\log\left(2\pi\right) + \sum_{t=1}^{T}\log\left(\sigma_{m,\,t}^{2}\right) + \sum_{t=1}^{T}\frac{\varepsilon_{m,\,t}^{2}}{\sigma_{m,\,t}^{2}}\right], \tag{2.8}$$

where T stands for the total number of local innovations employed in the estimation and $\boldsymbol{\theta}$ for the vector of parameters entering the likelihood function for the data. The parameters are obtained by maximizing the log-likelihood function as in (2.8). The non-linear optimisation problem is solved by the Broyden-Fletcher-Goldfarb-Shanno (henceforth, BFGS) algorithm. To avoid local maxima, I supply at least ten initial values.

To determine whether the model is correctly specified, I take a closer look at the assumption that the innovation, $\varepsilon_{m,\,t}$, follows the normal distribution. Within the framework presented by Nelson [1991] for the test for normality, I check if the standardized residual,

$z_{m,\,t}=\frac{\hat{\varepsilon}_{m,\,t}}{\hat{\sigma}_{m,\,t}}, m\in${ID, IN, KR, LK, MY, PK, PH, TW, TH, VN}, violates the orthogonality conditions implied by the standard normal distribution. Listed below are the product moments up to the fourth order of a random variable with mean zero and unit variance subject to the standard normal distribution:

$$E\left(z_{m,t}z_{m,t-k}\right)=0\left(k=1,2,...,5\right), \tag{2.9a}$$

$$E\left[\left(z_{m,t}^{2}-1\right)\left(z_{m,t-k}^{2}-1\right)\right]=0\left(k=1,2,...,5\right), \tag{2.9b}$$

$$E\left(z_{m,t}\right)=0, \tag{2.9c}$$

$$E\left(z_{m,t}^{2}-1\right)=0, \tag{2.9d}$$

$$E\left(z_{m,t}^{3}\right)=0, \tag{2.9e}$$

$$E\left(z_{m,t}^{4}-3\right)=0. \tag{2.9f}$$

Similar to the normality test previously conducted, the specification test is based on the generalized method of moments as well. Moment conditions (2.9a) and (2.9b) examine whether the residuals and squared residuals of country m are autocorrelated up to the fifth order, respectively—(2.9a) tests whether the conditional mean is correctly specified while (2.9b) deals with the conditional variance. Both conditions are tested separately with the test statistics asymptotically following the $\chi^2(5)$ distribution. I employ moments (2.9c)–(2.9f) to test the null hypothesis that the residuals are subject to the standard normal distribution from the perspective of mean (2.9c), variance (2.9d), skewness (2.9e) and excess kurtosis (2.9f). The joint test produces a test statistic asymptotically $\chi^2\left(4\right)$ distributed. Additionally, moments (2.9a)–(2.9f) are tested simultaneously. The test statistic has 14 degrees of freedom.

The following moment conditions are exploited to investigate how capable the asymmetric specification is in capturing leverage-type asymmetries in the return series. Engle and Ng [1993] emphasize that the effect of a lagged shock on current variance and covariance may depend not only on the magnitude of the shock but on its sign as well. Moments (2.10a), (2.10b) and (2.10c) test whether the data display the sign, negative sign and positive sign biases, respectively. They are tested jointly with the test statistic asymptotically subject to the $\chi^2(3)$ distribution.

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} < 0\right)\right] = 0, \tag{2.10a}$$

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} < 0\right) z_{i,t-1}\right] = 0, \tag{2.10b}$$

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} \geq 0\right) z_{i,t-1}\right] = 0. \tag{2.10c}$$

2.4 Influence of Local, Regional and U.S. Factors on Local Markets

Interpretation of the estimation results focuses on three parts. Firstly, I discuss the results of the diagnostic tests, on which selection of the best-fitting model for each local market is mainly based. Secondly, I examine the independence assumption as in (2.6) in detail. Last but not least, I investigate which plays a dominant role in a local market's daily return—the local, regional or U.S. factor.

2.4.1 Diagnostic Test Results

In order to evaluate the fit of the two specifications (symmetric and asymmetric), I employ the GMM-based specification tests as in (2.9a)–(2.10c) while also referring to model comparison tests more commonly used such as likelihood ratio and Wald tests. When these diagnostic tests fail to give adequate support for an unambiguous conclusion to be drawn, I shall run regression of the squared residuals on the corresponding estimates of conditional variance, as suggested by Pagan and Schwert [1990]. It is the model with a greater determination coefficient in the aforementioned regression that is determined to be appropriate for a certain local market.

Tables A.1–A.3 in the appendices to this dissertation report the model diagnostics for each of the three regional center proxies included in the estimation of the model described in (2.4a), (2.4b) and (2.4c)/(2.4d), respectively. If both Wald and likelihood ratio tests suggest rejecting the restriction of no variance asymmetry ($\beta_3 = 0$), an asymmetric model is consistently found to outperform its symmetric counterpart since the specification tests always indicate rejection of one or several more of the null hypotheses in the absence of variance asymmetry. In the Australia–Korea case, for example, the null hypothesis, $\beta_3 = 0$, are rejected by both likelihood ratio and Wald tests, which indicates that variance asymmetry should be incorporated in the model. The distribution and asymmetry tests both suggest a rejection of the symmetric model while none of the specification tests rejects the asymmetric one. The asymmetric model is therefore preferred in this case. No matter whether the regional market is Australia, China or Japan, significant variance asymmetry is found in all of the local markets but Sri Lanka. In these nine cases, the asymmetry parameter is positive, implying that the subsequent conditional variance increases when a negative shock occurs.

Whenever there is discrepancy between the indications provided by the Wald and likelihood ratio tests, the results of the specification tests need to be carefully examined. Usually, an asymmetric model, given that the fewer associated specification test statistics are significant, does perform better compared with its symmetric contender. In some cases, however, although some test statistics appear insignificant, their p-values are so close to the conventional cutoff level that overall, the moment tests are rendered less effective. As a result, I follow Pagan and Schwert [1990]'s suggestion to compare the R^2 coefficients. For instance, in the China- and Japan-India cases, the results of the specification tests favor the symmetric model in spite of the ambivalent indications the likelihood ratio and Wald tests give, but given its p-value so close to 5%, the joint test statistic of the symmetric model is almost significant, which actually makes no difference between the two models, considering none of the rest of the nulls can be strongly rejected. Since its corresponding determination coefficient is larger, the asymmetric model receives preference over the symmetric one in both cases. Another situation where Pagan and Schwert [1990]'s analysis has to be carried out during the course of model selection is that none of the null hypotheses of the moment tests can be rejected while the Wald and likelihood ratio tests also give little clue. This is particularly evident in the Vietnamese cases, where none of the moment test statistics is significant even at the 10% level. The asymmetric model, given the greater corresponding R^2 coefficient, is chosen for the Vietnamese market.

The results of the same set of diagnostic tests are reported in Table A.4 in Appendices of Chapter 2 when all three regional markets are incorporated. In accordance with the selection criteria above, the asymmetric specification is pursued for all except for Sri Lanka. The likelihood ratio and Wald tests both indicate that variance asymmetry should be incorporated in the cases of Indonesia, Korea, Malaysia, Pakistan, Taiwan and Thailand. In addition, the asymmetry test also suggests rejection of the symmetric model in Pakistan, Taiwan and Thailand; the symmetric model is rejected by the joint test in Indonesia; both distribution and asymmetry tests reject the symmetric specification for Korea. Pagan and Schwert [1990]'s method provides evidence for the asymmetric model for the rest.

Next, I shall concentrate on the key assumption of the model that the local shock, $\varepsilon_{m,t}$, has zero conditional mean because this assumption is essential to the effectiveness of the model specification tests. Since testing the implications of the assumption is almost equivalent to testing the assumption directly, I apply a GMM framework to test the orthogonality conditions as in (2.7a)–(2.7c). The second column of Table 2.3 presents the results of testing moment condition (2.7a) separately. According to the reported heteroskedasticity and autocorrelation adjusted standard errors in panels *A*–*D*, the null can be rejected in none of the ten local markets. Columns 3–5 in Table 2.3 detail the results of separately testing orthogonality condition (2.7b) in the case of Australia, China and Japan, respectively, as the regional center. In each case, a similar conclusion can be drawn that little evidence is found against the regional implication of assumption (2.6) since the nulls cannot be rejected in any country. Furthermore, the same orthogonality condition is not violated in any market as well when all three regional markets are incorporated into this study.

The penultimate column reports the details of individually testing the implication of assumption (2.6) with regard to the interrelation between the local residual of market m and its own lagged return. It turns out that the null hypothesis cannot be rejected in any market whatever the presumption is regarding the identity of the regional center. Displayed in the last column of Table 2.3 are the Wald statistics of jointly testing moment conditions (2.7a), (2.7b) and (2.7c), which are asymptotically subject to the $\chi^2(3)$ distribution in panels *A*–*C* and to the $\chi^2(5)$ distribution in panel *D*. When only one regional market proxy is considered, these conditions are not jointly violated in all ten local markets. Additionally, the results demonstrate that if the effect of all three regional markets on a local market is taken into account, orthogonality conditions (2.7a)–(2.7c) are also not jointly violated in any local market. In summary, Table 2.3 shows that the null hypothesis that the local market shock has zero conditional mean is not rejected, which ensures that the GMM-based specification tests (2.9a)–(2.10c) are as effective as anticipated.

Table 2.3: Testing Zero Mean Assumption

In panels A–C, the following orthogonality conditions (2.7a)–(2.7c) are separately and jointly tested: $E(\hat{\varepsilon}_{m,t} R_{US,t-1}) = 0$, $E(\hat{\varepsilon}_{m,t} R_{j,t-1}) = 0$ and $E(\hat{\varepsilon}_{m,t} R_{m,t-1}) = 0$, where the local residuals, $\hat{\varepsilon}_{m,t}$, are derived from (2.4a), (2.4b) and (2.4c)/(2.4d) and only one associated regional center is incorporated. In the last panel, the returns of all three regional markets are included in the GMM framework above and the local residuals are given by (2.5a), (2.5b) and (2.5c)/(2.5d). All of the return series are one period lagged. The weight matrices are all adapted to be heteroskedasticity and autocorrelation consistent by using the Parzen kernel. HAC standard errors are given in parentheses and p-values in square brackets.

Local Residual	*Test Statistics*					
	(2.7a)	(2.7b)			(2.7c)	(2.7a)–(2.7c)
$\hat{\varepsilon}_{m,t}$	$R_{US,t-1}$	$R_{AU,t-1}$	$R_{CN,t-1}$	$R_{JP,t-1}$	$R_{m,t-1}$	
A. Australian Market as Regional Center						
India	−0.388	0.207	-	-	−0.095	0.446
	(0.732)	(0.797)			(0.600)	[0.931]

(***Continued on next page***)

Table 2.3 - Continued from previous page

Local Residual	*Test Statistics*					
	(2.7a)	(2.7b)			(2.7c)	(2.7a)–(2.7c)
$\hat{\varepsilon}_{m,t}$	$R_{US,t-1}$	$R_{AU,t-1}$	$R_{CN,t-1}$	$R_{JP,t-1}$	$R_{m,t-1}$	
Indonesia	-0.165	1.584	-	-	1.973	1.520
	(0.598)	(1.679)			(1.799)	[0.678]
Korea	-0.931	-0.150	-	-	0.716	1.794
	(0.930)	(1.253)			(1.753)	[0.616]
Malaysia	-0.640	0.090	-	-	0.123	1.762
	(0.615)	(0.396)			(0.154)	[0.623]
Pakistan	0.766	0.820	-	-	1.795	3.398
	(0.686)	(0.723)			(1.366)	[0.334]
Philippines	0.643	0.773	-	-	0.541	2.730
	(0.694)	(1.127)			(0.453)	[0.435]
Sri Lanka	0.372	0.207	-	-	-0.484	3.019
	(0.516)	(0.505)			(0.396)	[0.389]
Taiwan	-0.708	0.098	-	-	-0.248	2.746
	(0.608)	(0.812)			(0.458)	[0.432]
Thailand	-0.577	0.501	-	-	-0.804	1.830
	(0.983)	(1.115)			(0.744)	[0.609]
Vietnam	0.939	1.320	-	-	1.095	2.655
	(0.786)	(1.117)			(0.788)	[0.448]
B. Chinese Market as Regional Center						
India	-0.336	-	-0.210	-	-0.120	0.349
	(0.718)		(0.576)		(0.581)	[0.951]
Indonesia	-0.025	-	1.672	-	2.024	2.155
	(0.645)		(1.445)		(1.841)	[0.541]
Korea	-1.053	-	-0.387	-	0.512	1.870
	(0.954)		(0.888)		(1.718)	[0.600]
Malaysia	-0.598	-	0.205	-	0.118	1.886
	(0.606)		(0.275)		(0.155)	[0.596]
Pakistan	0.837	-	0.501	-	1.732	3.271
	(0.698)		(0.730)		(1.355)	[0.352]
Philippines	0.632	-	0.466	-	0.518	2.230
	(0.679)		(0.677)		(0.444)	[0.526]
Sri Lanka	0.373	-	0.101	-	-0.443	2.593
	(0.505)		(0.445)		(0.392)	[0.459]
Taiwan	-0.719	-	0.104	-	-0.215	2.256
	(0.613)		(0.503)		(0.463)	[0.521]
Thailand	-0.598	-	-0.187	-	-0.780	2.198
	(0.982)		(0.598)		(0.717)	[0.532]
Vietnam	0.909	-	1.433	-	1.041	2.988
	(0.760)		(0.921)		(0.783)	[0.393]
C. Japanese Market as Regional Center						
India	-0.319	-	-	-0.345	-0.109	0.555
	(0.721)			(0.719)	(0.583)	[0.907]

(***Continued on next page***)

Table 2.3 - Continued from previous page

Local Residual $\hat{\varepsilon}_{m,t}$	*Test Statistics* (2.7a) $R_{US,t-1}$	(2.7b) $R_{AU,t-1}$	$R_{CN,t-1}$	$R_{JP,t-1}$	(2.7c) $R_{m,t-1}$	(2.7a)–(2.7c)
Indonesia	−0.109	-	-	0.558	1.950	1.391
	(0.600)			(0.877)	(1.809)	[0.708]
Korea	−1.052	-	-	−0.758	0.490	3.468
	(0.963)			(0.564)	(1.711)	[0.325]
Malaysia	−0.613	-	-	0.104	0.115	1.270
	(0.610)			(0.293)	(0.154)	[0.736]
Pakistan	0.857	-	-	0.243	1.721	3.392
	(0.684)			(0.557)	(1.356)	[0.335]
Philippines	0.638	-	-	0.205	0.628	2.791
	(0.688)			(0.422)	(0.470)	[0.425]
Sri Lanka	0.390	-	-	−0.333	−0.435	2.602
	(0.508)			(0.427)	(0.395)	[0.457]
Taiwan	−0.703	-	-	−0.139	−0.180	1.907
	(0.603)			(0.590)	(0.475)	[0.592]
Thailand	−0.586	-	-	−0.332	−0.865	1.586
	(0.983)			(0.607)	(0.763)	[0.663]
Vietnam	0.920	-	-	0.848	1.052	2.573
	(0.784)			(0.667)	(0.797)	[0.462]
D. All Three Markets Included						
India	−0.512	0.148	−0.256	−0.244	−0.146	1.325
	(0.742)	(0.769)	(0.559)	(0.711)	(0.587)	[0.932]
Indonesia	−0.012	1.666	1.670	0.646	2.051	2.823
	(0.647)	(1.727)	(1.467)	(0.922)	(1.856)	[0.727]
Korea	−0.929	−0.140	−0.433	−0.849	0.726	3.964
	(0.928)	(1.253)	(0.866)	(0.587)	(1.753)	[0.555]
Malaysia	−0.598	0.108	0.229	0.146	0.128	1.963
	(0.600)	(0.403)	(0.282)	(0.291)	(0.156)	[0.854]
Pakistan	0.795	0.846	0.625	0.307	1.787	3.897
	(0.682)	(0.719)	(0.738)	(0.555)	(1.367)	[0.564]
Philippines	0.610	0.735	0.475	0.076	0.506	2.626
	(0.670)	(1.077)	(0.698)	(0.394)	(0.449)	[0.757]
Sri Lanka	0.296	0.126	0.077	−0.228	−0.467	2.662
	(0.486)	(0.488)	(0.427)	(0.424)	(0.400)	[0.752]
Taiwan	−0.670	0.167	0.142	−0.232	−0.208	3.503
	(0.585)	(0.847)	(0.496)	(0.568)	(0.474)	[0.623]
Thailand	−0.530	0.544	−0.211	−0.246	−0.767	2.356
	(0.983)	(1.123)	(0.611)	(0.508)	(0.733)	[0.798]
Vietnam	0.944	1.386	1.539	0.820	1.094	4.058
	(0.780)	(1.143)	(0.977)	(0.657)	(0.794)	[0.541]

2.4.2 Mean Spillover Effects of Local, Regional and U.S. Factors

In this section, I investigate whether the regional factor, compared with the local or U.S. factor, plays an important role in returns of a local equity market by checking if coefficients on lagged returns are significant. The second, fifth and eighth columns of Table 2.4 report the estimates of coefficients on lagged local returns ($\hat{\alpha}_1$'s) together with the standard White [1980, 1994] correction for heteroskedasticity with the Australian, Chinese and Japanese markets as the regional center, respectively. The local effects of the Korean, Pakistani, Sri Lankan and Vietnamese markets are all found significant at the 1% level. Among those four markets, the coefficient is negative for Korea while positive for the other three, which is broadly in line with the findings reported by Beirne et al. [2009]. According to the authors, if returns of regional emerging markets and global mature markets are endogenized, the estimated coefficient of the first-order autoregressive term is significantly positive for Pakistan and Sri Lanka while insignificantly negative for Korea. This study serves as a supplement to Beirne et al. [2009] in the sense that I treat returns of the regional and U.S. markets as independent variables.

The coefficients measuring the effect of the U.S. market ($\hat{\alpha}_2$'s) for each regional market are listed in the fourth, seventh and tenth columns of the same table. Without exception, these coefficients are positive and significant at least at the 5% level, which indicates that lagged U.S. market returns have a strong positive impact on the current returns of all of the local markets concerned. These findings bear striking similarities to the results obtained by Beirne et al. [2009] once more, although they used a weighted average of the indices of six mature markets while I apply two separate indices in my own research. Additionally, the three columns show that the U.S. market has a rather strong spillover effect upon Korea, Indonesia, Philippines and Taiwan.

The third, sixth and ninth columns of Table 2.4 present the coefficients on lagged regional returns ($\hat{\alpha}_3$'s) with their robust standard errors. Most of them are not significant—a

Table 2.4: Details on Estimated Coefficients (I)—Mean Equation

Displayed in this table are the estimated coefficients in mean equation (2.4a) together with their robust standard errors in parentheses—$\hat{\alpha}_1$ on lagged local returns, $\hat{\alpha}_2$ on lagged U.S. returns and $\hat{\alpha}_3$ on lagged regional returns. The asterisks, plus and double plus superscripts indicate significance at the 1%, 5% and 10% levels, respectively.

Market	*Australian Market as Regional Center*			*Chinese Market as Regional Center*			*Japanese Market as Regional Center*		
	Local Effect	*Regional Effect*	*U.S. Effect*	*Local Effect*	*Regional Effect*	*U.S. Effect*	*Local Effect*	*Regional Effect*	*U.S. Effect*
India	−0.022	−0.031	0.346^{*}	−0.045	0.021	0.336^{*}	−0.041	0.032	0.339^{*}
	(0.038)	(0.034)	(0.045)	(0.051)	(0.071)	(0.044)	(0.033)	(0.032)	(0.044)
Indonesia	−0.009	−0.032	0.523^{*}	0.017	$-0.087^{\dagger}$	0.520^{*}	−0.017	−0.033	0.505^{*}
	(0.044)	(0.048)	(0.051)	(0.043)	(0.044)	(0.048)	(0.040)	(0.040)	(0.048)
Korea	-0.166^{*}	$0.087^{\ddagger}$	0.702^{*}	-0.126^{*}	0.024	0.723^{*}	-0.119^{*}	0.017	0.728^{*}
	(0.037)	(0.046)	(0.044)	(0.037)	(0.045)	(0.041)	(0.027)	(0.025)	(0.042)
Malaysia	0.010	−0.006	0.314^{*}	0.025	−0.022	0.316^{*}	0.015	−0.019	0.311^{*}
	(0.045)	(0.024)	(0.025)	(0.054)	(0.025)	(0.024)	(0.067)	(0.021)	(0.025)
Pakistan	0.103^{*}	0.030	$0.063^{\dagger}$	0.104^{*}	0.027	$0.065^{\dagger}$	0.103^{*}	0.042	$0.072^{\dagger}$
	(0.032)	(0.022)	(0.026)	(0.033)	(0.036)	(0.027)	(0.033)	(0.029)	(0.030)
Philippines	$0.048^{\ddagger}$	−0.002	0.523^{*}	0.036	0.027	0.514^{*}	$0.068^{\dagger}$	$-0.051^{\ddagger}$	0.520^{*}
	(0.029)	(0.002)	(0.037)	(0.033)	(0.038)	(0.036)	(0.031)	(0.029)	(0.036)
Sri Lanka	0.258^{*}	−0.002	0.087^{*}	0.252^{*}	0.022	0.079^{*}	0.251^{*}	$0.041^{\ddagger}$	0.084^{*}
	(0.033)	(0.016)	(0.027)	(0.033)	(0.025)	(0.026)	(0.033)	(0.025)	(0.026)
Taiwan	−0.036	0.021	0.466^{*}	−0.020	−0.003	0.474^{*}	−0.006	−0.036	0.470^{*}
	(0.031)	(0.026)	(0.033)	(0.039)	(0.020)	(0.032)	(0.036)	(0.029)	(0.032)
Thailand	−0.044	0.003	0.387^{*}	−0.021	−0.036	0.393^{*}	−0.047	0.027	0.389^{*}
	(0.033)	(0.003)	(0.038)	(0.037)	(0.039)	(0.037)	(0.032)	(0.029)	(0.037)
Vietnam	0.166^{*}	0.022	0.282^{*}	0.172^{*}	0.024	0.283^{*}	0.181^{*}	−0.026	0.290^{*}
	(0.031)	(0.031)	(0.036)	(0.030)	(0.037)	(0.034)	(0.031)	(0.035)	(0.033)

few exceptions include the China-Indonesia case, where the coefficient is negative and significant at the 5% level, and three more cases where the coefficients are found weakly significant. Although returns of a regional market are treated differently in the mean equation, these findings agree with the results shown by Miyakoshi [2003], who argues that in terms of mean spillovers, the United States has a strong effect on emerging Asia whereas a large Asia-Pacific market such as Japan has little.

Table 2.5, the counterpart of Table 2.4 in the case where all three regional markets are incorporated in the mean equation, tells a very similar story regarding regional factors. Presented in columns 3–5 of Table 2.5, the coefficients on the three regional factors ($\hat{\alpha}_3$–$\hat{\alpha}_5$'s) suggest little mean spillovers from the regional to most of the local markets, whereas the parameter estimates for the U.S. effect ($\hat{\alpha}_2$'s) in the last column are significant in all of the markets. These results correspond to the financial spillover literature. For instance, in both studies conducted by Miyakoshi [2003] and Beirne et al. [2009], regional factors are found less important relative to global ones as few coefficients measuring regional effects are significant. Nonetheless, two exceptions to the above observations are the Korean and Philippine markets, on which lagged Australian and Japanese returns have a significant impact, respectively. On the other hand, the own-market effect measured by the coefficients on lagged local returns ($\hat{\alpha}_1$'s) is found significant in four local markets, among which only the Korean market is negatively affected by its own lagged returns.

In terms of the regional effects of the Greater Chinese and Australian markets, little is uncovered by the existing literature. It is, therefore, worth summarizing some of the interesting findings presented in Tables 2.4 and 2.5. Since the 2007–2009 global financial crisis, the lagged returns of the U.S. market have influenced all of the local markets concerned in this study in a nontrivial way—they all keep pace with the U.S. market, as suggested by the fact that the U.S. effect is uniformly positive. Predominantly export-orientated, the Asia-Pacific economies under study have established close trade relations with the United

Table 2.5: Details on Estimated Coefficients (II)—Mean Equation

Displayed in this table are the estimated coefficients in mean equation (2.5a) along with their robust standard errors in parentheses—$\hat{\alpha}_1$ on lagged local returns, $\hat{\alpha}_2$ on lagged U.S. returns and $\hat{\alpha}_3$—$\hat{\alpha}_5$ on lagged Australian, Chinese and Japanese returns, respectively. The asterisks, plus and double plus superscripts indicate significance at the 1%, 5% and 10% levels, respectively.

Market	*Local Effect*	*Regional Effect*			*U.S. Effect*
		Australian Market	*Chinese Market*	*Japanese Market*	
India	−0.033 (0.033)	−0.078 (0.050)	0.052 (0.054)	0.048 (0.040)	0.360* (0.047)
Indonesia	0.017 (0.043)	0.020 (0.082)	−0.094 (0.060)	−0.021 (0.034)	0.518* (0.055)
Korea	−0.166* (0.035)	0.088‡ (0.047)	0.002 (0.008)	−0.005 (0.008)	0.701* (0.043)
Malaysia	0.026 (0.038)	0.011 (0.044)	−0.026 (0.033)	−0.015 (0.024)	0.311* (0.028)
Pakistan	0.102* (0.033)	0.015 (0.020)	−0.003 (0.007)	0.033 (0.025)	0.067† (0.028)
Philippines	0.049 (0.032)	0.004 (0.005)	0.044 (0.035)	−0.068† (0.030)	0.509* (0.036)
Sri Lanka	0.255* (0.033)	−0.035 (0.033)	0.028 (0.027)	0.042 (0.028)	0.095* (0.029)
Taiwan	−0.022 (0.034)	0.038 (0.035)	−0.008 (0.046)	−0.048 (0.037)	0.457* (0.036)
Thailand	−0.028 (0.041)	0.013 (0.031)	−0.057 (0.037)	0.036 (0.032)	0.392* (0.038)
Vietnam	0.172* (0.048)	0.035 (0.102)	0.019 (0.238)	−0.063 (0.059)	0.271* (0.038)

States, which may contribute to further financial integration of these countries with the United States and thus vulnerability of their equity markets to U.S. shocks. What's more, for eight local markets, the estimated coefficients on lagged home returns are much smaller in terms of order of magnitude than those on lagged U.S. returns while the opposite is true for Sri Lanka and Pakistan. It is implied that all of the local markets may well become susceptible to U.S. market during the period covered by this study with the exception of Pakistan and Sri Lanka. Thus, although it might not be so effective for investors to diversify their portfolios by adding stocks originating in most of these economies, there might still be some room for further portfolio diversification by exploiting both exceptions.

On the contrary, lagged returns of a regional market, whether it be Australia, China or Japan, barely have any significant effect on the local markets. Consistent with what Dekker et al. [2001] find, these results extend the line of research on the dynamics of mean spillovers among a small Asia-Pacific equity market, a regional leading market and a global mature market to include the recent financial crisis. In addition, it must be noted that because Chi et al. [2006]'s sample data spanning over ten years enabled the authors to consider long-run equilibrium, their results contrast but do not necessarily conflict with mine, which are probably more related to short-term equilibrium as a result of a much smaller sample.

It is worth mentioning that the Vietnamese market reacts positively to both lagged information of its own and that from the U.S. market but insignificantly to any of the regional markets, which not merely adds to the current literature since the new emerging market, to my knowledge, has seldom been documented elsewhere but also provides preliminary insights for those financial practitioners interested in investing in its stock market.

Table 2.6 documents the details of estimating the conditional variances. The coefficients measuring the GARCH effect are significant for all of the small markets regardless of the assumption about which market plays the role of the regional center. The magnitude of the estimates of β_2's suggests a high degree of persistence of market sentiment towards previous domestic news in emerging Asia. More than half of the coefficients which estimate the ARCH effect (β_1's)are also significant. On average, the local markets in question become much more volatile during the shaded period, as shown in the upper left panels of Figures A.1–A.4 in the appendices. For most of them, the estimated conditional variances rose dramatically in October 2008 when the 2007–2008 U.S. sub-prime mortgage crisis started to spread worldwide. One exception is the Sri Lankan market, which turned quite volatile in June 2009 when NBER officially announced the end of the recent recession.

Several markedly different patterns have been observed so far as it relates to the dynamics of the level of market volatility during the recession period. The volatility levels of such markets as Taiwan and Vietnam appear to rise and fall by a moderate amount and it took these markets as long as six months to go back to normal; others like Korea and Thailand turned super-turbulent during a relatively short-lived period—their corresponding estimated variances surged and then plummeted within a few days or weeks.

A possible explanation for the observed patterns is that these countries may receive market news from abroad (mainly the U.S. market) through various channels—international trade ties, foreign currency policies, foreign direct investment, to name just a few. Easy access to such channels enables a market to keep updated on and react promptly to foreign information. As a result, any surprising news can be digested so well that the informationally efficient market will not be thrown into turmoil. However, it could take the market a long while to recover, as it synchronizes with the origin(s) of shocks. The domestic market of a country with little or no access to such channels will have a low degree of co-movement with global markets and follow a completely opposite pattern—it could turn extremely volatile within a very short period of time and quickly recover afterwards.

2.5 Conclusion

In this chapter, I study the dynamics of ten emerging Asian markets' annualized daily equity returns spanning June 2008 to May 2013 in an AR(1)–GARCH(1,1) model which takes into account mean spillovers from three large Asia-Pacific markets and the U.S. market. For this purpose, I incorporate lagged returns of the U.S. market and one regional market in the mean equation. An alternative model specification of the mean equation is also proposed which includes lagged returns of all three regional markets simultaneously. In the variance equation, market asymmetry is captured by the use of a GJR–GARCH model. Both symmetric and asymmetric model specifications are estimated; the better fitting model

Table 2.6: Details on Estimated Coefficients (III)—Variance Equation

Displayed in this table are the estimated coefficients in the variance equation together with their robust standard errors in parentheses—$\hat{\beta}_1$ measuring the ARCH effect and $\hat{\beta}_2$ the GARCH effect. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively.

Market	*Australia as Regional Center*		*China as Regional Center*		*Japan as Regional Center*		*All Three Markets Included*	
	ARCH Effect	*GARCH Effect*	*ARCH Effect*	*GARCH Effect*	*ARCH Effect*	*GARCH Effect*	*ARCH Effect*	*GARCH Effect*
India	0.046	0.921^{*}	0.047	0.919^{*}	0.046	0.919^{*}	0.045	0.920^{*}
	(0.032)	(0.021)	(0.033)	(0.022)	(0.031)	(0.021)	(0.032)	(0.021)
Indonesia	$0.035^{\dagger}$	0.919^{*}	$0.035^{\dagger}$	0.919^{*}	$0.036^{\dagger}$	0.919^{*}	$0.036^{\dagger}$	0.919^{*}
	(0.014)	(0.020)	(0.014)	(0.020)	(0.015)	(0.022)	(0.014)	(0.022)
Korea	0.010	0.892^{*}	0.005	0.898^{*}	0.005	0.897^{*}	0.010	0.892^{*}
	(0.018)	(0.032)	(0.007)	(0.024)	(0.008)	(0.024)	(0.015)	(0.031)
Malaysia	$0.030^{\dagger}$	0.915^{*}	$0.032^{\dagger}$	0.916^{*}	$0.031^{\dagger}$	0.917^{*}	$0.031^{\dagger}$	0.916^{*}
	(0.013)	(0.019)	(0.014)	(0.021)	(0.014)	(0.024)	(0.013)	(0.022)
Pakistan	0.062^{*}	0.829^{*}	0.060^{*}	0.830^{*}	0.060^{*}	0.830^{*}	0.062^{*}	0.828^{*}
	(0.020)	(0.028)	(0.020)	(0.027)	(0.020)	(0.027)	(0.021)	(0.029)
Philippines	0.080^{*}	0.850^{*}	0.077^{*}	0.857^{*}	0.077^{*}	0.853^{*}	$0.073^{\dagger}$	0.859^{*}
	(0.028)	(0.055)	(0.026)	(0.047)	(0.028)	(0.051)	(0.029)	(0.051)
Sri Lanka	0.117^{*}	0.883^{*}	0.119^{*}	0.881^{*}	0.122^{*}	0.880^{*}	0.121^{*}	0.881^{*}
	(0.027)	(0.024)	(0.029)	(0.027)	(0.030)	(0.027)	(0.029)	(0.026)
Taiwan	-4.970×10^{-4}	0.958^{*}	-0.001	0.960^{*}	-9.144×10^{-4}	0.960^{*}	8.175×10^{-4}	0.958^{*}
	(0.002)	(0.013)	(0.003)	(0.015)	(0.004)	(0.012)	(0.001)	(0.016)
Thailand	0.043^{*}	0.893^{*}	$0.041^{\dagger}$	0.894^{*}	0.042^{*}	0.892^{*}	$0.040^{\dagger}$	0.896^{*}
	(0.017)	(0.021)	(0.016)	(0.022)	(0.016)	(0.023)	(0.016)	(0.021)
Vietnam	0.134^{*}	0.791^{*}	0.132^{*}	0.792^{*}	$0.141^{\dagger}$	0.779^{*}	0.142^{*}	0.778^{*}
	(0.044)	(0.061)	(0.042)	(0.060)	(0.064)	(0.080)	(0.045)	(0.127)

is chosen based on the specification test results. The asymmetric model is more suitable for all of the local markets but Sri Lanka.

The empirical results lead to the following conclusions. Firstly, the own-market effect of four local markets (Pakistan, South Korea, Sri Lanka and Vietnam) are found to be significant at the 1% level over the covered period. Among them, only the Korean market is negatively affected by its own lagged returns. Secondly, the analysis suggests that the U.S. market has exerted a significant influence upon all of the local markets. In every local market except for Sri Lanka and Pakistan, the estimated coefficients on lagged domestic returns are much smaller in terms of order of magnitude than those on lagged U.S. returns. In contrast, the large Asia-Pacific markets involved in this study have few mean spillover effects upon the ten local markets in general. Finally, all of the small emerging markets under study show a high degree of persistence of market sentiment towards previous domestic news. Two distinct patterns, however, have been observed of how these markets reacted to foreign (mainly U.S.) shocks during the recent financial crisis.

In order to further investigate the spillover effects of a large Asia-Pacific market upon a small one, it is undoubtedly worthwhile to extend current research to incorporate volatility transmission. The next two chapters will concentrate on this extension—I shall employ a bivariate GARCH model to examine the linkage between the U.S. market and a large Asian market in Chapter 3 while discussing time-varying correlations of a local market to a regional market and to the U.S. market in Chapter 4.

CHAPTER 3

Volatility Transmission Between the U.S. and a Large Asia-Pacific Stock Market

Applying a simple AR–GARCH model and taking into consideration mean spillovers from the U.S. market and three large Asia-Pacific markets, I investigate the dynamics of ten emerging Asian markets' annualized daily equity returns spanning June 2008 to May 2013 in Chapter 2. In order to further study the spillover effect of the regional market upon a local one, I shall focus on the impact of volatility transmission in addition to that of mean spillovers. Before doing so, I need to correctly specify the underlying process of interaction between the regional and the U.S. market. In this chapter, I employ a bivariate GARCH model to examine the linkage between the U.S. and a large Asian market. The whole chapter is organized as follows. The employed bivariate GARCH specifications and post-estimation diagnostic tests are detailed in the first two sections. Section 3.3 gives in-depth analysis of the empirical findings. Conclusions are offered in the final section.

3.1 Two Bivariate GARCH Model Specifications

Bekaert and Harvey [1997] proposed a model, which allows the local and the world shock to impact dynamically upon the return and volatility of an emerging market. Ng [2000] extended their work by taking into account the effect of a regional shock. I employ the same extension as in Ng [2000] in order to compare the impact on the volatility of a local market of shocks of Chinese origin with the impact of those of Australian or Japanese origin. I deal with the first step of the two-step estimation procedure in Bekaert and Harvey [1997]'s approach in this chapter. The second step, which involves estimating a univariate volatility transmission model for the ten local markets, will be discussed in the next chapter.

I now turn to a discussion of Ng [2000]'s two-factor approach and elaborate on her methodology with the U.S.–China case. The same set of equations also applies to both the

U.S.–Australia and the U.S.–Japan cases. A bivariate VAR–GARCH model governs the joint process for daily returns of MSCI USA and MSCI Zhong Hua Indices, denoted by $\mathbf{R}_t = (R_{US,t}, R_{CN,t})^\top$:

$$\mathbf{R}_t = \boldsymbol{\alpha} + \boldsymbol{\beta}\mathbf{R}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{3.1a}$$

$$\boldsymbol{\varepsilon}_t | \mathcal{F}_{t-1} \sim \mathcal{N}(\mathbf{0}, \mathbf{H}_t), \tag{3.1b}$$

where $\boldsymbol{\alpha} = (\alpha_1, \alpha_2)^\top$ is the intercept vector and $\boldsymbol{\beta}$ a 2×2 matrix of parameters which link lagged returns in the American and the Chinese market to expected returns. The vector of innovations at time t, $\boldsymbol{\varepsilon}_t = (\varepsilon_{US,t}, \varepsilon_{CN,t})^\top$, is assumed to be normally distributed with zero mean and a 2×2 variance-covariance matrix $\mathbf{H}_t$, conditional on the information set up to time $t-1$, which includes $\mathbf{H}_{t-1}$, $\boldsymbol{\varepsilon}_{t-1}$ and their lagged values, i.e. $\mathcal{F}_{t-1} = \{\mathbf{H}_{t-1}, \boldsymbol{\varepsilon}_{t-1}, \mathcal{F}_{t-2}\}$. With regard to the form of $\mathbf{H}_t$, two different specifications are considered in this paper: a BEKK model proposed by Baba et al. [1989] and Engle and Kroner [1995] and a general dynamic covariance (henceforth, DC) model by Kroner and Ng [1998]. Both specifications incorporate and emphasize the features pertaining to asymmetries, persistence and time-varying correlations.

(I) *BEKK model*. The 'full' version of the BEKK model is illustrated as follows:

$$\mathbf{H}_t = \mathbf{C}'\mathbf{C} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{A} + \mathbf{G}'\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1}\mathbf{G}, \tag{3.2}$$

where $\mathbf{C} = \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{22} \end{pmatrix}$, $\mathbf{B} = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}$, $\mathbf{A} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix}$, and $\mathbf{G} = \begin{pmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{pmatrix}$ are all 2×2 matrices, with $\mathbf{C}$ upper triangular. The asymmetric BEKK model is an extension of its symmetric counterpart, taking into account the finding repeatedly recorded in the literature that the market turns more volatile subsequent to a negative shock in comparison with a positive one of the same magnitude. In order to incorporate market asymmetries, I include in equation (3.2) the term $\boldsymbol{\eta}_{t-1} = \left(\varepsilon_{US,t-1}\mathbf{I}, \varepsilon_{CN,t-1}\mathbf{I}\right)^{\top}$, in which the indicator function **I** takes the value of 1 when $\varepsilon_{US,t-1}$ $(\varepsilon_{CN,t-1})$ is negative and 0 otherwise. Glosten et al. [1993] first proposed modelling the leverage effect for a univariate GARCH process in this way. The BEKK model employed in this paper is 'full' in the sense that no extra restrictions except those which guarantee identifiability of the parameters and covariance stationarity of the multivariate GARCH process are imposed on the coefficient matrice **A**, **B** and **G**. If the off-diagonal elements of the matrices **A**, **B** and **G** are restricted to being zero, the Full-BEKK model will reduce to the Diag-BEKK model. The Scalar-BEKK model is derived by setting the elements of each coefficient matrix equal to one another. The setup of the full BEKK model ensures that the conditional covariance matrix is positive definite since all the terms on the right-hand side of equation (3.2) are expressed in quadratic forms. Twenty one parameters in total need estimating simultaneously for the asymmetric version of the VAR–BEKK model.

(II) *DC model*. The general dynamic covariance model is presented in equations (3.3)–(3.4):

$$\begin{aligned}\mathbf{H}_t &= \begin{pmatrix} \sqrt{\theta_{11,t}} & 0 \\ 0 & \sqrt{\theta_{22,t}} \end{pmatrix} \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \begin{pmatrix} \sqrt{\theta_{11,t}} & 0 \\ 0 & \sqrt{\theta_{22,t}} \end{pmatrix} + \begin{pmatrix} 0 & \lambda \\ \lambda & 0 \end{pmatrix} \circ \begin{pmatrix} \theta_{11,t} & \theta_{12,t} \\ \theta_{12,t} & \theta_{22,t} \end{pmatrix} \\ &= \begin{pmatrix} \theta_{11,t} & \rho\sqrt{\theta_{11,t}}\sqrt{\theta_{22,t}} + \lambda\theta_{12,t} \\ \rho\sqrt{\theta_{11,t}}\sqrt{\theta_{22,t}} + \lambda\theta_{12,t} & \theta_{22,t} \end{pmatrix},\end{aligned} \tag{3.3}$$

where $\circ$ represents entrywise matrix multiplication and $\boldsymbol{\theta}_t = \left(\begin{smallmatrix} \theta_{11,\,t} & \theta_{12,\,t} \\ \theta_{12,\,t} & \theta_{22,\,t} \end{smallmatrix}\right)$ shares a common specification with the conditional covariance matrix in the BEKK model:

$$\begin{aligned}
\boldsymbol{\theta}_t =& \mathbf{C}'\mathbf{C} + \mathbf{B}'\boldsymbol{\theta}_{t-1}\mathbf{B} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}\mathbf{A} + \mathbf{G}'\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1}\mathbf{G} \\
=& \begin{pmatrix} C_{11} & 0 \\ C_{12} & C_{22} \end{pmatrix} \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{22} \end{pmatrix} + \begin{pmatrix} B_{11} & B_{21} \\ B_{12} & B_{22} \end{pmatrix} \boldsymbol{\theta}_{t-1} \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} + \\
& \begin{pmatrix} A_{11} & A_{21} \\ A_{12} & A_{22} \end{pmatrix} \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} + \begin{pmatrix} G_{11} & G_{21} \\ G_{12} & G_{22} \end{pmatrix} \boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1} \begin{pmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{pmatrix}
\end{aligned} \tag{3.4}$$

so that the DC model is subject to the same system of inequalities which constrains the BEKK model as well. The DC model nests three multivariate GARCH parametrisations other than the BEKK model: the constant correlation (henceforth, CCORR) model of Bollerslev [1990], the factor ARCH (henceforth, FARCH) model of Ng et al. [1992] and the VEC model of Bollerslev et al. [1988]. Kroner and Ng [1998] provide detailed discussions on the conditions under which the DC model will be reduced to the aforementioned specifications. In order for the model to behave in a proper way, such two constraints as $|\rho| < 1$ and $|\rho| + |\lambda| < 1$ must be imposed besides those of the BEKK model. For the asymmetric VAR–DC model, twenty three parameters need to be simultaneously estimated.

The VAR–BEKK model (3.1a), (3.1b), (3.2) and the VAR–DC model (3.1a), (3.1b), (3.3), (3.4) are estimated by maximizing the quasi-likelihood function:

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\xi}) &= \sum_{t=1}^{T} l_t\left(\boldsymbol{\xi};\, \mathbf{R}_t,\, \mathbf{R}_{t-1}\right) \\
&= -T\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\Big[\log\left(\left|\mathbf{H}_t\left(\mathbf{R}_t,\, \mathbf{R}_{t-1};\, \boldsymbol{\xi}\right)\right|\right) + \boldsymbol{\varepsilon}_t^{\top}\left(\mathbf{R}_t,\, \mathbf{R}_{t-1};\, \boldsymbol{\xi}\right)\mathbf{H}_t^{-1}\boldsymbol{\varepsilon}_t\left(\mathbf{R}_t,\, \mathbf{R}_{t-1};\, \boldsymbol{\xi}\right)\Big],
\end{aligned} \tag{3.5}$$

where T represents the total number of vectors of innovation entering the estimation and $\boldsymbol{\xi}$ contains the entire parameters of the bivariate model. The prefix 'quasi' indicates that the conditional distribution of $\boldsymbol{\varepsilon}_t$ could be misspecified. Even though the true distribution of the error term is non-normal, the quasi-maximum likelihood estimates (QMLE) are asymptotically normally distributed under standard regularity conditions and generally consistent (see theorem 2.1 and conditions A.1 in Appendix A of Bollerslev and Wooldridge [1992]). Robust to misspecification of the distribution of errors, the Huber-White sandwich estimator is applied to estimate the variance-covariance matrix of the QMLEs (see White [1980, 1994]). The parameters are obtained by maximizing the quasi-log-likelihood functions in (3.5). I apply the BFGS algorithm to solve the non-linear optimisation problem and supply at least twenty initial values to avoid local maxima.

3.2 Diagnostic Tests

To determine whether the bivariate model is correctly specified, I take a closer look at the assumption that the vector of innovations $\boldsymbol{\varepsilon}_t = (\varepsilon_{US,t}, \varepsilon_{CN,t})^\top$ follows the bivariate normal distribution. Within the framework presented by Richardson and Smith [1993] for the test for multivariate normality, I check if the Cholesky residuals from the VAR model (3.1a)–(3.1b) violate the orthogonality conditions implied by the bivariate normal distribution.

The Cholesky residuals are computed by scaling the vector of residuals derived from the joint estimation of the VAR–BEKK (VAR–DC) model in the following way: $\mathbf{z}_t = \mathbf{U}^{\top}{}_t^{-1}\hat{\boldsymbol{\varepsilon}}_t$, where $\mathbf{U}_t$ is a upper triangular matrix with real and positive diagonal elements and the unique Cholesky factor of $\hat{\mathbf{H}}_t$: $\mathbf{U}^{\top}{}_t\mathbf{U}_t = \hat{\mathbf{H}}_t$. The set-up of both BEKK and dynamic covariance models ensures that the covariance matrix ($\mathbf{H}_t$) is symmetric positive definite (*s.p.d.*). Every *s.p.d.* matrix has one and only one Cholesky decomposition (see theorems 6.1 and 6.3 of Stefanica [2014]). Note that the residuals become uncorrelated after standardization.[1] Triantafyllopoulos [2002] discusses a general method for calculating moments of the multivariate Gaussian distributions. Listed below are the product moments up to the fourth order of two uncorrelated random variables subject to the bivariate normal distribution with mean zero and unit variance.

(a) *Serial correlation*. Moment conditions (3.6a)–(3.6c) examine whether the Cholesky and the squared Cholesky residual of country $i \in \{AU, CN, JP, US\}$ and the product of the Cholesky residuals of U.S. and regional market $j \in \{AU, CN, JP\}$ are autocorrelated up to the fifth order, respectively. These conditions are tested separately with the test statistics asymptotically following the $\chi^2(5)$ distribution; equations (3.6a), (3.6b) and (3.6c) are also estimated by a joint test, which gives a test statistic subject to the $\chi^2(25)$ distribution.

$$E\left(z_{i,t} z_{i,t-k}\right) = 0, \tag{3.6a}$$

$$E\left[\left(z_{i,t}^2 - 1\right)\left(z_{i,t-k}^2 - 1\right)\right] = 0, \tag{3.6b}$$

$$E\left[\left(z_{US,t} z_{j,t}\right)\left(z_{US,t-k} z_{j,t-k}\right)\right] = 0, k = 1, 2, ..., 5. \tag{3.6c}$$

(b) *Bivariate normality*. I employ the higher order moments below to test the null hypothesis that the residuals are subject to the bivariate normal distribution from the perspective of skewness (3.7a), cross-skewness (3.7b), kurtosis (3.7c) and cross-kurtosis (3.7d). All of the hypothesis tests have one degree of freedom except the one on cross-skewness,

[1] Let $\boldsymbol{\Sigma}_t = \left(\begin{smallmatrix} \sigma_{1,t}^2 & \rho_{12,t}\sigma_{1,t}\sigma_{2,t} \\ \rho_{12,t}\sigma_{1,t}\sigma_{2,t} & \sigma_{2,t}^2 \end{smallmatrix}\right)$ denote the covariance matrix of $\boldsymbol{\epsilon}_t = (\epsilon_{1,t}, \epsilon_{2,t})^\top$, where $\sigma_{1,t}, \sigma_{2,t} > 0$ are the standard deviations of $\epsilon_{1,t}$ and $\epsilon_{2,t}$, respectively, and $-1 \leq \rho_{12,t} \leq 1$ the correlation coefficient between them. $\mathbf{M}_t = \left(\begin{smallmatrix} \sigma_{1,t} & \rho_{12,t}\sigma_{2,t} \\ 0 & \sigma_{2,t}\sqrt{1-\rho_{12,t}^2} \end{smallmatrix}\right)$ is the Cholesky factor of Σ_t. The two random variables in the random vector $\mathbf{r}_t = \mathbf{M}_t^{\top -1}\boldsymbol{\epsilon}_t = \frac{1}{\sigma_{1,t}\sigma_{2,t}\sqrt{1-\rho_{12,t}^2}}\left(\begin{smallmatrix} \sigma_{2,t}\sqrt{1-\rho_{12,t}^2} & 0 \\ -\rho_{12,t}\sigma_{2,t}\sigma_{2,t} & \sigma_{1,t} \end{smallmatrix}\right)\left(\begin{smallmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \end{smallmatrix}\right) = \left(\begin{smallmatrix} \frac{\epsilon_{1,t}}{\sigma_{1,t}} \\ -\frac{\rho_{12,t}\epsilon_{1,t}}{\sigma_{1,t}\sqrt{1-\rho_{12,t}^2}} + \frac{\epsilon_{2,t}}{\sigma_{2,t}\sqrt{1-\rho_{12,t}^2}} \end{smallmatrix}\right)$ is uncorrelated, since $Cov\left(\frac{\epsilon_{1,t}}{\sigma_{1,t}}, -\frac{\rho_{12,t}\epsilon_{1,t}}{\sigma_{1,t}\sqrt{1-\rho_{12,t}^2}} + \frac{\epsilon_{2,t}}{\sigma_{2,t}\sqrt{1-\rho_{12,t}^2}}\right) = -\frac{\rho_{12,t}}{\sigma_{1,t}^2\sqrt{1-\rho_{12,t}^2}}\sigma_{1,t}^2 + \frac{1}{\sigma_{1,t}\sigma_{2,t}\sqrt{1-\rho_{12,t}^2}} Cov(\epsilon_{1,t}, \epsilon_{2,t}) = -\frac{\rho_{12,t}}{\sqrt{1-\rho_{12,t}^2}} + \frac{\rho_{12,t}}{\sqrt{1-\rho_{12,t}^2}} = 0.$

which derives a $\chi^2(2)$ statistic. A joint test (3.7a)–(3.7d) is also conducted with the test statistic asymptotically $\chi^2(7)$ distributed.

$$E\left(z_{i,t}^3\right) = 0, \tag{3.7a}$$

$$E\left(z_{US,t}^2 z_{j,t}\right) = 0, E\left(z_{US,t} z_{j,t}^2\right) = 0, \tag{3.7b}$$

$$E\left(z_{i,t}^4\right) = 3, \tag{3.7c}$$

$$E\left(z_{US,t}^2 z_{j,t}^2\right) = 1. \tag{3.7d}$$

(c) *Sign bias*. The following moment conditions check how capable the four model specifications are in capturing leverage-type asymmetries in the return series. As is emphasized by Engle and Ng [1993], the effect of a lagged shock on current variance and covariance may depend not only on the magnitude of the shock but on its sign as well. Moment conditions (3.8a), (3.8b) and (3.8c) test whether the data display the sign, the negative sign and the positive sign bias, respectively.

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} < 0\right)\right] = 0, \tag{3.8a}$$

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} < 0\right) z_{i,t-1}\right] = 0, \tag{3.8b}$$

$$E\left[\left(z_{i,t}^2 - 1\right) I\left(z_{i,t-1} \geq 0\right) z_{i,t-1}\right] = 0. \tag{3.8c}$$

The moment conditions mentioned above are tested with the general moment method. The weight matrix is adapted to be heteroskedasticity and autocorrelation consistent by the use of the Parzen kernel with the lag order selected by Newey and West [1994]'s optimal lag-selection algorithm. Significance of test statistics is evaluated by empirical p-values, which are obtained from 5,000 Monte-Carlo simulations. In all of the Monte Carlo experiments, weight matrices are also adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel. Proposed by Davison and Hinkley [1997], calculation of empirical p-values is carried out in the following way: $\hat{p} = \frac{m+1}{n+1}$, where m stands for the total number of those replicates that produce a test statistic greater than or equal to the one calculated for the actual data and n for the total number of simulations.

3.3 Empirical Results

3.3.1 Diagnostic Test Results

Tables 3.1–3.4 report the parameters obtained from estimating both BEKK and DC models in the previous section. The estimates provide guidance on selecting the more appropriate bivariate model specification. All parameters are well estimated, as is evidenced by their small standard errors. Firstly, I check whether the DC model can be reduced to the full BEKK or other multivariate GARCH model specifications. According to Kroner and Ng [1998], the dynamic covariance model will be reduced to the BEKK model if $\rho = 0$ and $\lambda = 1$, and to the CCORR model if $\lambda = 0$. The *t*-statistics for the null hypothesis of $\rho = 0$ are 16.097 (U.S.–Australia), 8.282 (U.S.–China) and 6.007 (U.S.–Japan). Thus, the null is rejected at the conventional significance levels in all three cases. The null of $\lambda = 1$ is also rejected with the corresponding *t*-statistics being -15.291 (U.S.–Australia), -15.515 (U.S.–China) and -1.710 (U.S.–Japan). I may also reject the null of $\lambda = 0$ in the U.S.–Australia and the U.S.–Japan cases (the corresponding *t*-statistics are 2.915 and 3.465, respectively). These results indicate that all of the estimated DC models statistically differ from the full BEKK one. Nonetheless, the dynamic covariance specification of the U.S.–China case can be reduced to the CCORR model, since the null hypothesis of $\lambda = 0$ cannot be rejected.

It is of utmost importance to specify the interrelationship between the American and regional market returns with appropriate multivariate GARCH models, as the main goal of this dissertation is to quantify interdependence among a small Asia-Pacific equity market, a large one and the American equity market. In each of the three regional cases, selection of a best fitting bivariate model is based mainly on the results of the GMM-based model spec-

Table 3.1: Estimation of Asymmetric BEKK Model

Table 3.1 reports the quasi-maximum likelihood estimates and their robust standard errors (in parentheses) of the VAR–BEKK model described by equation (3.1a): $R_{US,t} = \alpha_1 + \beta_{11}R_{US,t-1} + \beta_{12}R_{j,t-1} + \varepsilon_{US,t}$, $R_{j,t} = \alpha_2 + \beta_{21}R_{US,t-1} + \beta_{22}R_{j,t-1} + \varepsilon_{j,t}$, $j \in$ {AU, CN, JP}.

Parameters	*Estimates*		
	U.S.–Australia	*U.S.–China*	*U.S.–Japan*
α_1	0.136	0.123	−0.240
	(0.115)	(0.119)	(0.109)
α_2	0.150	0.042	−0.334
	(0.138)	(0.133)	(0.103)
β_{11}	−0.065	−0.062	−0.184
	(0.067)	(0.046)	(0.054)
β_{12}	2.168×10^{-4}	0.084	−0.053
	(7.926×10^{-4})	(0.034)	(0.067)
β_{21}	0.822	0.634	0.436
	(0.085)	(0.075)	(0.043)
β_{22}	−0.182	0.026	−0.205
	(0.035)	(0.055)	(0.032)

Table 3.2: Estimation of Asymmetric DC Model

Table 3.2 reports the quasi-maximum likelihood estimates and their robust standard errors (in parentheses) of the VAR–DC model described by equation (3.1a): $R_{US,t} = \alpha_1 + \beta_{11}R_{US,t-1} + \beta_{12}R_{j,t-1} + \varepsilon_{US,t}$, $R_{j,t} = \alpha_2 + \beta_{21}R_{US,t-1} + \beta_{22}R_{j,t-1} + \varepsilon_{j,t}$, $j \in$ {AU, CN, JP}.

Parameters	*Estimates*		
	U.S.–Australia	*U.S.–China*	*U.S.–Japan*
α_1	−0.018	0.274	0.648
	(0.032)	(0.103)	(0.133)
α_2	0.088	−0.345	0.379
	(0.122)	(0.122)	(0.135)
β_{11}	−0.094	0.105	−0.556
	(0.035)	(0.075)	(0.120)
β_{12}	0.028	0.091	−0.195
	(0.027)	(0.049)	(0.060)
β_{21}	0.699	0.585	0.324
	(0.050)	(0.062)	(0.143)
β_{22}	−0.130	−0.048	−0.103
	(0.037)	(0.047)	(0.042)

ification tests as in (3.6a)–(3.8c), which are presented in Table 3.5. If these diagnostic tests fail to lead to an unambiguous conclusion, I shall run regression of the products of standardized residuals on the corresponding estimates of conditional covariance, as suggested

Table 3.3: Estimation of Asymmetric BEKK Model—Continued

Table 3.3 reports the quasi-maximum likelihood estimates and their robust standard errors (in parentheses) of the VAR–BEKK model described by equation (3.2).

Parameters	*Estimates*		
	U.S.–Australia	*U.S.–China*	*U.S.–Japan*
C_{11}	0.775	0.687	3.618
	(0.189)	(0.284)	(0.497)
C_{12}	1.610	2.217	0.286
	(0.533)	(0.514)	(0.158)
C_{22}	2.681	1.880	0.300
	(0.270)	(0.610)	(0.507)
B_{11}	0.881	0.892	0.329
	(0.057)	(0.062)	(0.111)
B_{12}	0.233	0.041	0.509
	(0.068)	(0.148)	(0.113)
B_{21}	−0.076	−0.024	−0.372
	(0.061)	(0.141)	(0.158)
B_{22}	0.013	0.102	0.390
	(0.031)	(0.043)	(0.202)
A_{11}	0.017	0.263	0.067
	(0.017)	(0.169)	(0.248)
A_{12}	0.573	0.324	0.350
	(0.093)	(0.152)	(0.084)
A_{21}	0.269	0.009	−0.057
	(0.114)	(0.061)	(0.213)
A_{22}	0.084	0.414	0.394
	(0.155)	(0.155)	(0.142)
G_{11}	0.352	0.385	0.502
	(0.097)	(0.092)	(0.098)
G_{12}	−0.287	−0.385	0.133
	(0.323)	(0.121)	(0.161)
G_{21}	0.171	0.124	0.121
	(0.147)	(0.094)	(0.374)
G_{22}	0.554	0.308	−0.171
	(0.206)	(0.409)	(0.432)
Log-L	-6.608×10^3	-6.579×10^3	-6.691×10^3
	Pagan and Schwert's R^2		
$R^{2\,a}$	0.293	0.227	0.087
$R^{2\,b}$	0.053	0.117	0.144
$R^{2\,c}$	0.035	0.041	7.061×10^{-6}

[a] determination coefficient of the regression of the squared U.S. residual on the conditional U.S. variance; [b] determination coefficient of the regression of the squared regional residual on the conditional regional variance; [c] determination coefficient of the regression of the product of the U.S. and regional residuals on the conditional covariance.

Table 3.4: Estimation of Asymmetric DC Model—Continued

Table 3.4 reports the quasi-maximum likelihood estimates and their robust standard errors (in parentheses) of the VAR–DC model described by equations (3.3) and (3.4).

Parameters	*Estimates*		
	U.S.–Australia	*U.S.–China*	*U.S.–Japan*
C_{11}	1.928	0.005	2.132
	(0.328)	(0.032)	(0.667)
C_{12}	−1.863	−2.850	1.053
	(0.232)	(0.227)	(0.266)
C_{22}	0.750	0.020	1.226
	(0.177)	(0.127)	(0.177)
B_{11}	0.169	0.413	0.202
	(0.184)	(0.065)	(0.116)
B_{12}	−0.341	0.157	−1.000
	(0.135)	(0.046)	(0.172)
B_{21}	0.429	−0.770	−0.311
	(0.077)	(0.060)	(0.158)
B_{22}	−0.738	0.109	−0.114
	(0.110)	(0.138)	(0.089)
A_{11}	6.581×10^{-4}	0.650	0.415
	(0.003)	(0.135)	(0.157)
A_{12}	−0.058	0.381	−0.318
	(0.128)	(0.073)	(0.112)
A_{21}	0.474	0.004	0.353
	(0.062)	(0.031)	(0.130)
A_{22}	0.353	0.004	−0.589
	(0.141)	(0.026)	(0.086)
G_{11}	0.530	0.993	0.469
	(0.128)	(0.230)	(0.183)
G_{12}	0.793	−0.082	0.210
	(0.159)	(0.207)	(0.093)
G_{21}	0.322	0.017	0.250
	(0.146)	(0.070)	(0.321)
G_{22}	−0.090	0.797	−0.133
	(0.158)	(0.163)	(0.218)
ρ	0.547	0.330	0.329
	(0.034)	(0.040)	(0.055)
λ	0.159	−0.024	0.670
	(0.055)	(0.066)	(0.193)
Log-L	-6.612×10^{3}	-6.834×10^{3}	-6.836×10^{3}
	Pagan and Schwert's R^2		
$R^{2\,a}$	0.203	0.101	0.198
$R^{2\,b}$	0.184	0.317	0.148
$R^{2\,c}$	0.060	0.113	0.011

[a] determination coefficient of the regression of the squared U.S. residual on the conditional U.S. variance; [b] determination coefficient of the regression of the squared regional residual on the conditional regional variance; [c] determination coefficient of the regression of the product of the U.S. and regional residuals on the conditional covariance.

by Pagan and Schwert [1990]. It is the model with a greater determination coefficient in the aforementioned regression that is determined to be appropriate for a certain regional market.

In the U.S.–Australia case, the diagnostic test results of the BEKK model are quite similar to those of the DC model. Panels A and B show no evidence against both specifications for conditional covariance and the U.S. conditional mean. However, evidence is found against both models for the Australian conditional mean and the U.S. conditional variance. Moment conditions (3.6a)–(3.6c) are jointly violated for both specifications. The standardized Australian residuals may well follow the standard normal distribution, since neither (3.7a) nor (3.7c) is violated. In contrast, the test statistics of moment conditions (3.7a) and (3.7c) suggest that the null hypotheses of no skewness and no excess kurtosis are rejected for the standardized American residuals of both BEKK and DC models. Moment conditions (3.7a)–(3.7d) are not jointly violated for either specification, indicating joint conditional bivariate normality in the residual series. Those test statistics of asymmetry (3.8a)–(3.8c) suggest rejection of the null of no sign bias for $z_{US,t}$ of both models and for $z_{AU,t}$ of the dynamic covariance model. In summary, along every dimension examined, the BEKK and dynamic covariance models are both well-specified. In light of no preference given by the diagnostic tests for one model over another, I run regression of the products of the U.S. and Australian residuals on the estimates of conditional covariance between the two markets derived from the BEKK and DC models and then compare the coefficients of determination in order to rank the performance of the two specifications. The dynamic covariance model is favored over the BEKK one by Pagan and Schwert's regression because the former yields a slightly higher coefficient of determination. As a result, I choose the DC model as the underlying model which governs the joint process for $\mathbf{R}_t = (R_{US,t}, R_{AU,t})^\top$.

Table 3.5: Diagnosis Test Result of Bivariate Model

Given in square brackets, the empirical p-values are obtained from 5,000 Monte-Carlo simulations for 1,276 observations. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel. The asterisk and the plus superscript indicate significance at the 1% and 5% levels, respectively.

Moment Test	*U.S.–Australia*		*U.S.–China*		*U.S.–Japan*	
	U.S.	*Australia*	*U.S.*	*China*	*U.S.*	*Japan*
A. Asymmetric BEKK model						
Conditional Mean: (3.6a)	1.514	19.708*	8.532	29.439*	23.319*	14.033†
	[0.925]	[0.007]	[0.185]	[<0.001]	[0.001]	[0.034]
Conditional Variance: (3.6b)	39.558*	16.967†	34.898*	10.990	24.474*	9.961
	[<0.001]	[0.014]	[<0.001]	[0.091]	[0.001]	[0.125]
Conditional Covariance: (3.6c)	11.331		8.680		10.444	
	[0.075]		[0.166]		[0.096]	
Joint[1]: (3.6a)–(3.6c)	93.449*		101.500*		241.908*	
	[0.002]		[<0.001]		[<0.001]	
Skewness: (3.7a)	9.139*	1.427	10.960*	0.078	2.137	1.513
	[0.003]	[0.235]	[0.001]	[0.781]	[0.151]	[0.220]
Cross-skewness: (3.7b)	1.138		2.157		3.698	
	[0.589]		[0.365]		[0.178]	
Excess kurtosis: (3.7c)	6.942†	1.384	5.593†	1.890	0.873	1.406
	[0.017]	[0.260]	[0.031]	[0.195]	[0.370]	[0.256]
Cross-kurtosis: (3.7d)	1.610		3.447		0.510	
	[0.228]		[0.083]		[0.491]	
Joint[2]: (3.7a)–(3.7d)	21.417		18.120		42.832*	
	[0.056]		[0.087]		[0.004]	
Asymmetry: (3.8a)–(3.8c)	39.946*	2.053	69.558*	6.987	2.647	9.845†
	[<0.001]	[0.591]	[<0.001]	[0.122]	[0.488]	[0.046]
B. Asymmetric DC model						
Conditional Mean: (3.6a)	2.621	35.281*	46.094*	11.123	133.382*	20.502*

(***Continued on next page***)

Table 3.5 - Continued from previous page

Moment Test	*U.S.–Australia*		*U.S.–China*		*U.S.–Japan*	
	U.S.	*Australia*	*U.S.*	*China*	*U.S.*	*Japan*
	[0.787]	[<0.001]	[<0.001]	[0.086]	[<0.001]	[0.005]
Conditional Variance: (3.6b)	22.965*	7.197	21.287*	16.458†	7.755	77.090*
	[0.002]	[0.273]	[0.003]	[0.016]	[0.235]	[<0.001]
Conditional Covariance: (3.6c)	5.951		4.255		15.908†	
	[0.375]		[0.573]		[0.015]	
Joint[1]: (3.6a)–(3.6c)	75.454*		148.729*		415.551*	
	[0.009]		[<0.001]		[<0.001]	
Skewness: (3.7a)	4.680†	0.199	4.605†	8.553*	5.192†	0.691
	[0.034]	[0.655]	[0.036]	[0.004]	[0.025]	[0.403]
Cross-skewness: (3.7b)	3.676		5.185		6.706†	
	[0.179]		[0.086]		[0.044]	
Excess kurtosis: (3.7c)	5.488†	0.010	2.679	2.663	2.055	77.735*
	[0.033]	[0.925]	[0.125]	[0.126]	[0.178]	[<0.001]
Cross-kurtosis: (3.7d)	0.110		2.103		0.106	
	[0.752]		[0.168]		[0.757]	
Joint[2]: (3.7a)–(3.7d)	17.963		24.394†		142.581*	
	[0.089]		[0.037]		[<0.001]	
Asymmetry: (3.8a)–(3.8c)	36.889*	10.806†	144.488*	9.284	5.153	180.113*
	[<0.001]	[0.035]	[<0.001]	[0.057]	[0.205]	[<0.001]

No evidence is shown in panels A and B against both models for conditional covariance in the Chinese case. Moment conditions (3.6a) and (3.6b) are violated for the standardized Chinese and U.S. residuals obtained from the BEKK model respectively, whereas the corresponding significant test statistics in panel B constitute evidence against the DC model for the American conditional mean and variance and for the Chinese conditional variance. Again, moment conditions (3.6a)–(3.6c) are jointly violated for both models in the current case. For the BEKK model, the test statistics for zero skewness and excess kurtosis indicate that $z_{CN,t}$ follow the standard normal distribution, while the null hypotheses of no skewness and no excess kurtosis are rejected for $z_{US,t}$; for the dynamic covariance specification, the null hypothesis of zero skewness is rejected for both residual series. Moment conditions (3.7a)–(3.7d) are not jointly violated for the BEKK model, which, however, is not the case for the DC model. The null of no sign bias is rejected for the standardized U.S. residuals of both specifications. The results of the diagnostic tests support selection of the BEKK model in the U.S.–China case, since two more moment conditions are violated for the DC model. For the BEKK model, 6 out of 15 moment conditions are violated, whilst 8 of the same set of moment conditions are violated for the dynamic covariance model. Some of the violated conditions, e.g. conditional variance (3.6b), skewness (3.7a), asymmetry (3.8a)–(3.8c) and joint[1] (3.6a)–(3.6c), are overlapping across the two models.

It is the BEKK model that the diagnostic tests give preference to in the U.S.–Japan case. Both models fail those serial correlation tests—the BEKK model fails because moment condition (3.6a) is violated for both standardized U.S. and Japanese residuals and so is moment condition (3.6b) for the standardized U.S. residuals, whereas, for the DC model, the same moment conditions are also violated for the residual series. The test statistics show that both BEKK and DC models fail the joint test of serial correlation as well. Despite the fact that moment conditions (3.7a)–(3.7d) are jointly violated for both specifications, the BEKK model is still favored by the diagnostic tests as none of moment conditions (3.7a)–

(3.7d) is separately violated for both residual series of the BEKK model—this, however, is not true for the standardized residuals of the DC model. In addition, evidence is found against the dynamic covariance model for the conditional covariance between $z_{US,t}$ and $z_{JP,t}$. The null of no sign bias is rejected for the standardized Japanese residuals of both model specifications.

Figures A.5–A.7 display the estimated level of daily U.S. and regional variances and daily covariance and correlation between the two markets. The estimated conditional variances of the regional markets rose dramatically in October 2008 when the 2007–2008 U.S. sub-prime mortgage crisis started to spread globally. These markets turned super-turbulent during a relatively short period—their corresponding estimated variances skyrocketed and then plummeted within a few days or weeks. For most of the days covered in this study, the three regional markets are positively correlated with the U.S. market during the recent recession period. Moreover, the magnitude of negative correlations is usually smaller than that of positive correlations. It is worth noting that the BEKK model, compared with its contender, yields a correlation whose magnitude has a broader range. In the U.S.–China case, for instance, the BEKK correlation ranges from approximately -0.3 to 0.7 while the range of the DC correlation is only about 2.5%.

3.3.2 News Impact Surfaces

The two multivariate GARCH models employed in this study yield distinct estimates of conditional variance and covariance. Kroner and Ng [1998] extend news impact curves developed by Engle and Ng [1993] to news impact surfaces in order to address the question of whether the effect of asymmetry matters to variance and covariance estimates. A news impact surface plots against one-period lagged U.S. and regional innovations the conditional U.S. variance, the conditional regional variance or the conditional covariance between the U.S. and regional error terms, keeping the previous conditional (co)variance

($H_{11,\,t-1}$, $H_{22,\,t-1}$ and $H_{12,\,t-1}$) and the asymmetric terms ($\boldsymbol{\eta}_{t-1}$) constant at their respective unconditional sample means. In this section, I closely inspect the difference shown in the news impact surfaces for the two model specifications.

U.S. variance ($H_{11,\,t-1}$) is a function of previous U.S. and regional shocks:

$$
\begin{aligned}
H_{11,\,t} =& C_{11}^2 + A_{11}^2\varepsilon_{1,\,t-1}^2 + 2A_{11}A_{21}\varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + A_{21}^2\varepsilon_{2,\,t-1}^2 + B_{11}^2 H_{11,\,t-1} + \\
& 2B_{11}B_{21}H_{12,\,t-1} + B_{21}^2 H_{22,\,t-1} + G_{11}^2\eta_{1,\,t-1}^2 + 2G_{11}G_{21}\eta_{1,\,t-1}\eta_{2,\,t-1} + G_{21}^2\eta_{2,\,t-1}^2.
\end{aligned}
\tag{3.9}
$$

Variance of a large Asia-Pacific market ($H_{22,\,t-1}$) is a function of previous regional and American innovations as well:

$$
\begin{aligned}
H_{22,\,t} =& C_{12}^2 + C_{22}^2 + A_{12}^2\varepsilon_{1,\,t-1}^2 + 2A_{12}A_{22}\varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + A_{22}^2\varepsilon_{2,\,t-1}^2 + B_{12}^2 H_{11,\,t-1} + \\
& 2B_{12}B_{22}H_{12,\,t-1} + B_{22}^2 H_{22,\,t-1} + G_{12}^2\eta_{1,\,t-1}^2 + 2G_{12}G_{22}\eta_{1,\,t-1}\eta_{2,\,t-1} + G_{22}^2\eta_{2,\,t-1}^2.
\end{aligned}
\tag{3.10}
$$

Covariance between these two markets ($H_{12,\,t-1}$) takes the form of

$$
\begin{aligned}
H_{12,\,t} =& C_{11}C_{12} + A_{11}A_{12}\varepsilon_{1,\,t-1}^2 + \left(A_{11}A_{22} + A_{12}A_{21}\right)\varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + A_{21}A_{22}\varepsilon_{2,\,t-1}^2 + \\
& B_{11}B_{12}H_{11,\,t-1} + \left(B_{11}B_{22} + B_{12}B_{21}\right)H_{12,\,t-1} + B_{21}B_{22}H_{22,\,t-1} + G_{11}G_{12}\eta_{1,\,t-1}^2 + \\
& \left(G_{11}G_{22} + G_{12}G_{21}\right)\eta_{1,\,t-1}\eta_{2,\,t-1} + G_{21}G_{22}\eta_{2,\,t-1}^2
\end{aligned}
\tag{3.11}
$$

for the BEKK model, and

$$
\begin{aligned}
H_{12,\,t} =&\lambda[C_{11}C_{12} + \rho C_{11}^2 + \left(A_{11}A_{12} + \rho A_{11}^2\right)\varepsilon_{1,\,t-1}^2 + \left(A_{11}A_{22} + A_{21}A_{12} + 2\rho A_{11}A_{21}\right)\ldots \\
&\varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + \left(A_{21}A_{22} + \rho A_{21}^2\right)\varepsilon_{2,\,t-1}^2 + \left(B_{11}B_{12} + \rho B_{11}^2\right)H_{11,\,t-1}+ \\
&\left(B_{11}B_{22} + B_{21}B_{12} + 2\rho B_{11}B_{21}\right)H_{12,\,t-1} + \left(B_{21}B_{22} + \rho B_{21}^2\right)H_{22,\,t-1}+ \\
&\left(G_{11}G_{12} + \rho G_{11}^2\right)\eta_{1,\,t-1}^2 + \left(G_{11}G_{22} + G_{21}G_{12} + 2\rho G_{11}G_{21}\right)\eta_{1,\,t-1}\eta_{2,\,t-1}+ \\
&\left(G_{21}G_{22} + \rho G_{21}^2\right)\eta_{2,\,t-1}^2]^{\frac{1}{2}}[C_{12}^2 + C_{22}^2 + A_{12}^2\varepsilon_{1,\,t-1}^2 + 2A_{22}A_{12}\varepsilon_{1,\,t-1}\varepsilon_{2,\,t-1} + A_{22}^2\varepsilon_{2,\,t-1}^2 \\
&+ B_{12}^2H_{11,\,t-1} + 2B_{12}B_{22}H_{12,\,t-1} + B_{22}^2H_{22,\,t-1} + G_{12}^2\eta_{1,\,t-1}^2 + 2G_{12}G_{22}\eta_{1,\,t-1}\eta_{2,\,t-1}+ \\
&G_{22}^2\eta_{2,\,t-1}^2]^{\frac{1}{2}}
\end{aligned}
\tag{3.12}
$$

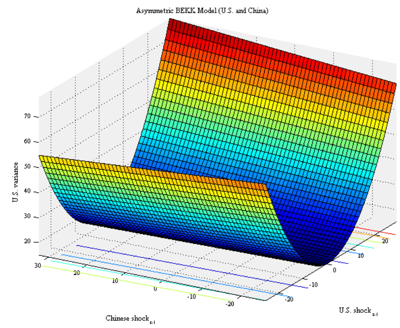
for the dynamic covariance model.

In equations (3.9)–(3.12), all explanatory variables but one-period lagged U.S. and regional shocks are fixed at their unconditional sample means. The news impact surfaces are provided for both models in Figures 3.1–3.3 on pages 56–58. The U.S. variance is computed by equation (3.9), the regional variance by (3.10), the BEKK covariance by (3.11) and the DC covariance by (3.12).

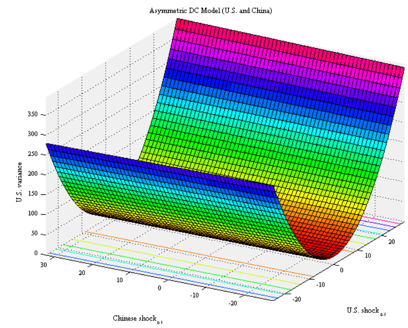
Figure 3.1 presents the news impact surfaces for both BEKK and DC models of the Chinese case. Panels (a) and (b) show that for both models the U.S. market responds solely to its own news and the level of market volatility increases with the magnitude of shocks. In panel (c), the Chinese variance for the BEKK model is affected by both domestic and American news. Furthermore, it is worthwhile to point out that asymmetric volatility spillovers from the United States to China are amply demonstrated in panel (c)—positive Chinese innovations have a greater impact on the Chinese variance than negative ones in the presence of good news about the U.S. equity market, and vice versa if the news turns out to be bad. For the dynamic covariance model, panel (d) of Figure 3.1 shows that U.S. shocks affect the Chinese variance significantly. The above discussion as to the Chinese variance

Figure 3.1: News Impact Surfaces for U.S. Variance, Chinese Variance, Covariance and Correlation with Respect to One-Period Lagged U.S. and Chinese Shocks Under Two GARCH Specifications

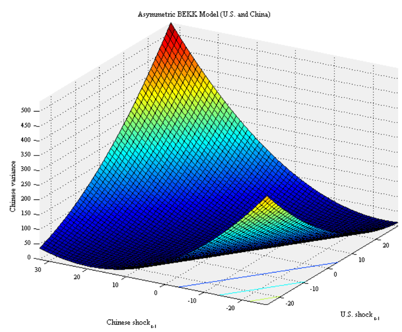
(a) U.S. Variance (BEKK model)



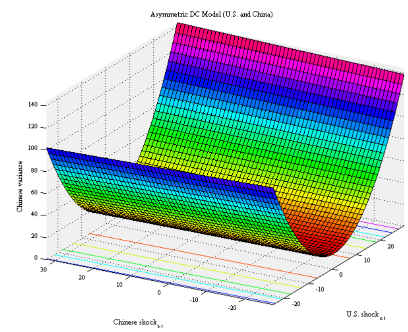
(b) U.S. Variance (DC model)



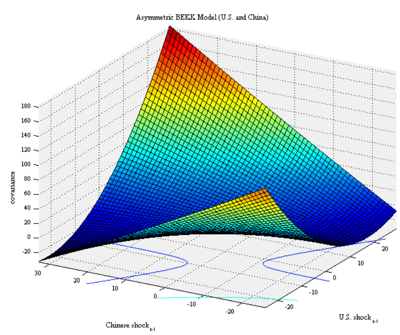
(c) Chinese Variance (BEKK model)



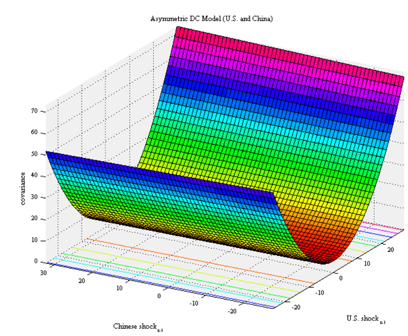
(d) Chinese Variance (DC model)



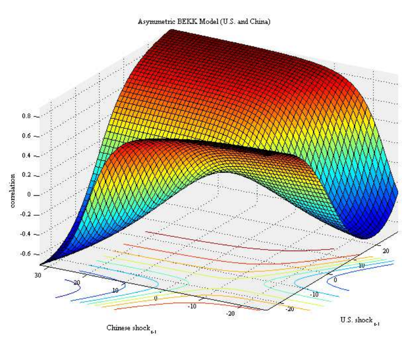
(e) U.S.–China Covariance (BEKK model)



(f) U.S.–China Covariance (DC model)



(g) U.S.–China Correlation (BEKK model)



(h) U.S.–China Correlation (DC model)

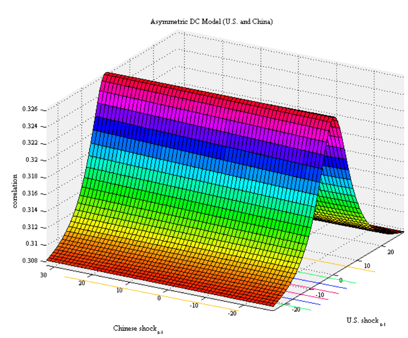
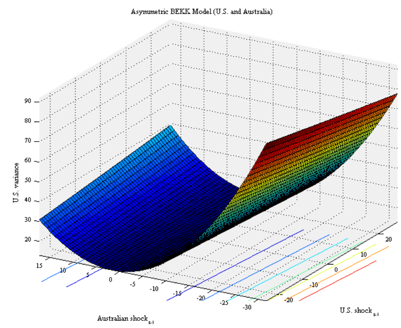
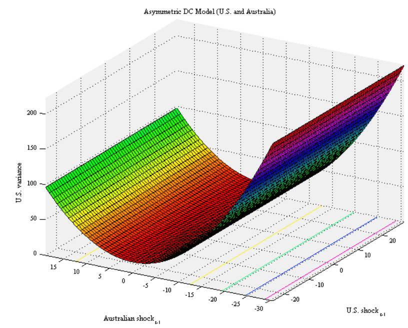


Figure 3.2: News Impact Surfaces for U.S. Variance, Australian Variance, Covariance and Correlation with Respect to One-Period Lagged U.S. and Australian Shocks Under Two GARCH Specifications

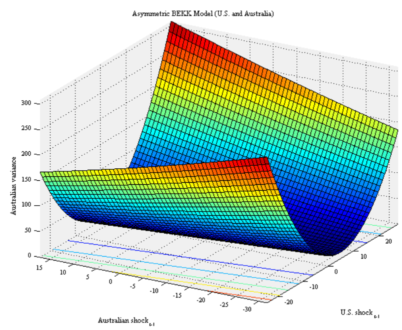
(a) U.S. Variance (BEKK model)



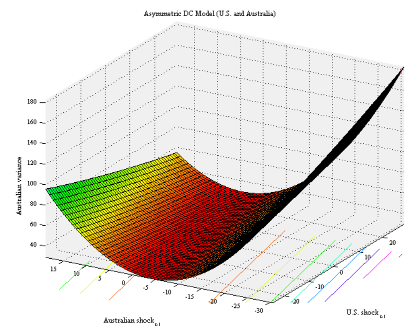
(b) U.S. Variance (DC model)



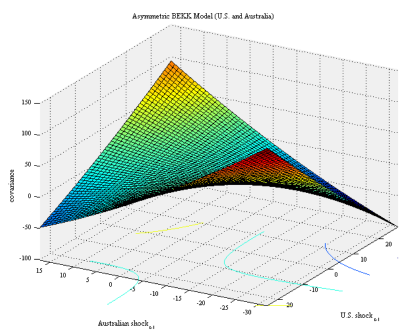
(c) Australian Variance (BEKK model)



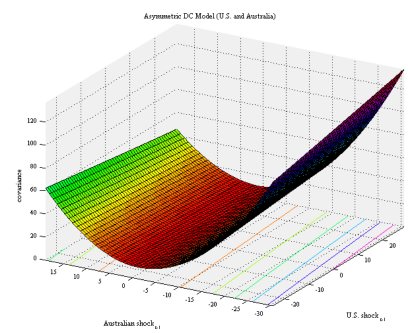
(d) Australian Variance (DC model)



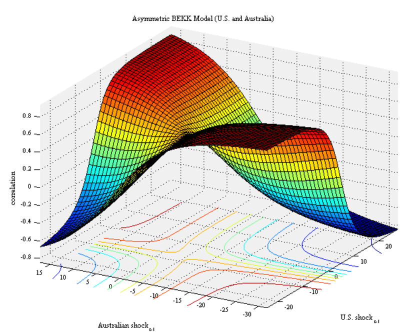
(e) U.S.–Australia Covariance (BEKK model)



(f) U.S.–Australia Covariance (DC model)



(g) U.S.–Australia Correlation (BEKK model)



(h) U.S.–Australia Correlation (DC model)

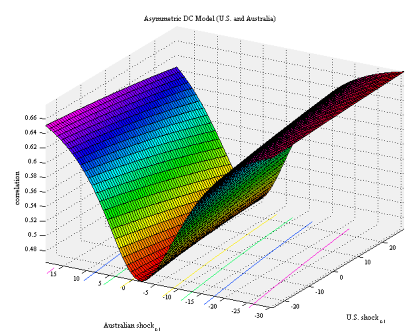
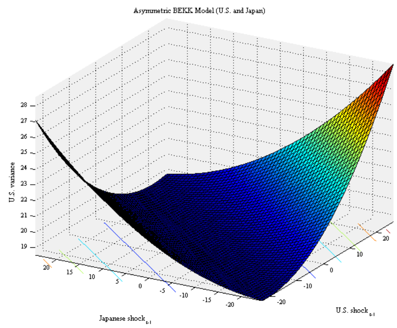
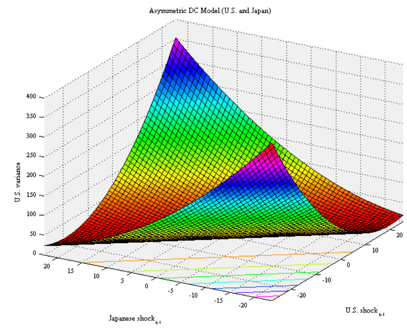


Figure 3.3: News Impact Surfaces for U.S. Variance, Japanese Variance, Covariance and Correlation with Respect to One-Period Lagged U.S. and Japanese Shocks Under Two GARCH Specifications

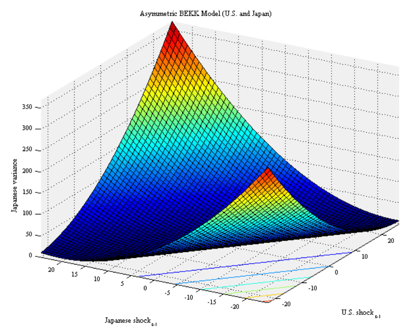
(a) U.S. Variance (BEKK model)



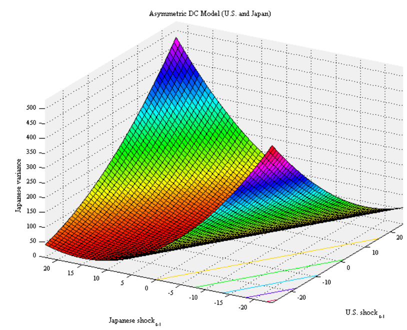
(b) U.S. Variance (DC model)



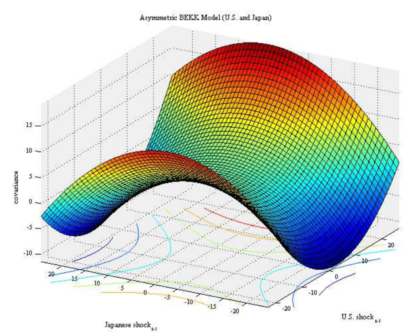
(c) Japanese Variance (BEKK model)



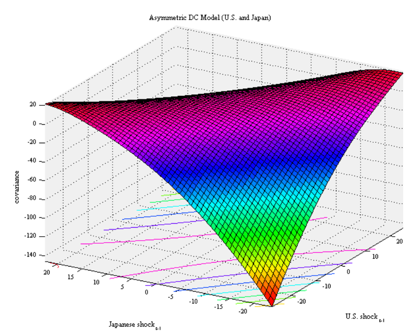
(d) Japanese Variance (DC model)



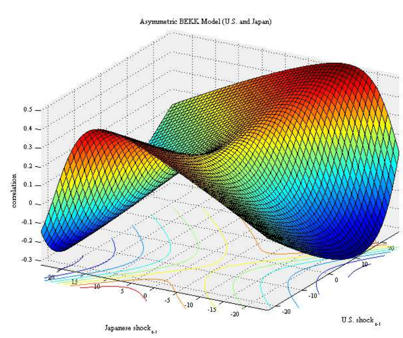
(e) U.S.–Japan Covariance (BEKK model)



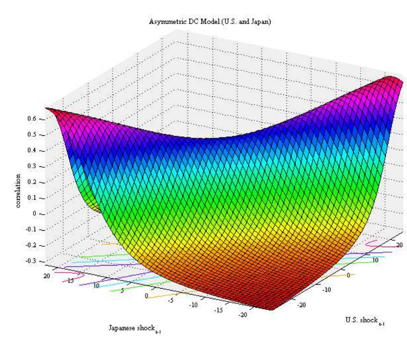
(f) U.S.–Japan Covariance (DC model)



(g) U.S.–Japan Correlation (BEKK model)



(h) U.S.–Japan Correlation (DC model)



also applies to the covariance between Chinese and U.S. innovations. With respect to the correlation between the two shocks, the news impact surface for the BEKK model in panel (g) is vaguely shaped like an upside-down saddle, indicating that the correlation is small or even negative when one-period lagged shocks to the Chinese and American markets are both great in magnitude and of the opposite signs, and that the two highly correlated markets are usually accompanied by considerable previous shocks of the same sign, whilst the news impact surface for the DC model in panel (h) looks like a parabolic cylinder—the correlation peaks when the U.S. market news is neutral. Panel (h) also shows that for the dynamic covariance specification, past shocks to the Chinese market, compared with those to the U.S. market, have only modest effect on the correlation between the two markets.

Figure 3.2 displays the news impact surfaces for both models in the U.S.–Australia case. In panels (a) and (b), both news impact surfaces show that the American market responds to Australian news in such an asymmetric way that negative innovations have a greater impact on the U.S. variance than positive ones. When it comes to the BEKK model, panel (c) demonstrates that the way U.S. shocks affect the Australian variance is not the same as the way the Australian market intertwines with its domestic news. Specifically, positive U.S. market news plays a more significant role than negative news in shaping the level of volatility in the Australian market in the presence of considerable Australian shocks. The impact of American shocks on the Australian variance, however, appears symmetric when bad news comes up about the Australian market. For the DC model, panel (d) shows that the Australian market is responsive to its own news, especially its own bad news. The above discussion as to the Australian variance also applies to the covariance between the U.S. and Australian markets. Panel (e) of Figure 3.2 indicates that there is an interesting asymmetric effect in covariance which has not been documented before. As is shown in the panel, the BEKK covariance is higher following shocks, both great in magnitude and of the identical sign, to the two markets, whilst small or even negative covariance is accompanied by considerable previous shocks of the opposite signs. For U.S.–Australia correlation, the BEKK model produces a news impact surface shaped like an upside-down saddle in panel (g) whereas the DC model produces one shaped like a parabolic cylinder in panel (h). Panel (g) reveals that the BEKK correlation is small or even negative when previous shocks to the Australian and American markets are both great in magnitude and of the opposite signs, and that considerable historical shocks of the same sign lead to the two highly correlated markets. The DC correlation falls to a trough when the Australian market news is neutral, as revealed in panel (h).

Presented in Figure 3.3 are the news impact surfaces in the Japanese case. Panel (a) shows clearly that the level of volatility in the American equity market is affected by both historical Japanese and U.S. shocks in an asymmetric manner. In the presence of great positive shocks to the Japanese market, negative American shocks have a positive impact on the U.S. variance, whereas positive U.S. market news increases the magnitude of U.S. market volatility if there is awful news in the Japanese stock market. Speaking of the way previous Japanese shocks affect the U.S. variance, positive Japanese market news increases the U.S. variance when the shock just hitting the American market turns out to be negative, whilst negative news has a positive effect on the U.S. market volatility in the presence of positive past U.S. innovations. The news impact surfaces in panels (b)–(d) are quite similar to those in panels (c) and (e) of Figure 3.1, as a result of which previous relevant interpretation can be easily applied to the current case. Interestingly enough, shown in panels (e) and (g), the news impact surfaces of both covariance and correlation for the BEKK model are saddle-shaped, suggesting that covariance (correlation) reaches a trough when historical American shocks are neutral while peaking in the presence of neutral Japanese market news. Panel (h) suggests that asymmetries in covariance may not be driven entirely by asymmetries in variance because impact on correlations of shared innovations is rather different from that of separate shocks. The news impact surface of the DC correlation in the panel demonstrates that the U.S.–Japan correlation is small or even negative when previous shocks to the American and Australian markets share the same sign whereas historical shocks of the opposite signs lead to the two highly correlated markets.

3.4 Conclusion

In this chapter, I employ two popular multivariate GARCH models and carefully examine the results of the diagnostic tests in order to find the better fitting model which governs the joint process for U.S. and regional stock returns. The empirical results lead to the following conclusions. Although the dynamic covariance specification of the U.S.–China case can be reduced to the CCORR model, the estimated DC models are all statistically different from the full BEKK model. Under the guidance of the diagnostic statistics together with Pagan and Schwert [1990]'s method, I regard the dynamic covariance model specification as more appropriate for the U.S.–Australia case, since Pagan and Schwert's regression yields a higher coefficient of determination for the DC model. Meanwhile, the BEKK model is favored by the diagnostic tests in both Chinese and Japanese cases. In order to quantify the volatility spillover effect on a small Asia-Pacific market of a large one and of the U.S. market, I shall employ a Markov-switching model and discuss it in detail in the next chapter.

CHAPTER 4

Volatility Spillovers from U.S. and Large Asia-Pacific Markets

In the third chapter, I have determined which of the two competing multivariate GARCH models is the better fitting one that governs the joint process for U.S. and regional stock returns by carefully examining the results of the diagnostic tests. The dynamic covariance model specification is more appropriate for the U.S.–Australia case, while the BEKK model is strongly preferred in both Chinese and Japanese cases. In this chapter, in order to measure the volatility spillover impact upon a small Asia-Pacific market of a large one and of the U.S. market, I propose three Markov-switching models and discuss their performance in quantifying volatility transmission effects. The rest of Chapter 4 is structured as follows. A brief review of the literature on practical use of Markov-switching models in empirical finance is summarized in the first section. Section 4.2 discusses in detail the employed regime-switching models and procedures for seeking the optimal specifications. Section 4.3 analyzes the empirical results in depth after elaborating on the performance of these models in each combination of a local market and a regional market proxy with concluding remarks offered in the last section.

4.1 Review of Literature on Markov Chain Models in Empirical Finance

Financial economists have traditionally found Markov-switching models useful particularly in fitting financial time series and testing hypotheses and implications derived from finance theories. There has been a burgeoning body of literature on application of this type of quantitative models at the univariate level since the 1980s. It is, therefore, advisable to discuss in this section those seminal studies in this field which lead to important findings. Amongst the very first applications during the two decades 1980–1999 of Markov-switching models in economics and finance research (e.g. Hamilton [1988, 1989], Tucker and Pond [1988], Turner et al. [1989], Engel and Hamilton [1990], Kandel and Stambaugh [1990], Kaminsky [1993], Schaller and Norden [1997]), the research conducted by Engel and Hamilton [1990] has been regarded highly successful since it has shown that researchers can formulate and test hypotheses more easily with the help of regime switching, whilst it would be difficult or even impossible for them to do so within a one-state framework. Compared with separating one state from another according to some predefined variable such as the NBER recession indicator or industrial production, the latent state approach works better with forward-looking equity return data, as it does not rely on any ex post information. In order to explain why the U.S. dollar had sharply risen against several main European currencies during the early 1980s and then slid later on, Engel and Hamilton were able to find clear-cut evidence of two regimes with their state-dependent intercept and heteroscedasticity model. A more recent study undertaken by Acharya et al. [2013] is also worthwhile mentioning here as it serves as an example of a simple regression model with switching intercepts and slopes still being capable of grasping the complexity of the 2007–2009 global financial crisis. The authors built up a simple regression model with the Markov-transition mechanism embedded in the slope and intercept coefficients, showing that over the period 1973–2007, U.S. corporate bonds switch their response to liquidity shocks to U.S. stocks and money market securities between a 'normal' and a 'stress' state. Readers who are interested in the Markov-switching regression method are advised to refer to a similar paper by Alexander and Kaeck [2008], who argued that interest rates, stock market returns and implied volatility all affect changes in the spreads of credit default swaps in a way that is dependent on the then prevailing market circumstances.

Another important line of research, in which Markov-transition models are actively involved usually on the multivariate level, focuses on the area of international finance. Since time-varying correlations are of particular interest to academics specializing in financial interdependence and contagion, it is natural for them to construct a multivariate regime-switching model. Baele [2005] applied Makov-switching techniques to what is known as the shock spillover model in an attempt to carry out quantitative research—from the perspective of the time-variation as well as magnitude of volatility spillovers—into the degree to which increasing globalisation and regional integration influence financial interdependence amongst thirteen European stock markets. Baele's approach is not only novel but also meaningful in the sense that it allows spillover intensities to switch in an endogenous rather than exogenous way so that the main drawback—continuing and increasing market interdependence could be mistaken for contagion—of all contagion tests based on constant factor models can be overcome. The empirical results in Baele [2005] demonstrate that although both E.U. and U.S. spillover intensities increase considerably in the 1980s and 1990s, the rise is more substantial for E.U. innovations. Common European shocks account for approximately 8% of local variance on average during the period 1980–1985, and this proportion increases to 23% by the end of the 1990s. In addition, he also found extensive evidence of contagion from the U.S. to several European stock markets. When it comes to the multivariate Markov-switching models which have more than two regimes, it is worthwhile to pay attention to the in-depth research done by Ang and Bekaert [2002], who developed a first-order eight-state Markov chain in an effort to explore the joint dynamics of short-term interest rates within the U.S., the U.K. and Germany. Rigorously constructing and extensively using residual tests to compare the performance of competing models, Ang and Bekaert concluded that their high-dimensional Markov-transition model is outperformed by alternative simpler specifications in terms of the results of residual tests. A more recent paper by Baele et al. [2010] is recommended to those who would like to see how to develop a multivariate Markov-switching model for a large number of endogenous variables, while keeping the number of regimes as small as possible, in a study of dynamic correlations amongst various classes of assets.

4.2 Methodology

Similar to Baele [2005], I adopt the two-step approach first developed by Bekaert and Harvey [1997] and further extended by Ng [2000]. The first step is to estimate the bivariate model presented in section 3.1 of Chapter 3. Based on the results of the diagnostic tests discussed in section 3.2, the better performing one is selected of the two proposed specifications of multivariate GARCH models. The next step is to impose the orthogonalized innovations of the regional and U.S. markets upon the univariate volatility transmission model described in section 4.2.1 of the current chapter.[1]. The two-step approach relies on two important assumptions: (I) in the second chapter the joint probability density function of $\boldsymbol{\varepsilon}_t$ conditional on $\mathcal{F}_{t-1} = \{\mathbf{H}_{t-1},\, \boldsymbol{\varepsilon}_{t-1},\, \mathcal{F}_{t-2}\}$ is determined solely by the entire parameters ($\boldsymbol{\xi}$) of the bivariate model; (II) in the univariate model the local shock is correlated with neither the regional nor the U.S. orthogonalized disturbance.

4.2.1 A Univariate Volatility Transmission Model

This section discusses the univariate model, which allows me to quantify the relative influence of the U.S. market and a regional center in the Asia-Pacific area upon a small equity market in the same region. The daily price return of a small Asian market $m \in${ID, IN, KR, LK, MY, PK, PH, TW, TH, VN}, denoted by $R_{m,\,t}$, is determined by the expected return conditional on the previous information sets of market m and a disturbance term $\epsilon_{m,\,t}$:

$$R_{m,\,t} = E\left(R_{m,\,t}|\Omega_{m,\,t-1},\, \mathcal{F}_{t-1}\right) + \epsilon_{m,\,t}, \tag{4.1}$$

[1] I shall elaborate on the procedures of orthogonalisation in section 4.2.1 In addition, some important statistic properties of orthogonalized residuals will be discussed as well.

where the expected return, conditional upon the information available up to time $t-1$, is modelled as an AR(1) process:

$$E\left(R_{m,t}|\Omega_{m,t-1},\,\mathcal{F}_{t-1}\right)=\gamma_0+\gamma_1 R_{m,t-1}+\gamma_2 R_{US,t-1}. \tag{4.2}$$

In the preceding chapter, lagged returns of a regional market, whether it be Australia, China or Japan, have been found to have barely any significant effect on the local markets and are, therefore, not included in equation (4.2). The disturbance term can be further decomposed into shocks of three different origins—one idiosyncratic to the local market measured by $\varepsilon_{m,t}$, another from regional center j $\in${AU, CN, JP} by $e_{j,t}$ and the third from the U.S. market by $e_{US,t}$:

$$\epsilon_{m,t}=\delta_t e_{j,t}+\zeta_t e_{US,t}+\varepsilon_{m,t}, \tag{4.3}$$

where δ_t and ζ_t measure volatility spillovers from regional center j and from the U.S. market to the local market, respectively. The set-up of the univariate model allows the unexpected return of a local market to be driven by the concurrent innovations from the U.S. market and the regional center.

The estimated residuals of the chosen bivariate model are orthogonalized by equation (4.4). Assuming that innovations of regional market j are not merely driven by purely idiosyncratic shocks but also by the U.S. market innovations, the disturbances to a small Asian market from regional center j and the U.S. market can be derived from the residuals and variance-covariance estimates of the bivariate model:

$$\begin{pmatrix} e_{US,t} \\ e_{j,t} \end{pmatrix}=\mathbf{L}_t^{-1}\begin{pmatrix} \varepsilon_{US,t} \\ \varepsilon_{j,t} \end{pmatrix}, \tag{4.4}$$

where $\mathbf{L}_t = \left(\begin{smallmatrix} 1 & 0 \\ \iota_t & 1 \end{smallmatrix}\right)$ is the lower unitriangular matrix and calculated through the unique $\mathrm{LDL}^\top$ decomposition of $\mathbf{H}_t$:[2]

$$\begin{pmatrix} 1 & 0 \\ \iota_t & 1 \end{pmatrix} \begin{pmatrix} \sigma^2_{US,\,t} & 0 \\ 0 & \sigma^2_{j,\,t} \end{pmatrix} \begin{pmatrix} 1 & \iota_t \\ 0 & 1 \end{pmatrix} = \mathbf{H}_t. \tag{4.5}$$

Note that

$$\begin{aligned}
\sigma^2_{US,\,t} &= Var\left(\varepsilon_{US,\,t}|\mathcal{F}_{t-1}\right), \\
\sigma^2_{j,\,t} &= Var\left(\varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right) - \iota_t^2 Var\left(\varepsilon_{US,\,t}|\mathcal{F}_{t-1}\right) \\
&= Var\left(\varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right) - \frac{Cov^2\left(\varepsilon_{US,\,t},\, \varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right)}{Var\left(\varepsilon_{US,\,t}|\mathcal{F}_{t-1}\right)}, \\
\iota_t &= \frac{Cov\left(\varepsilon_{US,\,t},\, \varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right)}{Var\left(\varepsilon_{US,\,t}|\mathcal{F}_{t-1}\right)}.
\end{aligned}$$

Hence,

$$\begin{pmatrix} e_{US,\,t} \\ e_{j,\,t} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -\iota_t & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_{US,\,t} \\ \varepsilon_{j,\,t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{US,\,t} \\ \varepsilon_{j,\,t} - \iota_t \varepsilon_{US,\,t} \end{pmatrix}, \tag{4.6}$$

which implies

$$\begin{aligned}
Var\left(e_{US,t}|\mathcal{F}_{t-1}\right) &= Var\left(\varepsilon_{US,t}|\mathcal{F}_{t-1}\right) = \sigma^2_{US,\,t}, \\
Var\left(e_{j,\,t}|\mathcal{F}_{t-1}\right) &= \iota_t^2 Var\left(e_{US,t}|\mathcal{F}_{t-1}\right) + Var\left(\varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right) - 2\iota_t Cov\left(\varepsilon_{US,\,t},\, \varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right) \\
&= \iota_t^2 Var\left(e_{US,t}|\mathcal{F}_{t-1}\right) + \sigma^2_{j,\,t} + \iota_t^2 Var\left(\varepsilon_{US,t}|\mathcal{F}_{t-1}\right) - 2\iota_t Cov\left(\varepsilon_{US,\,t}, \varepsilon_{j,\,t}|\mathcal{F}_{t-1}\right) \\
&= \sigma^2_{j,\,t},
\end{aligned}$$

[2]The set-up of both BEKK and dynamic covariance models ensures that the covariance matrix ($\mathbf{H}_t$) is symmetric positive definite (*s.p.d.*). Moreover, since *any s.p.d.* matrix is non-singular and has a Cholesky decomposition, $\mathbf{H}_t$ is non-singular and its Cholesky decomposition exists. A symmetric non-singular matrix which has a Cholesky factorisation can be *uniquely* factored into the $\mathrm{LDL}^\top$ form. See chapters 5 and 6 (pp. 139–191) of Stefanica [2014].

and

$$
\begin{aligned}
Cov\left(e_{US,t},\, e_{j,t}|\mathcal{F}_{t-1}\right) &= Cov\left(\varepsilon_{US,t},\, \varepsilon_{j,t} - \iota_t \varepsilon_{US,t}|\mathcal{F}_{t-1}\right)\\
&= Cov\left(\varepsilon_{US,t},\, \varepsilon_{j,t}|\mathcal{F}_{t-1}\right) - \iota_t Var\left(\varepsilon_{US,t}|\mathcal{F}_{t-1}\right)\\
&= Cov\left(\varepsilon_{US,t},\, \varepsilon_{j,t}|\mathcal{F}_{t-1}\right) - \frac{Cov\left(\varepsilon_{US,t},\, \varepsilon_{j,t}|\mathcal{F}_{t-1}\right)}{Var\left(\varepsilon_{US,t}|\mathcal{F}_{t-1}\right)} Var\left(\varepsilon_{US,t}|\mathcal{F}_{t-1}\right)\\
&= 0.
\end{aligned}
$$

A Markov-transition model, which was formally introduced into economic research by Hamilton [1989], is presented as follows, in which both non-linearity of $\epsilon_{m,t}$ in $e_{j,t}$ and $e_{US,t}$ and time-variation in the conditional variance of $\varepsilon_{m,t}$ are taken into account:

$$\epsilon_{m,t} = \varepsilon_{m,t} + \delta_{S^*_{m,t}} e_{j,t} + \zeta_{S^\dagger_{m,t}} e_{US,t}, \tag{4.7a}$$

$$\varepsilon_{m,t}|\Omega_{m,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,t,S^\ddagger_{m,t}}\right), \tag{4.7b}$$

$$\ln\left(\sigma^2_{m,t,S^\ddagger_{m,t}}\right) = \nu_{0,S^\ddagger_{m,t}} + \nu_{1,S^\ddagger_{m,t}} R_{EM,t-1} + \nu_{2,S^\ddagger_{m,t}} |R_{EM,t-1}| \mathbf{I}\left(R_{EM,t-1} < 0\right). \tag{4.7c}$$

One of the primary goals of my research is to detect if there is any systematic change in the dynamics of each local market's financial dependency on the regional and the U.S. markets across the crisis (January 2008–June 2009) and post-crisis (July 2009–present) periods. The model, therefore, assumes that the loadings on orthogonalized U.S. and regional shocks are switching between two possible states, while the constant term and the coefficient on one-period lagged returns are time-invariant, i.e. $\zeta_{S^\dagger_{m,t}=1} = \zeta_1$, $\zeta_{S^\dagger_{m,t}=2} = \zeta_2$; $\delta_{S^*_{m,t}=1} = \delta_1$, $\delta_{S^*_{m,t}=2} = \delta_2$, where the latent variables $S^*_{m,t}$ and $S^\dagger_{m,t}$ control the stochastic process of the regional center's and the U.S. spillover intensities in market m, respectively. It is also assumed that the local innovation follows the normal distribution with mean zero and variance switching. The conditional variance of the local shock depends on the state of the local economy, $S^\ddagger_{m,t}$, along with the overall performance of emerging stock markets measured by the logarithmic difference of daily values of the MSCI EM Beyond BRIC Index.[3] The local market asymmetry is captured by $|R_{EM,\,t-1}|\mathbf{I}\,(R_{EM,\,t-1} < 0)$, where the indicator function $\mathbf{I}$ equals one when $R_{EM,\,t-1} < 0$ and zero otherwise. This set-up allows me to investigate how the conditional variance of the local shock relates to the overall return of emerging equity markets. The coefficient $\nu_{2,\,S^{\ddagger}_{m,t}}$ is expected to be positive, for a local market may be disturbed by negative news about other emerging markets. I leave out ARCH effects in equation (4.7c) in an effort to keep the already complex model specifications as simple as I can.

Some empirical research suggests that small equity markets in the Asia-Pacific area can be driven by the U.S. market or a big regional market like Japan. Through in-depth analysis of co-movement amongst nine small Asian markets, the Japanese and the U.S. stock markets, Ghosh et al. [1999] report the findings as follows: (I) the U.S. equity market has dominant influence upon the markets in Hong Kong, India, Malaysia and South Korea in the long run; (II) those markets in Indonesia, Philippines and Singapore have a much closer relationship with the Japanese stock market; (III) the Taiwanese and the Thai stock markets seem to be independent of both Japanese and U.S. markets. Their study indicated that a local market is likely to share the common underlying random process with either a regional center or the U.S. market or neither of them. Significant progress has so far been achieved in the integration of goods and capital markets within the Asia-Pacific area (Park [2013]). With the cyclical patterns of Asian economies having become more synchronized, it is natural to query if there exists a global business cycle which drives market conditions worldwide in such a way that a local, a regional and the U.S. market all react in exactly the same way to front-page market news. After all, in light of global investors' efforts to optimize portfolio and capital allocation and minimize unsystematic risk, such a large-scale business cycle

[3] The MSCI EM Beyond BRIC Index evaluates the performance of those emerging markets other than Brazil, Russia, India and China, covering the following markets: Chile, Colombia, Czech, Egypt, Greece, Hungary, Indonesia, Korea, Malaysia, Mexico, Peru, Philippines, Poland, South Africa, Taiwan, Thailand and Turkey.

is not inconceivable. I am also keen to know how important common regional shocks are compared to global ones in terms of the degree to which the volatility level for an individual Asian market is affected by external risks. Hence, bearing in mind the main purposes of my research, I assume that the stochastic processes are identical which control the switching of the U.S. and regional spillover parameters and the conditional variance of $e_{m,t}$, i.e. $S^{*}_{m,\,t} = S^{\dagger}_{m,\,t} = S^{\ddagger}_{m,\,t} = \mathcal{S}_{m,\,t}$. The latent variables can take the value of either 1 or 2.

The underlying random processes develop in accordance with a first-order Markov chain, whose transition probability matrix is defined as

$$\begin{bmatrix} P\left(\mathcal{S}_{m,t} = 1 | \mathcal{S}_{m,t-1} = 1\right) & 1 - P\left(\mathcal{S}_{m,t} = 2 | \mathcal{S}_{m,t-1} = 2\right) \\ 1 - P\left(\mathcal{S}_{m,t} = 1 | \mathcal{S}_{m,t-1} = 1\right) & P\left(\mathcal{S}_{m,t} = 2 | \mathcal{S}_{m,t-1} = 2\right) \end{bmatrix}, \tag{4.8}$$

where $P\left(\mathcal{S}_{m,\,t} = 1 | \mathcal{S}_{m,\,t-1} = 1\right)$ and $P\left(\mathcal{S}_{m,\,t} = 2 | \mathcal{S}_{m,\,t-1} = 2\right)$ denote the conditional probabilities of the underlying processes for market m at time t staying in the same state as those at time $t-1$. Because the steady state of every market may shift through time, it would be ideal to incorporate heterogeneity in transition probabilities by letting them depend on one or multiple economic indicators (Filardo [1994], Gray [1996]) or state durations (Maheu and McCurdy [2000]) or endogenous variables (Ang and Bekaert [2002]). However, as reported by Guidolin [2011], there is very little literature on comparing the predictive performance of a time-varying transition probability Markov-switching system with that of its constant counterpart. Considering the limited availability of relevant data for some Asian markets and, more importantly, my efforts in bringing down the complexity of the model specifications, I prefer to adopt the standard set-up of the Markov-switching method, which often assumes constant state transition probabilities.

In the above model, I include regime changes in both variance of idiosyncratic local shocks and loadings on U.S. and regional risk factors. Alternatively, two parsimonious specifications are also proposed—regime switching is allowed for in either loadings on foreign shocks or local variance—as in equations (4.9a)–(4.9c) and (4.9d)–(4.9f), respectively:

$$\epsilon_{m,\,t} = \varepsilon_{m,\,t} + \delta_{S^{*}_{m,\,t}} e_{j,t} + \zeta_{S^{\dagger}_{m,\,t}} e_{US,\,t}, \tag{4.9a}$$

$$\varepsilon_{m,\,t}|\Omega_{m,\,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,\,t}\right), \tag{4.9b}$$

$$\ln\left(\sigma^2_{m,\,t}\right) = \nu_0 + \nu_1 R_{EM,\,t-1} + \nu_2 |R_{EM,\,t-1}| \mathbf{I}\left(R_{EM,\,t-1} < 0\right), \tag{4.9c}$$

$$\epsilon_{m,\,t} = \varepsilon_{m,\,t} + \delta e_{j,t} + \zeta e_{US,\,t}, \tag{4.9d}$$

$$\varepsilon_{m,\,t}|\Omega_{m,\,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,\,t,\,S^{\ddagger}_{m,\,t}}\right), \tag{4.9e}$$

$$\ln\left(\sigma^2_{m,\,t,\,S^{\ddagger}_{m,t}}\right) = \nu_{0,\,S^{\ddagger}_{m,\,t}} + \nu_{1,\,S^{\ddagger}_{m,\,t}} R_{EM,\,t-1} + \nu_{2,\,S^{\ddagger}_{m,\,t}} |R_{EM,\,t-1}| \mathbf{I}\left(R_{EM,\,t-1} < 0\right). \tag{4.9f}$$

In order to determine whether the regime-switching models can make improvement to in-sample fit, an even more parsimonious specification, which excludes regime changes completely as in equations (4.10a)–(4.10c), serves as a benchmark model:

$$\epsilon_{m,\,t} = \varepsilon_{m,\,t} + \delta e_{j,t} + \zeta e_{US,\,t}, \tag{4.10a}$$

$$\varepsilon_{m,\,t}|\Omega_{m,\,t-1} \sim \mathcal{N}\left(0, \sigma^2_{m,\,t}\right), \tag{4.10b}$$

$$\ln\left(\sigma^2_{m,\,t}\right) = \nu_0 + \nu_1 R_{EM,\,t-1} + \nu_2 |R_{EM,\,t-1}| \mathbf{I}\left(R_{EM,\,t-1} < 0\right). \tag{4.10c}$$

For the sake of clarity and succinctness, I hereafter refer to the model described by equations (4.7a)–(4.7c) as RS–I, (4.9a)–(4.9c) as RS–II, (4.9d)–(4.9f) as RS–III and (4.10a)–(4.10c) as NRS.

$\Omega_{m,\,t-1}$ denotes the information pertinent to country m at time $t-1$, which contains $R_{m,\,t-1}, R_{EM,\,t-1}$ and lagged values of these variables: $\Omega_{m,\,t-1} = \{R_{m,\,t-1}, R_{EM,\,t-1}, \Omega_{m,\,t-2}\}$.

The local shock $\varepsilon_{m,\,t}$ is assumed to be uncorrelated with either $e_{j,\,t}$ or $e_{US,\,t}$:

$$Cov\left(\varepsilon_{m,\,t},\; e_{j,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right) = 0, \tag{4.11a}$$

$$Cov\left(\varepsilon_{m,\,t},\; e_{US,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right) = 0, \tag{4.11b}$$

which suggests that the variance of the disturbance term is the sum of the variance of the local shock and orthogonalized innovations of a regional center and the U.S. market:

$$Var\left(\epsilon_{m,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right) = Var\left(\varepsilon_{m,\,t}|\Omega_{m,\,t-1}\right) + \delta_t^2\sigma_{j,\,t}^2 + \zeta_t^2\sigma_{US,\,t}^2, \tag{4.12a}$$

$$Cov\left(\epsilon_{m,\,t},\; e_{US,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right) = \zeta_t\sigma_{US,\,t}^2, \tag{4.12b}$$

$$Cov\left(\epsilon_{m,\,t},\; e_{j,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right) = \delta_t\sigma_{j,\,t}^2. \tag{4.12c}$$

The conditional correlation between market m and the U.S. or regional market at time t is easy to compute and takes the following general form:

$$\begin{aligned} VR_{t\cdot\Omega_{m,\,t-1},\mathcal{F}_{t-1}}^{m,\,US} = \quad & \left(\rho_{t\cdot\Omega_{m,\,t-1},\mathcal{F}_{t-1}}^{m,\,US}\right)^2 = \frac{\zeta_t^2\sigma_{US,\,t}^2}{Var\left(\epsilon_{m,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right)} \\ & = \frac{\zeta_t^2\sigma_{US,\,t}^2}{Var\left(\varepsilon_{m,\,t}|\Omega_{m,\,t-1}\right) + \delta_t^2\sigma_{j,\,t}^2 + \zeta_t^2\sigma_{US,\,t}^2}, \quad (4.13a) \\ VR_{t\cdot\Omega_{m,\,t-1},\mathcal{F}_{t-1}}^{m,\,j} = \quad & \left(\rho_{t\cdot\Omega_{m,\,t-1},\mathcal{F}_{t-1}}^{m,\,j}\right)^2 = \frac{\delta_t^2\sigma_{j,\,t}^2}{Var\left(\epsilon_{m,\,t}|\Omega_{m,\,t-1},\; \mathcal{F}_{t-1}\right)} \\ & = \frac{\delta_t^2\sigma_{j,\,t}^2}{Var\left(\varepsilon_{m,\,t}|\Omega_{m,\,t-1}\right) + \delta_t^2\sigma_{j,\,t}^2 + \zeta_t^2\sigma_{US,\,t}^2}. \quad (4.13b) \end{aligned}$$

The proportion of local variance attributed to U.S. or regional shocks is just the square of the conditional correlation.

Next, I shall briefly discuss the likelihood function of the univariate model to be maximized. For the sake of simplicity, I shall present the likelihood function of the most complicated specification of the data-generating process where $S_{m,\,t}^{*} = S_{m,\,t}^{\dagger} = S_{m,\,t}^{\ddagger} = \mathcal{S}_{m,\,t} =$

1, 2 only. The very same logic applies to the other two Markov-transition model specifications as well. Assuming that the conditional density of the local innovation is Gaussian (mixtures of normals are demonstrated to be capable of dealing with error terms, even though they may be actually subject to a great variety of fat-tailed distributions), the probability density function conditional on $\varepsilon_{m,t}$ being in state $i = 1,\, 2$ takes the form

$$f\left(R_{m,t} | \mathcal{S}_{m,t} = i,\, \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right) = \frac{1}{\sqrt{2\pi}\sigma^i_{m,t}} e^{-\frac{\left(R_{m,t} - \gamma_0 - \gamma_1 R_{m,t-1} - \delta^i e_{j,t} - \zeta^i e_{US,t}\right)^2}{2\sigma^{2\,i}_{m,t}}}, \tag{4.14}$$

where $\boldsymbol{\Pi}$ denotes the parameter vector of the univariate volatility transmission model. Note that the switching parameters are assumed to be constant within each state, although these coefficients are allowed to vary between the two states. The log-likelihood function is

$$\mathcal{L}\left(\boldsymbol{\Pi}\right) = \sum_{t=1}^{T} \log\left[\lambda\left(R_{m,t} | \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right)\right], \tag{4.15}$$

where T represents the total number of vectors of innovation entering the estimation. $\lambda\left(\cdot\right)$ is the sum of probability-weighted state densities of $f\left(\cdot\right)$ across the two states:

$$\begin{aligned} &\lambda\left(R_{m,t} | \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right) \\ &= \sum_{i=1}^{2} f\left(R_{m,t} | \Omega_{m,t-1},\, \mathcal{F}_{t-1},\, \mathcal{S}_{m,t} = i; \boldsymbol{\Pi}\right) P\left(\mathcal{S}_{m,t} = i | \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right), \end{aligned} \tag{4.16}$$

where $P\left(\mathcal{S}_{m,t} = i | \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right)$ is the probability of being in state i at time t given the previous information sets. According to the law of total probability, the state probabilities are computed in the following way:

$$
\begin{aligned}
& P\left(\mathcal{S}_{m,t}=i \mid \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right) \\
& = \sum_{j=1}^{2} P\left(\mathcal{S}_{m,t}=i \mid \mathcal{S}_{m,t-1}=j\right) P\left(\mathcal{S}_{m,t-1}=j \mid \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right).
\end{aligned}
\tag{4.17}
$$

Eventually, the filtered state probability at $t-1$ can be calculated by Bayes' formula recursively:

$$
\begin{aligned}
& P\left(\mathcal{S}_{m,t-1}=j \mid \Omega_{m,t-1},\, \mathcal{F}_{t-1}; \boldsymbol{\Pi}\right) \\
& = P\left(\mathcal{S}_{m,t-1}=j \mid R_{m,t-1},\, R_{EM,t-1},\, \Omega_{m,t-2},\, \mathbf{H}_{t-1},\, \boldsymbol{\varepsilon}_{t-1},\, \mathcal{F}_{t-2}; \boldsymbol{\Pi}\right) \\
& = \frac{f\left(R_{m,t-1} \mid \mathcal{S}_{m,t-1}=j,\, \Omega_{m,t-2},\, \mathcal{F}_{t-2}; \boldsymbol{\Pi}\right) P\left(\mathcal{S}_{m,t-1}=j \mid \Omega_{m,t-2},\, \mathcal{F}_{t-2}; \boldsymbol{\Pi}\right)}{\sum_{j=1}^{2} f\left(R_{m,t-1} \mid \mathcal{S}_{m,t-1}=j,\, \Omega_{m,t-2},\, \mathcal{F}_{t-2}; \boldsymbol{\Pi}\right) P\left(\mathcal{S}_{m,t-1}=j \mid \Omega_{m,t-2},\, \mathcal{F}_{t-2}; \boldsymbol{\Pi}\right)}.
\end{aligned}
\tag{4.18}
$$

The parameters are estimated by directly maximizing the log-likelihood function in equation (4.15). The non-linear optimisation problem is solved by the BFGS algorithm. To avoid local maxima, I supply at least ten starting values.

4.2.2 Post-estimation Diagnostic Procedures

(a) GMM-based tests on standard residuals. In order to determine whether the model is correctly specified, I will take a closer look at the assumption that the innovation, $\varepsilon_{m,t}$, follows the normal distribution. Within the framework presented by Nelson [1991] for the test for normality, I check if the standardized residual of the univariate model, $z_{m,t}=\frac{\hat{\varepsilon}_{m,t}}{\hat{\sigma}_{m,t}}$, $m \in$ {ID, IN, KR, LK, MY, PK, PH, TW, TH, VN}, violates the orthogonality conditions implied by the standard normal distribution.[4] Listed below are the product moments up

[4] For the three regime-switching models, I apply to the diagnostic tests the conditional standardized residual. When necessary, I calculate probability-weighted residuals and standard deviations.

to the fourth order of a random variable with zero mean and unit variance subject to the standard normal distribution:

$$E\left(z_{m,t}z_{m,t-k}\right) = 0, \tag{4.19a}$$

$$E\left[\left(z_{m,t}^2 - 1\right)\left(z_{m,t-k}^2 - 1\right)\right] = 0, k = 1, 2, ..., 5, \tag{4.19b}$$

$$E\left(z_{m,t}\right) = 0, \tag{4.19c}$$

$$E\left(z_{m,t}^2 - 1\right) = 0, \tag{4.19d}$$

$$E\left(z_{m,t}^3\right) = 0, \tag{4.19e}$$

$$E\left(z_{m,t}^4 - 3\right) = 0. \tag{4.19f}$$

Similar to the normality test previously carried out, the diagnostic test is based on the generalized method of moments as well. Moment conditions (4.19a) and (4.19b) examine whether the residuals and squared residuals of country m are autocorrelated up to the fifth order, respectively—(4.19a) tests whether the conditional mean is correctly specified while (4.19b) deals with the conditional variance. Both test statistics asymptotically follow the $\chi^2(5)$ distribution. I employ moments (4.19c)–(4.19f) to test the null hypothesis that the residuals are subject to the standard normal distribution from the perspective of mean (4.19c), variance (4.19d), skewness (4.19e) and excess kurtosis (4.19f). The joint test produces a test statistic asymptotically $\chi^2\left(4\right)$ distributed. Additionally, moments (4.19a)–(4.19f) are tested simultaneously. The test statistic has 14 degrees of freedom.

(b) Likelihood ratio test on the number of regimes. In the literature about applications of Markov-switching models in empirical finance, one of the topics posing some challenging questions to researchers is concerned with determining the number of regimes. Under the null hypothesis of single-state normality, the parameters $P_{1,1}$ and $P_{2,2}$ become unidentified. Owing to the presence of these unidentified parameters, the standard likelihood ratio test statistic is no longer asymptotically χ^2 distributed, which contributes to the test's being inapplicable.[5] Under these circumstances, Turner et al. [1989] propose employing a modified likelihood ratio statistic so as to test the alternative hypothesis of a mixture of normals against the null of single-state normality. The modified likelihood ratio statistic is constructed in the following way:

$$LRT = -\frac{2}{T}\left(T-3\right)\left(l_n - l_a\right), \tag{4.20}$$

where l_n and l_a are the log-likelihood values of the null model (NRS) and the alternative one (RS–I/RS–II/RS–III), respectively. The test statistic converges in distribution to χ^2 with two degrees of freedom.[6] Rejection of NRS is indicated by significant LRTs.

(c) Bayesian information criterion (BIC). Besides hypothesis testing, one may also find complexity-penalized likelihood criteria very helpful in assessing the performance of competing models, whether they are nested or not. According to Granger et al. [1995], these criteria are arguably even more suitable than hypothesis testing when it comes to model comparison and selection, since none of the competing models is chosen to be the null usually unfairly favored by hypothesis testing. In addition, selection of the significance level, indispensable for formal testing, is at researchers' discretion, while methods based on information criteria do not require researchers to choose the level of significance. Similarly, Psaradakis and Spagnolo [2003] report that as long as the sample size is not too small and parameters do not change inconsiderably, procedures based on likelihood criteria are rather efficient and effective in determining the total number of regimes in Markov-switching au-

[5]These nuisance parameters give rise to a likelihood surface with many freedom degrees, which makes it computationally impossible for researchers to reject the null. Alternatively, as suggested by McLachlan [1987], one may rely on the critical values derived from bootstrapping the likelihood ratio test statistic for normal mixtures. Nonetheless, it should be kept in mind that it has yet to be established and is far from conspicuous whether such resampling methods are asymptotically flawless.

[6]LRT converges to the χ^2 distribution with $K\left(K-1\right)$ degrees of freedom, where K represents the total number of regimes in Markov-transition models. There are $K\left(K-1\right)$ elements of the transition probability matrix which would not need to be estimated for the lack of switching states.

toregressive models. McLachlan and Peel [2005] review the literature on normal mixtures and suggest that the Bayesian information criterion may be able to serve as an indicator for the number of components incorporated in mixed models. In this study, BIC is employed to evaluate the performance of the four data-generating processes specified in section 4.2.1.

(d) Regime classification measure (RCM). Since the early work by Hamilton [1988], RCM has been developed to assess how capable a Markov-transition model is in distinguishing regimes sharply. A superb regime-switching model will yield smoothed probabilities near either zero or one, whereas an inferior one will make them in closer proximity to $\frac{1}{K}$. A popular RCM exclusively for two-state models proposed by Ang and Bekaert [2002] is given as follows:

$$RCM = \frac{400}{T}\sum_{t=1}^{T}\tilde{p_t}\left(1-\tilde{p_t}\right), \tag{4.21}$$

where $\tilde{p_t}$ stands for the smoothed probability at period t and the purpose of the constant is to normalize the measure so that it falls between 0 and 100. The statistic approximates 0 for a model which excels in differentiating one regime from the other and 100 for a poorly performing model. The lower the value of its associated RCM, the more capable a model is of classifying regimes unambiguously. This indicator will play a particularly important role in selecting the best fitting model for each local market.

4.3 Estimation Results

In Table 4.1, I present the results of a GMM-based normality test on the standardized residuals of the above four models in columns 2–5. The average of the joint test statistics is greatest for NRS (72.61) and smallest for RS–II (42.57). The three regime-switching models are rejected by the normality test in only six cases. In stark contrast, the same test rejects NRS for all local markets at the conventional significance levels. Results of the GMM-based diagnostic test suggest that overall the Markov-switching models outperform the benchmark one. This contention is further substantiated by the results of the modified likelihood ratio test displayed in columns 6–8.

Table 4.1: Comparison of Four Univariate Spillover Model Specifications

Table 4.1 reports the results of jointly testing (4.19a)–(4.19f) in columns 2–5. The likelihood ratio test statistics based on (4.20) are given in columns 6–8. The joint and the modified likelihood ratio test statistics are χ^2 distributed with 14 and 2 degrees of freedom, respectively. Whether a joint test statistic is significant or not is totally determined by empirical p-values obtained from 5,000 Monte-Carlo simulations for 1,152 observations. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel. The finalized results of model selection are given in the last column.

Market	*GMM-based Diagnosis Test*				*Likelihood Ratio Test*			*Final*
	RS–I[a]	RS–II[b]	RS–III[c]	NRS[d]	RS–I[a]	RS–II[b]	RS–III[c]	*Choice*
				A. Australian Market as Regional Center				
India	45.65‡	42.43	46.85‡	58.92†	256.90*	157.28*	252.25*	RS–I
Indonesia	66.98†	58.04†	59.33†	93.88*	204.41*	64.73*	196.33*	RS–III
Korea	25.80	34.64	24.57	92.83*	211.23*	101.22*	208.04*	RS–III
Malaysia	41.78	71.73†	64.29†	95.19*	151.26*	45.48*	145.63*	RS–I
Pakistan	45.82‡	26.89	46.95‡	72.82†	356.13*	72.39*	355.99*	RS–III
Philippines	54.27†	59.29†	50.49‡	79.44*	108.45*	17.73*	104.77*	RS–I
Sri Lanka	119.35*	34.48	115.97*	116.17*	517.62*	171.33*	515.26*	RS–III
Taiwan	35.59	50.19‡	41.97	78.49*	156.81*	50.72*	152.60*	RS–III
Thailand	38.83	33.60	52.09‡	63.75†	128.64*	49.97*	125.76*	RS–I
Vietnam	37.11	26.79	37.21	53.08†	177.47*	33.80*	176.74*	RS–I
				B. Chinese Market as Regional Center				
India	39.67	30.08	41.78	64.09†	235.15*	155.75*	234.64*	RS–III
Indonesia	52.04‡	37.10	46.87‡	57.52†	203.07*	38.03*	197.32*	RS–I
Korea	59.27†	27.27	59.62†	65.87†	185.81*	78.23*	181.93*	RS–I
Malaysia	36.43	40.28	38.20	61.69†	161.31*	65.52*	155.84*	RS–I
Pakistan	45.00‡	46.01‡	46.99‡	71.11†	355.48*	86.71*	353.68*	RS–III
Philippines	63.56†	64.46†	63.22†	81.89*	106.94*	27.61*	106.45*	RS–I
Sri Lanka	124.25*	32.37	124.14*	116.43*	514.29*	181.50*	512.68*	RS–III
Taiwan	39.43	37.50	36.30	61.42†	127.44*	34.57*	125.11*	RS–III
Thailand	54.59†	72.01†	55.19†	91.37*	127.54*	24.27*	127.25*	RS–I
Vietnam	39.77	49.85‡	39.46	52.71†	176.07*	23.37*	171.95*	RS–III
				C. Japanese Market as Regional Center				
India	43.23	33.81	43.31‡	57.77†	242.88*	138.98*	241.83*	RS–III
Indonesia	40.77	40.92	39.03	59.87†	203.77*	52.17*	198.87*	RS–III
Korea	32.75	27.75	34.10	59.73†	173.76*	71.15*	150.23*	RS–I
Malaysia	36.49	37.13	36.79	65.56†	162.59*	41.02*	161.08*	RS–III
Pakistan	45.95‡	29.16	48.19‡	74.01†	354.21*	60.33*	352.68*	RS–III
Philippines	31.34	38.57	31.15	50.93‡	106.20*	35.41*	102.28*	RS–I
Sri Lanka	121.34*	77.64*	120.60*	112.59*	514.58*	144.27*	512.19*	RS–III

(***Continued on next page***)

Table 4.1 - Continued from previous page

Market	*GMM-based Diagnosis Test*				*Likelihood Ratio Test*			*Final*
	RS–I[a]	RS–II[b]	RS–III[c]	NRS[d]	RS–I[a]	RS–II[b]	RS–III[c]	*Choice*
Taiwan	42.76	47.59‡	51.15‡	66.60†	112.71*	41.46*	129.95*	RS–III
Thailand	29.69	34.37	48.00‡	47.63‡	114.92*	23.20*	107.43*	RS–I
Vietnam	39.36	35.19	39.91	54.83†	174.10*	23.82*	173.90*	RS–I

[a] Specification I of the regime-switching process: (4.7a)–(4.7c); [b] Specification II: (4.9a)–(4.9c); [c] Specification III: (4.9d)–(4.9f); [d] Single-state model: (4.10a)–(4.10c). $*$, † and ‡ indicate significance at the 1%, 5% and 10% levels, respectively.

The purpose of the likelihood ratio test is to investigate if the two-state models (I–III) are statistically different than the single-state one (NRS). Without exception, the test statistics reject the null of single-state normality at the 1% level of significance and thus favor the alternative hypothesis of a mixture of normals, confirming the prior results that the effect of switching states is important to either the spillover coefficients or the variance of local shocks or both. Although one would also want to compare from the perspective of hypothesis testing which regime-switching model works best, no straightforward test is readily available that circumvents cumbersome computation, since neither RS–II nor RS–III is nested in RS–I. Nevertheless, the modified likelihood ratio statistics may still give an inkling of how to rank the three Markov-transition models amongst themselves. In all cases, RS–I has the greatest significant LRTs. From this perspective, RS–I appears to outperform the other two Markov-switching models in all local markets, suggesting that two switching regimes do matter to both variance of indigenous shocks and spillover intensity.

Table 4.2 reports the values of BIC and RCM for the three regime-switching models (RS–I, RS–II & RS–III) and benchmark model (NRS) with columns 2–5 presenting the BIC statistics and columns 6–8 the RCM statistics. Compared with RS–II and NRS, RS–I and RS–III have lower values of BIC in all cases, which indicates that RS–I and RS–III are favored over RS–II and NRS. Furthermore, RS–I is still on a par with RS–III, although it has the smallest BIC in all but the Japan-Korea case, in the light of the slight difference between

Table 4.2: Comparison of Four Univariate Spillover Model Specifications—Continued

Market	*Bayesian Information Criterion*				*RCM*		
	RS–I[a]	RS–II[b]	RS–III[c]	NRS[d]	RS–I[a]	RS–II[b]	RS–III[c]
	A. Australian Market as Regional Center						
India	6.18×10^3	6.25×10^3	6.17×10^3	6.38×10^3	1.58	0.66	1.98
Indonesia	6.08×10^3	6.20×10^3	6.07×10^3	6.24×10^3	26.34	10.59	25.86✓
Korea	5.96×10^3	6.05×10^3	5.95×10^3	6.13×10^3	11.52	75.52	10.66✓
Malaysia	4.56×10^3	4.65×10^3	4.55×10^3	4.66×10^3	29.28	18.48	18.89✓
Pakistan	5.94×10^3	6.21×10^3	5.93×10^3	6.25×10^3	20.22	0.45	20.17✓
Philippines	5.65×10^3	5.72×10^3	5.64×10^3	5.71×10^3	39.12	9.97	41.83
Sri Lanka	5.66×10^3	5.99×10^3	5.65×10^3	6.13×10^3	32.00	3.84	31.98✓
Taiwan	5.51×10^3	5.59×10^3	5.50×10^3	5.62×10^3	6.64	3.93	5.91✓
Thailand	6.03×10^3	6.09×10^3	6.02×10^3	6.11×10^3	28.62	4.61	30.04
Vietnam	6.45×10^3	6.577×10^3	6.44×10^3	6.583×10^3	29.26	51.14	29.30
	B. Chinese Market as Regional Center						
India	6.09×10^3	6.15×10^3	6.08×10^3	6.28×10^3	5.49	0.81	5.33✓
Indonesia	5.91×10^3	6.05×10^3	5.90×10^3	6.06×10^3	23.93	84.76	24.07
Korea	5.92×10^3	6.00×10^3	5.91×10^3	6.05×10^3	10.85	21.20	11.54
Malaysia	4.47×10^3	4.55×10^3	4.46×10^3	4.58×10^3	8.64	11.28	9.01
Pakistan	5.94×10^3	6.19×10^3	5.93×10^3	6.25×10^3	20.36	0.85	20.32✓
Philippines	5.60×10^3	5.6541×10^3	5.58×10^3	5.6536×10^3	46.48	16.57	47.90
Sri Lanka	5.66×10^3	5.98×10^3	5.65×10^3	6.13×10^3	32.08	3.38	31.90✓
Taiwan	5.39×10^3	5.46×10^3	5.38×10^3	5.47×10^3	14.46	59.80	12.88✓
Thailand	5.85×10^3	5.94×10^3	5.84×10^3	5.93×10^3	26.76	10.21	26.97
Vietnam	6.46×10^3	6.594×10^3	6.45×10^3	6.589×10^3	33.50	79.59	32.18✓
	C. Japanese Market as Regional Center						
India	6.34×10^3	6.42×10^3	6.33×10^3	6.54×10^3	3.27	0.98	3.20✓
Indonesia	6.22×10^3	6.35×10^3	6.21×10^3	6.37×10^3	26.89	35.44	26.23✓
Korea	6.21×10^3	6.29×10^3	6.22×10^3	6.33×10^3	7.27✓	49.43	8.93
Malaysia	4.77×10^3	4.87×10^3	4.76×10^3	4.88×10^3	14.68	13.61	12.59✓
Pakistan	5.94×10^3	6.22×10^3	5.93×10^3	6.25×10^3	20.38	4.44	20.26✓
Philippines	5.71×10^3	5.76×10^3	5.70×10^3	5.77×10^3	37.79	3.81	40.80
Sri Lanka	5.66×10^3	6.01×10^3	5.65×10^3	6.13×10^3	32.51	5.86	32.43✓
Taiwan	5.74×10^3	5.79×10^3	5.71×10^3	5.81×10^3	71.37	11.20	13.87✓
Thailand	6.14×10^3	6.212×10^3	6.13×10^3	6.207×10^3	28.11	5.93	31.35
Vietnam	6.46×10^3	6.59×10^3	6.44×10^3	6.58×10^3	32.06	12.10	32.49

[a] Specification I of the regime-switching process: (4.7a)–(4.7c); [b] Specification II: (4.9a)–(4.9c); [c] Specification III: (4.9d)–(4.9f); [d] Single-state model: (4.10a)–(4.10c).
✓marks the model of initial choice in each case.

their BIC values, which generally lies between 10 and 30. In order to further compare RS–I and RS–III, I assess their regime classification performance by RCM. Again, the two models are almost equally good—there are seventeen out of thirty cases in which the values of RCM are lower for RS–III and thirteen for RS–I. The ticks mark the Markov-transition models, either RS–I or RS–III, whose RCM and BIC are both smaller.

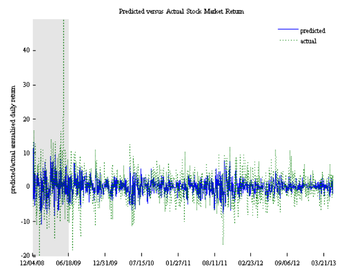
When selecting the better fitting Markov-transition model for each country, I tend to give top priority to those models with smaller BIC, since likelihood criteria do not require that the models being compared be nested. Meanwhile, I also take into account a Markov-transition model's ability to distinguish states by reference to its RCM so that whether RS–I or RS–III will receive preference partly depends on which has smaller RCM. As shown in the last two columns of Table 4.2, there are eighteen models in total whose RCM and BIC values are both lower and which become my initial choices. For the rest of the thirty cases, I shall base my model selection procedures on the results of the normality test along with the modified likelihood ratio test. Provided that the normality test gives inconclusive results, I will select whichever model has higher LRT. Actually, the GMM-based diagnosis test is regarded as an important component of the model selection procedures because a significant test statistic reveals that the distribution of errors could be erroneously specified. If an initially selected model fails the diagnosis test, the choice previously made has to be modified accordingly. For instance, in the Australia-Malaysia case, RS–I instead of RS–III is selected, even though the latter is preferred by both model performance indicators. In summary, according to the model selection criteria as stipulated above, RS–I turns out to perform better than RS–III in nearly half of the thirty cases. To see how well the selected regime-switching models fit the sample data, I plot the predicted (in blue solid line) and the actual (in green dotted line) stock returns on the same graph for each combination of the local markets and regional center proxies.

In Table 4.3, I present the yearly average U.S. and regional spillover intensities spanning 2009 to 2013 wherever RS–I is selected as the main model in order to better understand volatility spillovers from the U.S. and Australian/Chinese/Japanese equity markets to a small one in the Asia-Pacific area. The spillover intensities at each period are calculated

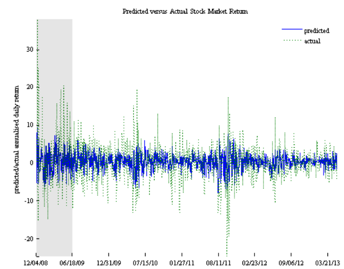
Figure 4.1: Predicted Returns Versus Actual Returns in Thirty Combinations of Local Markets and Regional Center Proxies

A. Australian Market as Regional Center

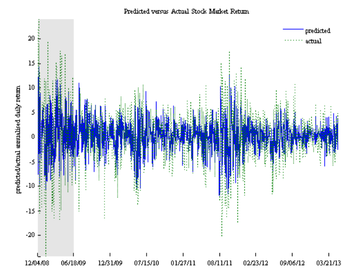
a. India



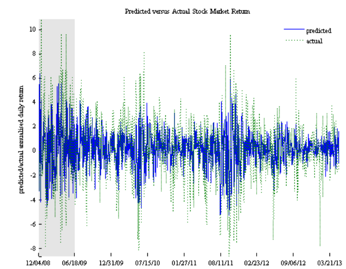
b. Indonesia



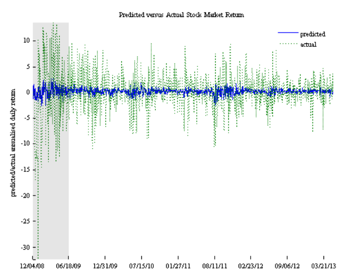
c. Korea



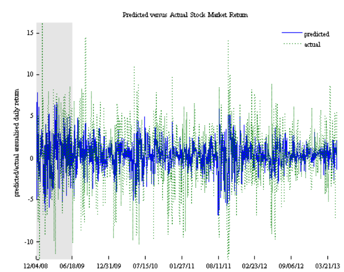
d. Malaysia



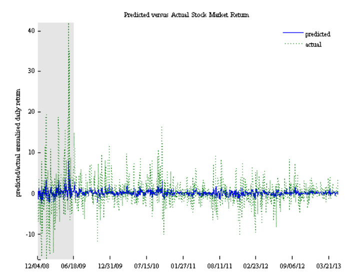
e. Pakistan



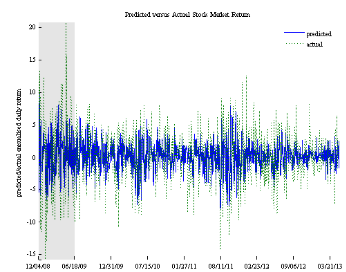
f. The Philippines



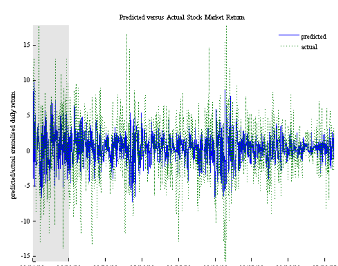
g. Sri Lanka



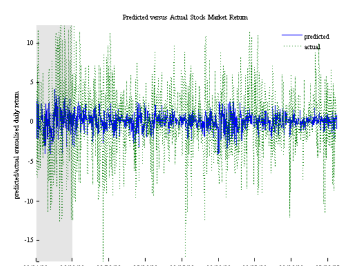
h. Taiwan



i. Thailand

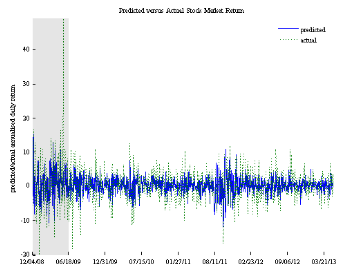


j. Vietnam

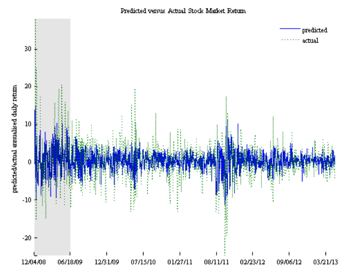


B. Chinese Market as Regional Center

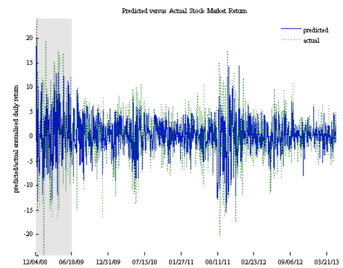
a. India



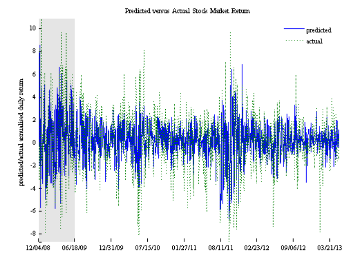
b. Indonesia



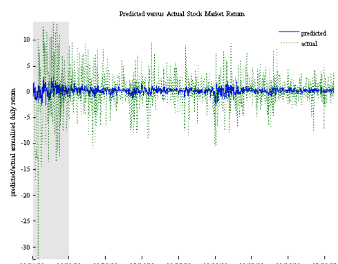
c. Korea



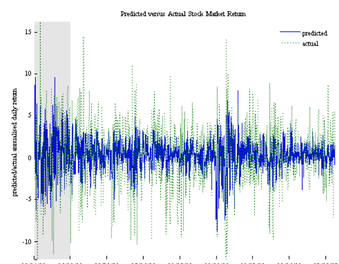
d. Malaysia



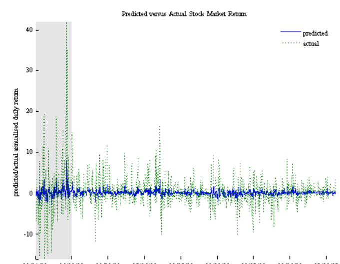
e. Pakistan



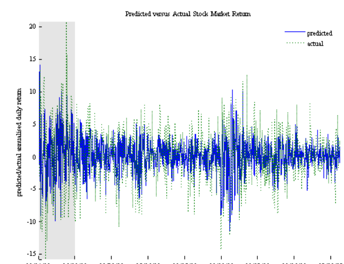
f. The Philippines



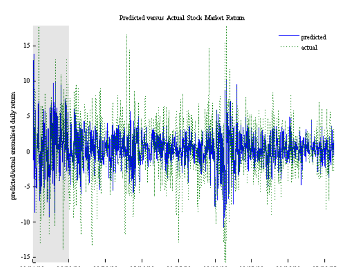
g. Sri Lanka



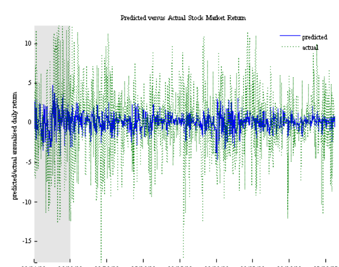
h. Taiwan



i. Thailand

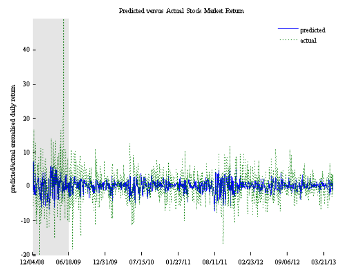


j. Vietnam

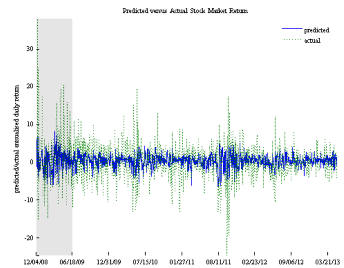


C. Japanese Market as Regional Center

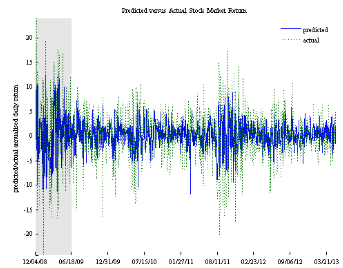
a. India



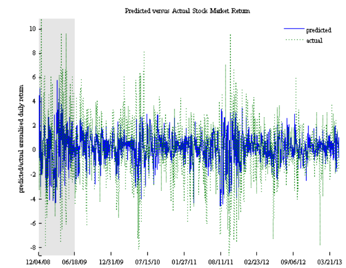
b. Indonesia



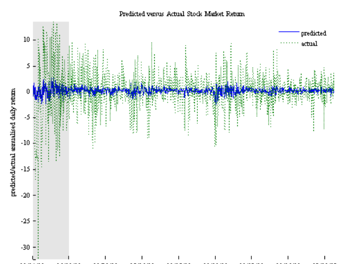
c. Korea



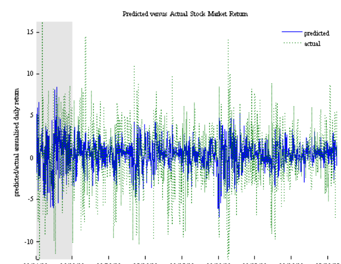
d. Malaysia



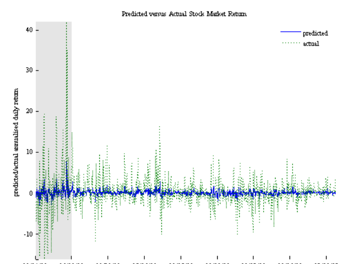
e. Pakistan



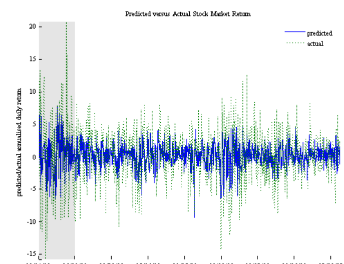
f. The Philippines



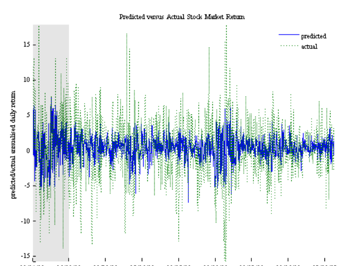
g. Sri Lanka



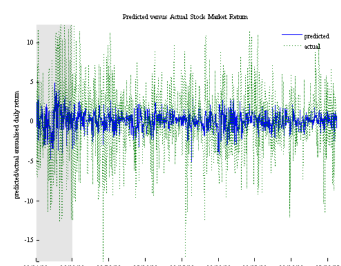
h. Taiwan



i. Thailand



j. Vietnam



by multiplying the switching spillover coefficients by the filtered probabilities during that period. In all fourteen cases, a local market's sensitivity to regional shocks, compared with that to U.S. shocks, was noticeably greater during all subsample periods, indicating that on average, the regional shocks may have exerted an even more profound impact upon the local markets in this study during the covered period than did innovations originating in the States. Wherever the Australian or the Japanese market serves as the regional center, the U.S. together with the regional spillover intensities peaked in 2009 and then gradually fell afterwards, which suggests reduced exposure of these local markets to shocks originating in the U.S. market and the regional center in the post-crisis period.

Table 4.3: Annual Average U.S. and Regional Spillover Intensity from 2009 to 2013

For those cases where RS–I is chosen to be the main model, Table 4.3 displays the yearly average spillover intensities from the U.S. and the Australian/Chinese/Japanese markets during the period 1 January 2009–3 May 2013. The switching spillover coefficients are multiplied by the filtered probabilities at period t, which yields the spillover intensities during that period.

Year	India	Indonesia	Korea	Malaysia	Pakistan	Philippines	Sri Lanka	Taiwan	Thailand	Vietnam
A. Australian Market as Regional Center										
Panel (a) U.S. Spillover Intensity										
2009	0.509	-	-	0.176	-	0.119	-	-	0.317	0.076
2010	0.387	-	-	0.167	-	0.107	-	-	0.267	0.055
2011	0.392	-	-	0.172	-	0.092	-	-	0.283	0.063
2012	0.388	-	-	0.164	-	0.092	-	-	0.240	0.057
2013	0.386	-	-	0.167	-	0.092	-	-	0.248	0.067
Overall	**0.419**	-	-	**0.170**	-	**0.102**	-	-	**0.276**	**0.063**
Panel (b) Regional Spillover Intensity										
2009	0.519	-	-	0.303	-	0.272	-	-	0.412	0.098
2010	0.429	-	-	0.273	-	0.264	-	-	0.394	0.121
2011	0.432	-	-	0.289	-	0.254	-	-	0.400	0.113
2012	0.429	-	-	0.263	-	0.254	-	-	0.384	0.119
2013	0.428	-	-	0.271	-	0.254	-	-	0.387	0.108
Overall	**0.452**	-	-	**0.282**	-	**0.261**	-	-	**0.397**	**0.112**
B. Chinese Market as Regional Center										
Panel (a) U.S. Spillover Intensity										

(***Continued on next page***)

Table 4.3 - Continued from previous page

Year	India	Indonesia	Korea	Malaysia	Pakistan	Philippines	Sri Lanka	Taiwan	Thailand	Vietnam
2009	-	0.185	0.340	0.150	-	0.079	-	-	0.249	-
2010	-	0.202	0.429	0.178	-	0.080	-	-	0.255	-
2011	-	0.206	0.393	0.166	-	0.083	-	-	0.253	-
2012	-	0.213	0.436	0.187	-	0.083	-	-	0.259	-
2013	-	0.216	0.436	0.171	-	0.083	-	-	0.258	-
Overall	-	**0.202**	**0.400**	**0.169**	-	**0.082**	-	-	**0.254**	-
Panel (b) Regional Spillover Intensity										
2009	-	0.626	0.746	0.329	-	0.318	-	-	0.561	-
2010	-	0.579	0.733	0.323	-	0.315	-	-	0.554	-
2011	-	0.567	0.738	0.326	-	0.310	-	-	0.557	-
2012	-	0.547	0.732	0.321	-	0.310	-	-	0.549	-
2013	-	0.538	0.732	0.325	-	0.310	-	-	0.551	-
Overall	-	**0.578**	**0.737**	**0.325**	-	**0.313**	-	-	**0.555**	-
C. Japanese Market as Regional Center										
Panel (a) U.S. Spillover Intensity										
2009	-	-	0.434	-	-	0.118	-	-	0.329	0.084
2010	-	-	0.402	-	-	0.111	-	-	0.268	0.070
2011	-	-	0.422	-	-	0.101	-	-	0.294	0.075
2012	-	-	0.392	-	-	0.101	-	-	0.237	0.070
2013	-	-	0.388	-	-	0.100	-	-	0.241	0.078
Overall	-	-	**0.412**	-	-	**0.107**	-	-	**0.280**	**0.075**
Panel (b) Regional Spillover Intensity										
2009	-	-	0.571	-	-	0.168	-	-	0.284	0.126
2010	-	-	0.404	-	-	0.155	-	-	0.215	0.123
2011	-	-	0.507	-	-	0.138	-	-	0.244	0.124
2012	-	-	0.356	-	-	0.137	-	-	0.181	0.123
2013	-	-	0.333	-	-	0.136	-	-	0.184	0.125
Overall	-	-	**0.455**	-	-	**0.149**	-	-	**0.229**	**0.124**

Interestingly, in contrast to what was previously found whenever I chose Japan or Australia to be the regional market, the yearly average value of Chinese spillover intensity reached its maximum in 2009, whereas the average of U.S. spillover intensity during the same period turned out comparatively low. It appeared that the five local economies became more integrated with the Greater Chinese market by increasing exposure to Chinese innovations. A possible explanation is provided as follows for the marked difference in the dynamics of U.S. and regional spillover intensity under various assumptions about which market dominates the Asia-Pacific region. The year of 2009 witnessed a wider spread of the sub-prime mortgage crisis beginning in the U.S. market at the end of 2007. Unlike shocks to the Australian and the Japanese markets, which may carry information more or less similar to what U.S. shocks contain, Chinese shocks may be somewhat or even totally heterogeneous in nature. The mainland market is relatively close because the government exercises strict control over international capital flows.[7] As a result, the role played by foreign-funded banks in the financial system of mainland China remained limited during the 2009 global crisis. Other factors such as a high level of foreign exchange reserves and strong fiscal position also account for the fact that the country is not susceptible to the risk of an abrupt change in global financial markets. This research suggests that several Asia-Pacific equity markets tended to take advantage of the inherent heterogeneity of shocks of Chinese origin by means of strengthening integration with the Chinese market in order to circumvent some, albeit not all, global risk factors.

In Figure 4.2, I also plot the probability-weighted U.S. and Australian/Chinese/Japanese spillover intensities with the shaded area indicating the latest recession period announced by NBER to facilitate the analysis of how they developed through time. It should be noted that for some local markets, those factors underlying the dynamics of U.S. and regional spillover intensities reveal a more cyclical than structural nature. For instance, it is obvious in the Philippine, Thai and Vietnamese cases that U.S. and regional spillover intensities switched rather frequently between a low spillover state and a high one after the crisis ended. On the contrary, in spite of a few short-lived jumps, both regional and U.S. spillover inten-

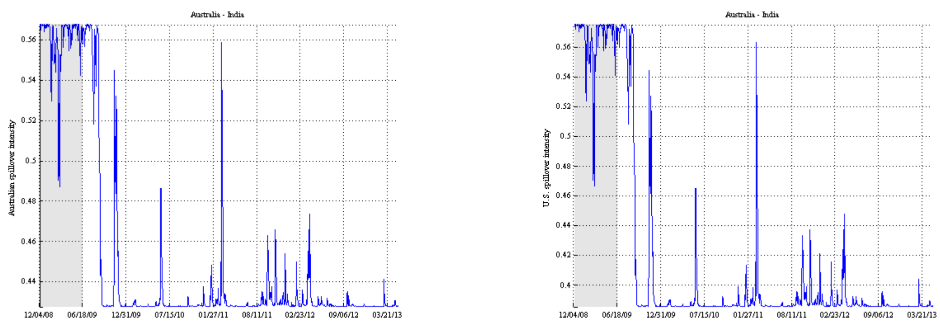
[7]China Daily reported on 7 July 2008 that the total assets of foreign-funded banks in mainland China was approximately $193 billion by the end of March of that year, accounting for only 2.44% of total bank assets in the country.

Figure 4.2: Regional and U.S. Spillover Intensity from 4 December 2008 to 3 May 2013

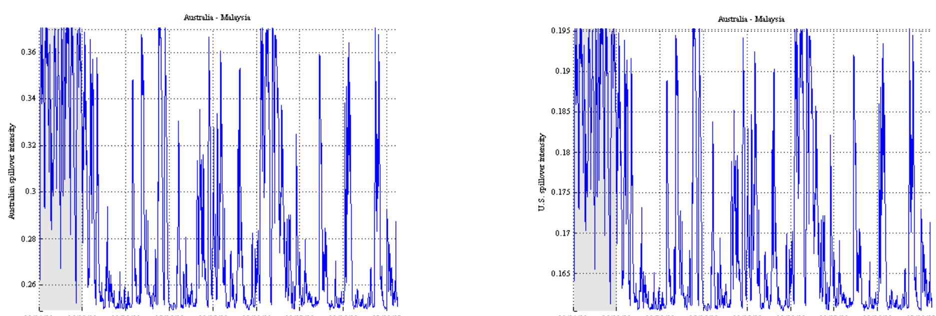
For those cases where RS–I is chosen to be the main model, Figure 4.2 displays the spillover intensities from the Australian/Chinese/Japanese (on the left side) and the U.S. (on the right side) markets during the period 4 December 2008–3 May 2013. The switching spillover coefficients are multiplied by the filtered probabilities at period t, which yields the spillover intensities during that period. The shaded area covers the recent U.S. recession and financial crisis.

A. Australian Market as Regional Center

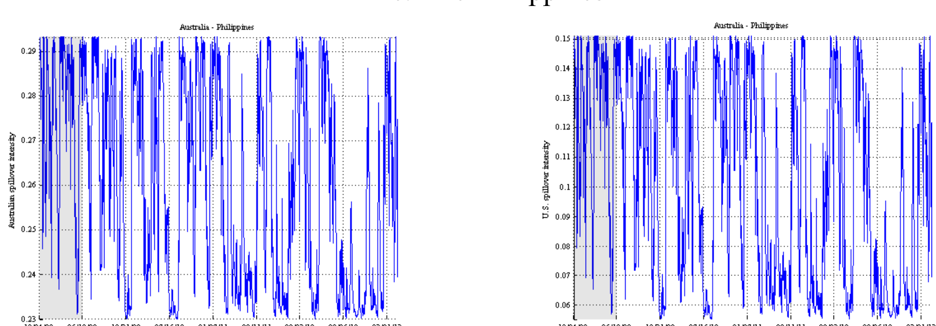
a. India



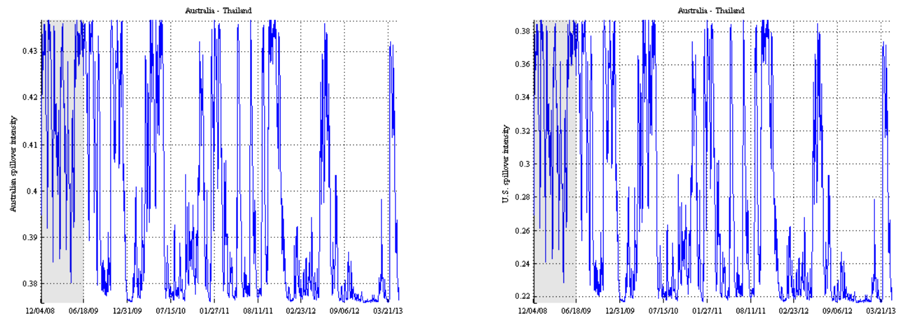
b. Malaysia



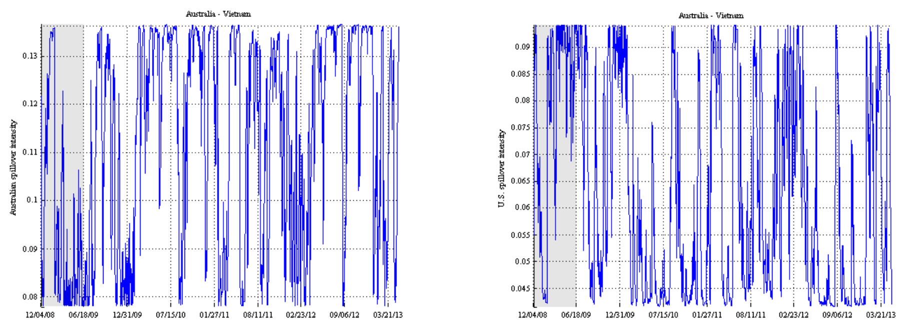
c. The Philippines



d. Thailand

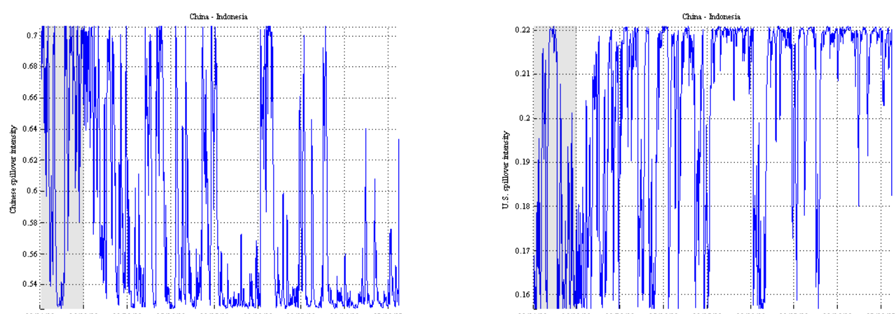


e. Vietnam

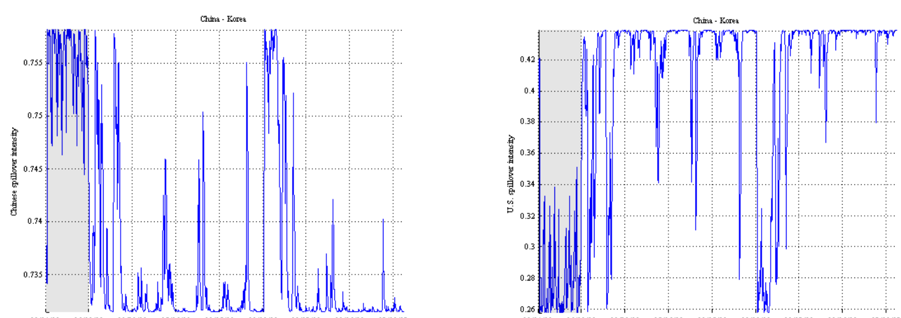


B. Chinese Market as Regional Center

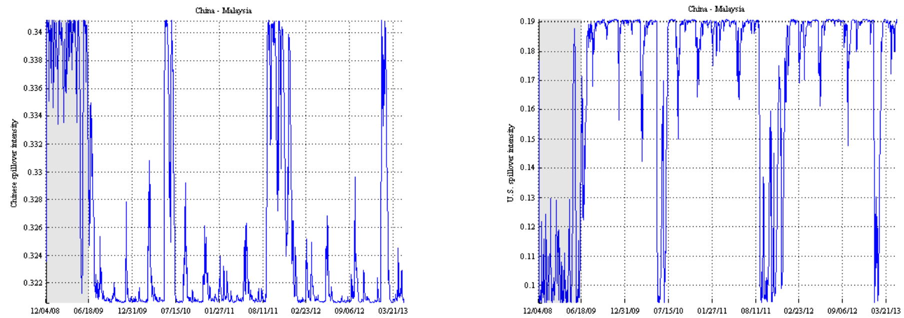
a. Indonesia



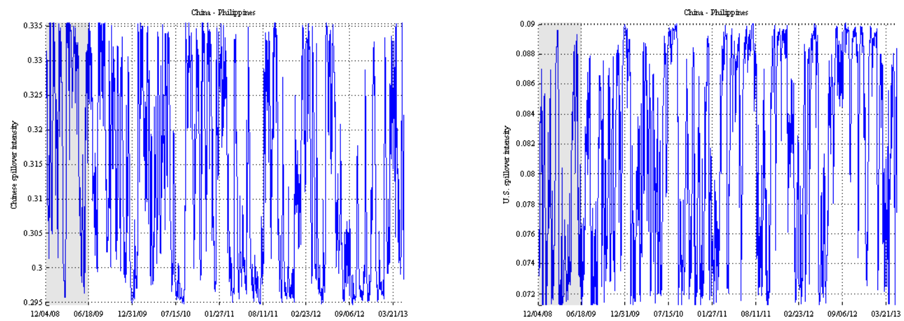
b. Korea



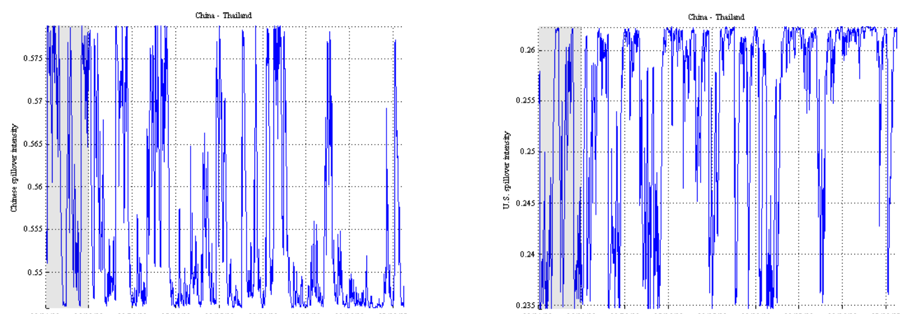
c. Malaysia



d. The Philippines

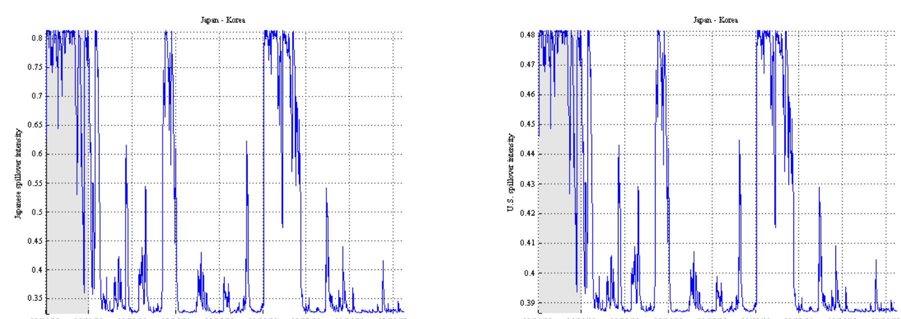


e. Thailand

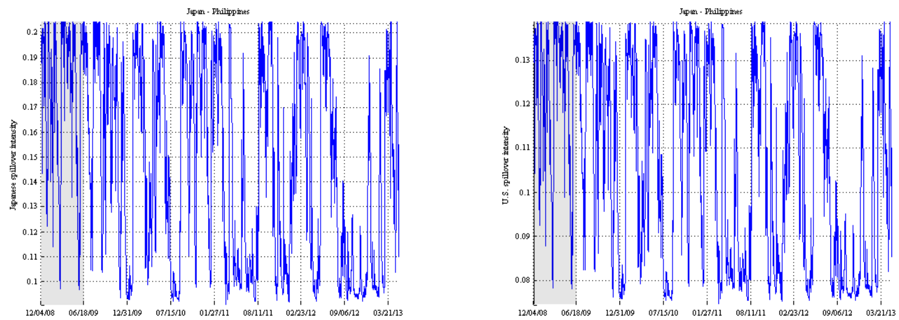


C. Japanese Market as Regional Center

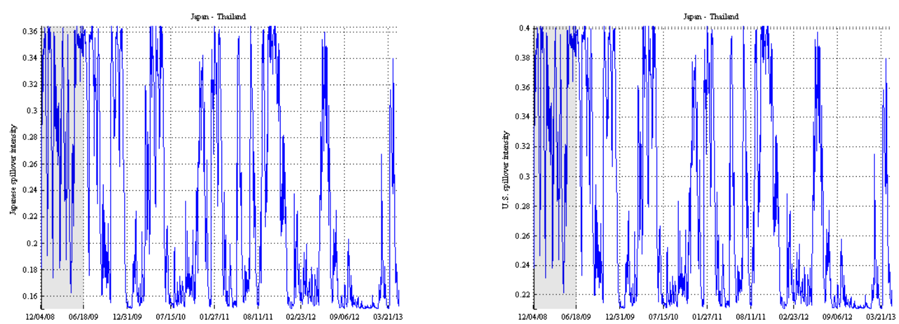
a. Korea



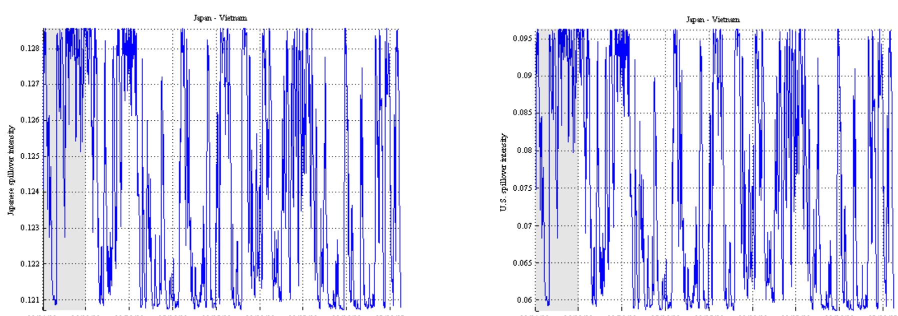
b. The Philippines



c. Thailand



d. Vietnam



sities appeared less volatile in the Australia-India, China-Malaysia and both China-Korea and Japan-Korea cases. The dynamics of regional and U.S. spillover intensities are more structural in nature in these four cases.

Table 4.4 reports the annual average proportions of local variance attributed to shocks to the U.S. and the Australian/Chinese/Japanese markets from 2009 to 2013. Whenever RS–I is chosen for a certain local market, I apply the probability-weighted spillover coefficients to formulae (4.13a) and (4.13b) to compute the required variance ratios. Over the entire sample period (04/December/2008–03/May/2013), the highest average proportions of local variance attributed to U.S. shocks are observed in the cases where the Japanese market serves as the regional center—India (19.04%), Korea (17.69%) and Malaysia (13.43%); the lowest in Pakistan and Sri Lanka, regardless of the presumptions about the regional center. The highest overall averages of proportion explained by regional shocks are seen in the China-Taiwan (35.25%), China-Korea (35.16%) and Australia-Korea (29.08%) cases, while the lowest again in Sri Lanka and Pakistan. Wherever the Chinese or the Australian market is chosen to be the regional center, regional shocks accounted for a larger share of local variance than did U.S. shocks during the full sample period in nearly all twenty cases, which suggests that in most of the local markets involved in this research, the volatility spillover effect of the regional market might well dominate that of the U.S. market during the end of 2008 to mid-2013. Surprisingly, despite being the largest in Asia in terms of market capitalisation, the Japanese market seemed to have a less significant impact of volatility transmission on the studied local markets than anticipated. The greatest proportion of local variance explained by shocks of Japanese origin from December 2008 until May 2013 merely exceeded 10% by a narrow margin.

Table 4.4: Annual Average U.S. and Regional Variance Ratio from 2009 to 2013

Table 4.4 reports the yearly average proportions of local variance attributable to shocks to the U.S. and the Australian/Chinese/Japanese markets during the period 1 January 2009–3 May 2013. When RS–I is chosen for a certain local market, I must apply the probability-weighted spillover coefficients to formulae (4.13a) and (4.13b) to calculate the required variance ratios.

Year	India	Indonesia	Korea	Malaysia	Pakistan	Philippines	Sri Lanka	Taiwan	Thailand	Vietnam
A. Australian Market as Regional Center										
Panel (a) Proportion of Local Variance Attributed to Shocks to U.S. Market										
2009	11.66%	3.67%	8.49%	8.07%	0.03‰	1.98%	0.07‰	6.64%	8.03%	0.43%
2010	11.83%	4.01%	10.02%	7.69%	0.05‰	1.34%	0.08‰	7.81%	6.08%	0.26%
2011	12.92%	4.71%	9.44%	7.83%	0.06‰	1.39%	0.11‰	7.05%	6.86%	0.35%
2012	9.27%	3.89%	9.13%	6.39%	0.04‰	0.87%	0.06‰	5.89%	4.50%	0.17%
2013	9.21%	4.02%	8.80%	5.90%	0.04‰	0.81%	0.08‰	5.98%	4.33%	0.17%
Overall	**11.29%**	**4.06%**	**9.21%**	**7.38%**	**0.04‰**	**1.37%**	**0.08‰**	**6.77%**	**6.28%**	**0.30%**
Panel (b) Proportion of Local Variance Attributed to Shocks to Regional Market										
2009	12.41%	12.60%	26.99%	23.84%	0.06%	11.08%	0.23%	24.95%	14.49%	1.15%
2010	14.54%	13.15%	31.13%	20.05%	0.11%	8.64%	0.26%	28.88%	13.31%	1.46%
2011	16.04%	15.64%	29.56%	21.70%	0.13%	11.29%	0.35%	26.23%	14.83%	1.42%
2012	11.66%	13.10%	29.26%	16.68%	0.09%	6.95%	0.19%	22.51%	11.76%	1.01%
2013	11.39%	13.06%	27.78%	15.44%	0.09%	6.68%	0.24%	22.46%	11.10%	0.60%
Overall	**13.52%**	**13.61%**	**29.08%**	**20.32%**	**0.10%**	**9.37%**	**0.25%**	**25.42%**	**13.49%**	**1.21%**
B. Chinese Market as Regional Center										
Panel (a) Proportion of Local Variance Attributed to Shocks to U.S. Market										
2009	8.51%	3.30%	6.44%	5.85%	0.09‰	1.02%	0.06‰	6.27%	5.90%	0.34%
2010	9.91%	2.73%	9.61%	6.66%	0.13‰	0.66%	0.06‰	5.74%	4.33%	0.27%
2011	10.51%	3.91%	8.56%	6.99%	0.18‰	1.08%	0.10‰	6.54%	5.55%	0.33%
2012	6.80%	2.49%	7.56%	5.76%	0.11‰	0.54%	0.04‰	3.79%	3.45%	0.18%
2013	6.13%	2.41%	7.04%	4.41%	0.11‰	0.50%	0.05‰	3.66%	3.10%	0.11%
Overall	**8.84%**	**3.08%**	**8.06%**	**6.19%**	**0.13‰**	**0.83%**	**0.07‰**	**5.57%**	**4.78%**	**0.28%**
Panel (b) Proportion of Local Variance Attributed to Shocks to Regional Market										
2009	17.76%	24.63%	29.30%	27.35%	0.07%	13.70%	0.10%	31.28%	25.54%	0.11%
2010	26.63%	26.22%	37.63%	29.40%	0.15%	12.33%	0.13%	38.48%	26.15%	0.13%
2011	22.87%	28.54%	34.04%	27.74%	0.15%	14.52%	0.16%	35.61%	26.20%	0.12%
2012	25.12%	28.55%	38.81%	30.42%	0.16%	12.80%	0.13%	35.42%	28.27%	0.11%
2013	24.91%	29.44%	39.02%	26.56%	0.16%	12.94%	0.18%	37.13%	27.07%	0.08%
Overall	**23.11%**	**27.16%**	**35.16%**	**28.47%**	**0.14%**	**13.38%**	**0.13%**	**35.25%**	**26.57%**	**0.12%**
C. Japanese Market as Regional Center										
Panel (a) Proportion of Local Variance Attributed to Shocks to U.S. Market										
2009	11.55%	5.14%	14.93%	10.70%	0.01‰	2.40%	0.08‰	10.29%	10.46%	0.61%

(***Continued on next page***)

Table 4.4 - Continued from previous page

Year	India	Indonesia	Korea	Malaysia	Pakistan	Philippines	Sri Lanka	Taiwan	Thailand	Vietnam
2010	21.21%	7.30%	18.80%	14.36%	0.02‰	2.28%	0.11‰	15.27%	9.58%	0.62%
2011	21.23%	7.47%	16.60%	13.32%	0.01‰	2.36%	0.12‰	13.06%	10.10%	0.63%
2012	21.73%	8.74%	19.86%	15.58%	0.02‰	2.21%	0.11‰	14.69%	9.28%	0.60%
2013	22.82%	9.35%	20.84%	13.99%	0.02‰	2.24%	0.16‰	15.58%	9.38%	0.55%
Overall	**19.04%**	**7.30%**	**17.69%**	**13.43%**	**0.01‰**	**2.31%**	**0.11‰**	**13.42%**	**9.84%**	**0.61%**
Panel (b) Proportion of Local Variance Attributed to Shocks to Regional Market										
2009	0.23%	1.78%	14.31%	3.04%	0.05%	2.99%	0.05‰	6.66%	4.78%	0.98%
2010	0.35%	2.04%	9.08%	3.60%	0.11%	2.25%	0.07‰	8.39%	3.13%	1.07%
2011	0.41%	2.37%	11.87%	3.78%	0.12%	2.58%	0.09‰	8.02%	3.99%	1.12%
2012	0.33%	2.25%	7.61%	3.63%	0.12%	1.91%	0.07‰	7.45%	2.54%	0.96%
2013	0.37%	2.55%	7.64%	3.41%	0.13%	2.02%	0.10‰	8.09%	2.72%	0.76%
Overall	**0.33%**	**2.14%**	**10.68%**	**3.50%**	**0.10%**	**2.43%**	**0.07‰**	**7.67%**	**3.59%**	**1.01%**

I consider moderate the total volatility spillover effect of foreign shocks (from the U.S. and a large Asia-Pacific market) during and after the global crisis on the small Asia-Pacific stock markets covered in this research. In the China-Korea case, foreign shocks accounted for 43.22% of local market volatility in total, which was the highest average proportion throughout the whole sample period among all cases. In other words, innovations idiosyncratic to each local market played an equally or more important role in the dynamics of the variance of each local market's unexpected returns. It is worthwhile to point out that regional and U.S. shocks explained less than 1% of market volatility in both Pakistan and Sri Lanka. Furthermore, the estimation results in the second chapter demonstrate that for Sri Lanka and Pakistan, the estimated coefficients on lagged home returns are much bigger in terms of order of magnitude than those on lagged U.S. returns. Both Pakistani and Sri Lankan markets are thought to be isolated from a great number of global and regional risk factors, given that the U.S. and the regional markets have an almost negligible impact of mean and volatility transmission upon these two South Asian markets. It is implied that all of the local markets were susceptible to varying extents to both mean and volatility spillover from the U.S. and the Australian/Chinese/Japanese markets throughout the period covered by this research with the exception of Pakistan and Sri Lanka. Thus, there may still be some room for further portfolio diversification by exploiting both exceptions. Last but not least, neither the U.S. nor the regional market had profound volatility spillover effects on the Vietnamese market—the proportions attributable to international shocks added up to 1.62% at most. In addition, as discussed in Chapter 2, Vietnam reacted positively to both lagged information of its own and that from the U.S. market but insignificantly to any large Asia-Pacific market. The Vietnamese cases studied here in a detailed way add to the current literature, since the new emerging market, to the best of my knowledge, has seldom been well documented elsewhere.

4.4 Conclusion

In this chapter, I investigate the dynamics of volatility spillover amongst three large and ten small Asia-Pacific stock markets from December 2008 until May 2013 with a regime-switching model, which takes into account the effects of structural break the latest U.S. recession and global financial crisis had upon these markets by allowing for time-varying. For this purpose, I decomposed the unexpected market return into two uncorrelated innovations from the regional center proxies and from the U.S. market, respectively, and a third one idiosyncratic to the local market. In the most complex model specification, it is assumed that variance of shocks indigenous to each local market, in addition to the loadings on the U.S. and the regional factors, is also switching. Several alternative specifications are also proposed which leave out regime switching in either a local market's unexpected return or variance of idiosyncratic local shocks or both. All proposed Markov-switching and single-state models are estimated multiple times with various sets of initial parameter values; the best fitting model is chosen based on a series of model performance indicators including the results of normality and likelihood ratio tests, complexity-penalized likelihood criteria and regime classification measures. In all thirty cases, the single-state model is rejected by the likelihood ratio test. Almost all model performance indicators improve once switching regimes are allowed for.

The empirical results lead to the following findings, which may have implications for international portfolio diversification. First of all, in all fourteen cases where the loadings on the regional and the U.S. risk factors are switching, the local markets were more sensitive to regional shocks during all subsample periods, though two distinct patterns have been observed of how these markets reacted to foreign shocks under the three regional center scenarios. Secondly, shocks from the Australian/Chinese market accounted for a higher percentage of local variance than did those from the U.S. market, while Japanese shocks were found to have only modest volatility spillover effects upon the studied local markets. Thirdly, innovations idiosyncratic to each local market continue to play a significant or even dominant role in the dynamics of the variance of the market's unexpected returns. Finally, both Pakistani and Sri Lankan markets are fairly insulated from external influences with both mean and volatility spillover effects of the U.S. and the regional markets found to be minimal.

CHAPTER 5

Summary

This dissertation investigates the dynamics of mean and volatility spillovers from the U.S. stock market and the regional market in the Asia-Pacific area to ten local ones in the same region through use of the MSCI Global Equity Indices spanning June 2008 to May 2013. In order to have a comprehensive view of the volatility spillover among the Asian equity markets, I let each of the three largest Asia-Pacific stock markets—the Australian, the Greater Chinese and the Japanese markets—serve as a proxy for the regional market.

In the second chapter, in order to examine the impact of lagged American and regional returns on the local markets, I construct a univariate autoregressive model, which treats lagged regional and U.S. returns as exogenous variables. The local markets are found to have statistically significant exposure to lagged returns of their own and the U.S. market only. The own-market effect of four local markets (Pakistan, South Korea, Sri Lanka and Vietnam) are found to be significant at the 1% level over the entire period covered. The empirical results indicate that lagged U.S. returns have exerted considerable mean spillover effect upon most of the local markets, while the large Asia-Pacific markets involved in this study have few such impacts.

In the third chapter, I study the linkage between the U.S. market and each of the regional market proxies by employing two specifications of the bivariate GARCH process—the BEKK and general dynamic covariance models—to capture common features of equity return data. A choice of the better fitting model for each regional market is made based on the results of carefully constructed diagnostic tests. In-depth analysis of the news impact surfaces also guides me through the process of model selection. The BEKK model is shown to be more appropriate for the U.S.–China and U.S.–Japan cases and the DC model for the U.S.–Australia case.

I discuss time-varying correlation of a local market with each regional market and with the U.S. market in Chapter 4. I propose three Markov-switching shock spillover models and compare their performance under the guidance of a series of model selection criteria. In fourteen cases, the local market is found to be more sensitive to regional shocks in general during the sample period. Disturbances from two regional markets (Australia and Greater China) account for a higher proportion of local variance than do those of U.S. origin. Taking into consideration the main findings in Chapter 2, I conclude that the regional market, although having little mean spillover effect upon the local markets in the Asia-Pacific area, has become increasingly influential in terms of volatility spillovers.

Further studies need to be conducted on whether the dynamic patterns of volatility spillovers in a local market change under various scenarios of interaction between the U.S. market and the regional market.[1] The Markov-switching framework developed in this dissertation can be easily applied to these extended studies by loosening the restriction on the stochastic process that controls the regional and the U.S. spillover intensities.

[1] Several possible scenarios are listed in Appendices of Chapter 4. In each scenario, detailed discussion centers on how to generate the latent variables and construct the transition probability matrix.

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APPENDICES

Appendices of Chapter 2

Displayed on pages 105–108, Tables A.1–A.4 detail the results of the diagnostic tests under four different assumptions on the identity of the regional center. Based on the aforementioned selection criteria, the asymmetric specification is chosen for all of the local markets apart from Sri Lanka.

Table A.5 presents the results of Engle's Lagrange multiplier test under various presumptions about the identity of the regional market with the asterisks indicating significance at the 1% level of significance. The LM ARCH(5) test checks whether the residuals from an OLS regression of a local market's return at time t on one-period lagged regional and U.S. market returns exhibit autoregressive conditional heteroskedasticity. The test statistic is obtained by running one more OLS regression on the lagged residuals up to the fifth order and multiplying the coefficient of determination by the sample size. Under the null hypothesis of no ARCH effects, the test statistic follows a $\chi^2(5)$ distribution. Each local market, according to the test results, is conditionally heteroskedastic at the 1% level.

Figures A.1–A.4 on pages 110–119 present the estimated level of daily volatility and the local, regional and U.S. portions of the expected daily return in the ten smaller markets. The shaded area indicates the most recent recession period reported by NBER.

Table A.1: Specification Test Result: Australia as Regional Center

P-values are given in square brackets. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively. Empirical p-values are used in determining the significance of a specification test statistic. Empirical critical values are obtained by 5,000 Monte Carlo experiments with the sample size equal to the number of observations in a particular case for each experiment. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel.

Market	*Specification Test Statistics*					β_3	*Pagan and Schwert's* R^2	*Log-L* $(\times 10^3)$	*Model Comparison Test Statistics*		*Selected or not*
	Conditional Mean: (2.9a)	*Conditional Variance*: (2.9b)	*Distribution*: (2.9c)–(2.9f)	*Joint*: (2.9a)–(2.9f)	*Asymmetry*: (2.10a)–(2.10c)				*Likelihood Ratio Test*[a]: $\chi^2(1)$	*Wald Test*[b]: $\chi^2(1)$	
					A. Asymmetric Specification						
India	7.547	9.911	5.490	62.442†	2.070	0.055	0.068	-3.628	9.317*	2.625	yes
	[0.241]	[0.117]	[0.325]	[0.020]	[0.595]	[0.106]			[0.002]	[0.105]	
Indonesia	9.635	4.108	27.912*	36.623	3.938	0.079*	0.133	-3.534	19.662*	8.245*	yes
	[0.130]	[0.602]	[0.006]	[0.120]	[0.312]	[0.004]			[<0.001]	[0.004]	
Korea	6.183	4.335	7.266	22.540	5.998	0.170*	0.185	-3.596	39.935*	12.880*	yes
	[0.352]	[0.568]	[0.196]	[0.411]	[0.151]	[<0.001]			[<0.001]	[<0.001]	
Malaysia	3.860	9.860	5.457	28.387	3.038	0.066†	0.148	-2.754	11.425*	6.485†	yes
	[0.619]	[0.119]	[0.327]	[0.246]	[0.428]	[0.011]			[0.001]	[0.011]	
Pakistan	3.514	1.297	4.817	21.312	1.735	0.144*	0.197	-3.259	24.199*	11.877*	yes
	[0.666]	[0.954]	[0.387]	[0.456]	[0.657]	[<0.001]			[<0.001]	[0.001]	
Philippines	4.258	8.801	6.914	27.419	1.114	0.077	0.048	-3.218	7.803*	2.590	yes
	[0.565]	[0.165]	[0.215]	[0.267]	[0.795]	[0.108]			[0.005]	[0.108]	
Sri Lanka	15.413†	6.496	9.785	70.408*	6.403	0.047	0.043	-3.177	4.849†	1.299	no
	[0.022]	[0.323]	[0.103]	[0.010]	[0.132]	[0.255]			[0.028]	[0.254]	
Taiwan	3.025	3.241	15.538†	32.287	8.297	0.073*	0.144	-3.291	30.244*	8.819*	yes
	[0.734]	[0.724]	[0.034]	[0.176]	[0.072]	[0.003]			[<0.001]	[0.003]	
Thailand	3.256	7.859	14.667†	37.748	7.494	0.087*	0.209	-3.496	14.948*	6.817*	yes
	[0.703]	[0.224]	[0.039]	[0.111]	[0.092]	[0.009]			[<0.001]	[0.009]	
Vietnam	7.031	4.126	4.711	23.798	1.459	0.030	0.115	-3.581	0.840	0.575	yes
	[0.277]	[0.600]	[0.396]	[0.368]	[0.713]	[0.449]			[0.360]	[0.448]	
					B. Symmetric Specification						
India	6.572	10.644	9.075	55.566†	3.689	-	0.057	-3.633	-	-	no
	[0.317]	[0.095]	[0.123]	[0.031]	[0.338]						
Indonesia	10.951	5.824	36.818*	53.547†	8.198	-	0.117	-3.544	-	-	no
	[0.088]	[0.390]	[0.002]	[0.036]	[0.074]						
Korea	4.164	3.072	14.554†	34.018	16.558*	-	0.108	-3.616	-	-	no
	[0.576]	[0.747]	[0.040]	[0.152]	[0.006]						
Malaysia	4.903	9.618	6.217	31.764	3.741	-	0.115	-2.760	-	-	no
	[0.488]	[0.129]	[0.261]	[0.187]	[0.333]						
Pakistan	3.693	1.655	6.803	26.740	13.640†	-	0.189	-3.271	-	-	no
	[0.642]	[0.920]	[0.222]	[0.283]	[0.014]						
Philippines	4.400	8.824	6.958	32.058	3.406	-	0.043	-3.222	-	-	no
	[0.546]	[0.163]	[0.213]	[0.181]	[0.377]						
Sri Lanka	15.149†	5.646	12.912	69.860†	6.612	-	0.044	-3.179	-	-	yes
	[0.023]	[0.410]	[0.055]	[0.010]	[0.123]						
Taiwan	3.084	3.516	21.755†	54.002†	11.541†	-	0.125	-3.306	-	-	no
	[0.726]	[0.683]	[0.014]	[0.035]	[0.025]						
Thailand	2.249	7.019	15.624†	40.513	20.700*	-	0.174	-3.503	-	-	no
	[0.837]	[0.279]	[0.033]	[0.091]	[0.003]						
Vietnam	7.065	3.997	4.597	24.314	1.492	-	0.114	-3.582	-	-	no
	[0.275]	[0.615]	[0.411]	[0.349]	[0.706]						

[a, b] The restricted model of both likelihood ratio and Wald tests is the symmetric specification: (2.4a), (4b) and (2.4c).

Table A.2: Specification Test Result: China as Regional Center

P-values are given in square brackets. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively. Empirical p-values are used in determining the significance of a specification test statistic. Empirical critical values are obtained by 5,000 Monte Carlo experiments with the sample size equal to the number of observations in a particular case for each experiment. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel.

Market	*Specification Test Statistics* — *Conditional Mean*: (2.9a)	*Conditional Variance*: (2.9b)	*Distribution*: (2.9c)–(2.9f)	*Joint*: (2.9a)–(2.9f)	*Asymmetry*: (2.10a)–(2.10c)	β_3	*Pagan and Schwert's* R^2	*Log-L* ($\times 10^3$)	*Model Comparison Test Statistics* — *Likelihood Ratio Test*[a]: $\chi^2(1)$	*Wald Test*[b]: $\chi^2(1)$	*Selected or not*
					A. Asymmetric Specification						
India	5.734	9.881	5.269	54.274†	2.628	0.056	0.068	-3.653	9.472*	2.593	yes
	[0.385]	[0.119]	[0.351]	[0.034]	[0.480]	[0.108]			[0.002]	[0.107]	
Indonesia	9.223	3.943	31.173*	39.714	4.170	0.079*	0.129	-3.556	20.193*	8.744*	yes
	[0.142]	[0.623]	[0.005]	[0.105]	[0.225]	[0.003]			[<0.001]	[0.003]	
Korea	8.792	4.392	8.537	30.171	5.723	0.168*	0.183	-3.619	41.472*	14.226*	yes
	[0.166]	[0.560]	[0.158]	[0.224]	[0.160]	[<0.001]			[<0.001]	[<0.001]	
Malaysia	3.908	10.000	5.725	30.083	2.464	0.062†	0.141	-2.773	10.305*	5.725†	yes
	[0.613]	[0.121]	[0.311]	[0.229]	[0.515]	[0.017]			[0.001]	[0.017]	
Pakistan	3.667	1.289	4.970	22.678	1.757	0.149*	0.193	-3.284	26.321*	12.985*	yes
	[0.650]	[0.951]	[0.379]	[0.407]	[0.655]	[<0.001]			[<0.001]	[<0.001]	
Philippines	4.208	10.654	6.889	33.110	1.615	0.074	0.049	-3.241	7.604*	3.074	yes
	[0.575]	[0.096]	[0.230]	[0.178]	[0.682]	[0.080]			[0.006]	[0.080]	
Sri Lanka	15.341†	6.553	9.680	72.281*	4.693	0.049	0.043	-3.190	5.080†	1.336	no
	[0.020]	[0.328]	[0.117]	[0.010]	[0.242]	[0.248]			[0.024]	[0.248]	
Taiwan	3.241	3.506	15.553†	32.334	7.757	0.071*	0.144	-3.314	31.278*	8.625*	yes
	[0.695]	[0.688]	[0.039]	[0.190]	[0.084]	[0.003]			[<0.001]	[0.003]	
Thailand	3.966	7.526	16.211†	40.026	7.210	0.092*	0.211	-3.512	16.884*	8.311*	yes
	[0.605]	[0.249]	[0.031]	[0.102]	[0.105]	[0.004]			[<0.001]	[0.004]	
Vietnam	6.424	3.970	4.513	22.377	1.234	0.032	0.114	-3.601	0.985	1.030	yes
	[0.323]	[0.628]	[0.428]	[0.418]	[0.768]	[0.310]			[0.321]	[0.310]	
					B. Symmetric Specification						
India	4.683	10.859	8.775	47.953	3.800	-	0.058	-3.658	-	-	no
	[0.501]	[0.083]	[0.149]	[0.054]	[0.311]						
Indonesia	10.464	5.584	38.913*	54.490†	8.430	-	0.112	-3.566	-	-	no
	[0.100]	[0.420]	[0.003]	[0.034]	[0.067]						
Korea	5.786	3.194	13.274	42.528	15.231†	-	0.100	-3.640	-	-	no
	[0.381]	[0.734]	[0.060]	[0.084]	[0.013]						
Malaysia	4.887	10.103	6.476	33.760	3.424	-	0.113	-2.779	-	-	no
	[0.489]	[0.117]	[0.257]	[0.170]	[0.380]						
Pakistan	4.015	1.645	7.011	28.843	15.403†	-	0.185	-3.297	-	-	no
	[0.600]	[0.921]	[0.224]	[0.252]	[0.010]						
Philippines	4.375	10.287	7.003	36.906	3.793	-	0.045	-3.245	-	-	no
	[0.555]	[0.108]	[0.224]	[0.132]	[0.334]						
Sri Lanka	15.020†	5.805	12.920	71.394*	4.995	-	0.044	-3.192	-	-	yes
	[0.023]	[0.398]	[0.060]	[0.010]	[0.218]						
Taiwan	3.591	3.951	21.807†	55.472†	10.546†	-	0.124	-3.330	-	-	no
	[0.648]	[0.622]	[0.014]	[0.031]	[0.037]						
Thailand	2.732	6.789	17.694†	42.185	22.323*	-	0.174	-3.521	-	-	no
	[0.772]	[0.305]	[0.025]	[0.086]	[0.002]						
Vietnam	6.451	3.925	4.394	22.694	1.423	-	0.113	-3.601	-	-	no
	[0.321]	[0.633]	[0.440]	[0.407]	[0.729]						

[a, b] The restricted model of both likelihood ratio and Wald tests is the symmetric specification: (2.4a), (4b) and (2.4c).

Table A.3: Specification Test Result: Japan as Regional Center

P-values are given in square brackets. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively. Empirical p-values are used in determining the significance of a specification test statistic. Empirical critical values are obtained by 5,000 Monte Carlo experiments with the sample size equal to the number of observations in a particular case for each experiment. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel.

Market	*Specification Test Statistics*					β_3	*Pagan and Schwert's* R^2	*Log-L* $(\times 10^3)$	*Model Comparison Test Statistics*		*Selected or not*
	Conditional Mean: (2.9a)	*Conditional Variance*: (2.9b)	*Distribution*: (2.9c)–(2.9f)	*Joint*: (2.9a)–(2.9f)	*Asymmetry*: (2.10a)–(2.10c)				*Likelihood Ratio Test*[a]: $\chi^2(1)$	*Wald Test*[b]: $\chi^2(1)$	
					A. Asymmetric Specification						
India	5.305	10.440	5.089	54.648†	2.704	0.058	0.070	-3.653	9.913*	2.926	yes
	[0.434]	[0.097]	[0.363]	[0.033]	[0.468]	[0.087]			[0.002]	[0.087]	
Indonesia	10.037	3.961	31.320*	39.980	3.883	0.077*	0.133	-3.558	19.315*	7.143*	yes
	[0.111]	[0.620]	[0.005]	[0.103]	[0.301]	[0.008]			[<0.001]	[0.008]	
Korea	8.656	4.251	8.430	29.247	5.742	0.170*	0.182	-3.619	42.184*	13.289*	yes
	[0.172]	[0.580]	[0.162]	[0.242]	[0.159]	[<0.001]			[<0.001]	[<0.001]	
Malaysia	4.253	9.453	6.001	28.859	2.640	0.061†	0.142	-2.774	10.229*	5.067†	yes
	[0.569]	[0.142]	[0.287]	[0.251]	[0.487]	[0.025]			[0.001]	[0.024]	
Pakistan	3.673	1.289	4.954	23.920	3.024	0.149*	0.194	-3.282	26.302*	12.203*	yes
	[0.650]	[0.951]	[0.380]	[0.367]	[0.437]	[<0.001]			[<0.001]	[<0.001]	
Philippines	4.253	7.920	7.202	27.761	0.808	0.077	0.046	-3.239	8.089*	2.794	yes
	[0.569]	[0.221]	[0.212]	[0.274]	[0.854]	[0.095]			[0.005]	[0.095]	
Sri Lanka	14.564†	6.209	10.199	70.876*	4.569	0.052	0.044	-3.188	5.607†	1.644	no
	[0.026]	[0.361]	[0.104]	[0.010]	[0.251]	[0.200]			[0.018]	[0.200]	
Taiwan	3.664	3.513	17.299†	36.612	6.863	0.070*	0.143	-3.313	30.488*	8.801*	yes
	[0.637]	[0.686]	[0.029]	[0.132]	[0.112]	[0.003]			[<0.001]	[0.003]	
Thailand	3.401	7.945	14.945†	36.066	7.916	0.093*	0.214	-3.513	16.798*	7.496*	yes
	[0.681]	[0.219]	[0.039]	[0.139]	[0.082]	[0.006]			[<0.001]	[0.006]	
Vietnam	6.202	3.836	4.303	20.968	1.506	0.035	0.117	-3.601	1.001	0.227	yes
	[0.344]	[0.646]	[0.450]	[0.473]	[0.706]	[0.634]			[0.317]	[0.634]	
					B. Symmetric Specification						
India	4.506	11.264	8.655	48.093	3.916	-	0.058	-3.658	-	-	no
	[0.521]	[0.074]	[0.154]	[0.054]	[0.298]						
Indonesia	11.490	5.531	39.880*	57.450†	7.986	-	0.116	-3.568	-	-	no
	[0.073]	[0.426]	[0.002]	[0.025]	[0.077]						
Korea	5.717	3.062	13.218	43.049	14.090†	-	0.098	-3.640	-	-	no
	[0.386]	[0.751]	[0.061]	[0.081]	[0.015]						
Malaysia	5.285	9.291	6.750	32.026	4.177	-	0.113	-2.779	-	-	no
	[0.440]	[0.148]	[0.238]	[0.194]	[0.292]						
Pakistan	3.952	1.619	7.124	29.756	15.401†	-	0.185	-3.295	-	-	no
	[0.607]	[0.923]	[0.216]	[0.236]	[0.010]						
Philippines	4.370	7.992	7.249	31.078	2.775	-	0.042	-3.243	-	-	no
	[0.555]	[0.216]	[0.208]	[0.212]	[0.469]						
Sri Lanka	14.376†	5.504	13.849	72.118*	4.846	-	0.044	-3.191	-	-	yes
	[0.028]	[0.433]	[0.050]	[0.010]	[0.230]						
Taiwan	4.231	4.057	24.193†	62.397†	8.946	-	0.121	-3.329	-	-	no
	[0.558]	[0.606]	[0.011]	[0.020]	[0.057]						
Thailand	2.399	7.271	16.373†	38.859	22.241*	-	0.176	-3.521	-	-	no
	[0.814]	[0.268]	[0.030]	[0.110]	[0.002]						
Vietnam	6.244	3.852	4.201	21.517	1.361	-	0.116	-3.601	-	-	no
	[0.342]	[0.644]	[0.464]	[0.451]	[0.744]						

[a, b] The restricted model of both likelihood ratio and Wald tests is the symmetric specification: (2.4a), (4b) and (2.4c).

Table A.4: Specification Test Result: All Three Markets Incorporated in Mean Equation

P-values are given in square brackets. The asterisks and plus superscripts indicate significance at the 1% and 5% levels, respectively. Empirical p-values are used in determining the significance of a specification test statistic. Empirical critical values are obtained by 5,000 Monte Carlo experiments with the sample size equal to the number of observations in a particular case for each experiment. In each of these Monte Carlo simulations, the weight matrix is adapted to be heteroskedasticity and autocorrelation consistent through the use of the Parzen kernel.

Market	*Specification Test Statistics*					β_3	*Pagan and Schwert's* R^2	*Log-L* $(\times 10^3)$	*Model Comparison Test Statistics*		*Selected or not*
	Conditional Mean: (2.9a)	*Conditional Variance*: (2.9b)	*Distribution*: (2.9c)–(2.9f)	*Joint*: (2.9a)–(2.9f)	*Asymmetry*: (2.10a)–(2.10c)				*Likelihood Ratio Test*^{a}: $\chi^2(1)$	*Wald Test*^{b}: $\chi^2(1)$	
					A. Asymmetric Specification						
India	5.987	10.620	5.274	61.011†	2.335	0.057	0.071	-3.627	9.597*	2.548	yes
	[0.367]	[0.095]	[0.345]	[0.022]	[0.547]	[0.111]			[0.002]	[0.111]	
Indonesia	8.874	3.740	29.120*	38.079	4.112	0.079*	0.129	-3.532	19.469*	6.851*	yes
	[0.165]	[0.648]	[0.006]	[0.109]	[0.293]	[0.009]			[<0.001]	[0.009]	
Korea	6.216	4.352	7.269	22.691	5.961	0.169*	0.185	-3.596	39.789*	12.655*	yes
	[0.350]	[0.566]	[0.196]	[0.405]	[0.152]	[<0.001]			[<0.001]	[<0.001]	
Malaysia	4.282	10.289	5.906	30.788	2.124	0.066†	0.148	-2.753	11.506*	5.557†	yes
	[0.562]	[0.105]	[0.289]	[0.201]	[0.586]	[0.019]			[<0.001]	[0.018]	
Pakistan	3.587	1.358	5.045	23.185	2.836	0.147*	0.198	-3.258	24.531*	11.778*	yes
	[0.656]	[0.949]	[0.365]	[0.390]	[0.458]	[<0.001]			[<0.001]	[<0.001]	
Philippines	4.371	7.881	7.306	29.809	0.945	0.077	0.049	-3.215	8.434*	3.303	yes
	[0.551]	[0.223]	[0.194]	[0.219]	[0.835]	[0.069]			[0.004]	[0.069]	
Sri Lanka	14.938†	6.523	10.044	73.726*	6.624	0.050	0.043	-3.174	5.127†	1.281	no
	[0.025]	[0.320]	[0.097]	[0.009]	[0.123]	[0.258]			[0.024]	[0.258]	
Taiwan	3.362	3.214	17.796†	38.085†	6.829	0.071*	0.141	-3.290	28.420*	7.353*	yes
	[0.687]	[0.728]	[0.023]	[0.109]	[0.116]	[0.007]			[<0.001]	[0.007]	
Thailand	3.469	7.324	15.824†	38.776	7.849	0.089*	0.208	-3.495	16.039*	7.428*	yes
	[0.671]	[0.260]	[0.032]	[0.101]	[0.082]	[0.007]			[<0.001]	[0.006]	
Vietnam	6.762	3.938	4.495	23.186	1.041	0.033	0.116	-3.580	0.901	0.072	yes
	[0.301]	[0.621]	[0.420]	[0.390]	[0.811]	[0.789]			[0.343]	[0.789]	
					B. Symmetric Specification						
India	5.098	11.329	8.840	54.621†	3.977	-	0.059	-3.631	-	-	no
	[0.466]	[0.074]	[0.130]	[0.034]	[0.308]						
Indonesia	9.785	5.674	36.833*	52.508†	8.124	-	0.113	-3.541	-	-	no
	[0.122]	[0.407]	[0.002]	[0.040]	[0.076]						
Korea	4.192	3.109	14.579†	34.303	16.523*	-	0.109	-3.616	-	-	no
	[0.572]	[0.743]	[0.040]	[0.149]	[0.006]						
Malaysia	5.311	10.537	6.697	34.834	3.253	-	0.116	-2.759	-	-	no
	[0.437]	[0.097]	[0.227]	[0.142]	[0.398]						
Pakistan	3.731	1.618	6.843	27.280	14.091†	-	0.190	-3.270	-	-	no
	[0.635]	[0.923]	[0.219]	[0.270]	[0.013]						
Philippines	4.520	7.668	7.152	33.645	3.374	-	0.044	-3.219	-	-	no
	[0.532]	[0.236]	[0.202]	[0.156]	[0.380]						
Sri Lanka	14.803†	5.582	13.218	73.275*	6.898	-	0.044	-3.177	-	-	yes
	[0.026]	[0.416]	[0.051]	[0.009]	[0.114]						
Taiwan	3.553	3.613	24.655*	62.502†	9.476†	-	0.121	-3.304	-	-	no
	[0.662]	[0.666]	[0.009]	[0.020]	[0.047]						
Thailand	2.352	6.458	16.841†	41.337	22.577*	-	0.172	-3.503	-	-	no
	[0.823]	[0.327]	[0.027]	[0.085]	[0.002]						
Vietnam	6.821	3.835	4.396	23.960	1.185	-	0.115	-3.580	-	-	no
	[0.296]	[0.636]	[0.430]	[0.362]	[0.774]						

$^{a,\,b}$ The restricted model of both likelihood ratio and Wald tests is the symmetric specification: (2.5a), (5b) and (2.5c).

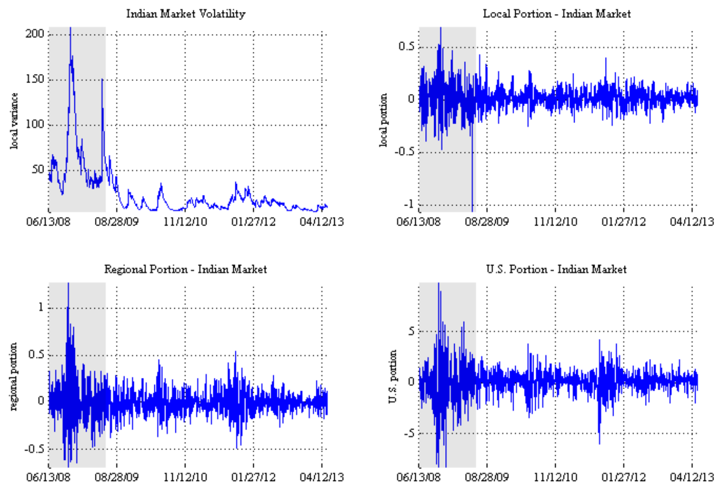
Table A.5: Engle's Lagrange Multiplier Test (II)

Local Market	*Regional Center Assumption*		
	Australian Market	*Japanese Market*	*All Three Markets*
India	47.037*	46.604*	47.495*
	[<0.001]	[<0.001]	[<0.001]
Indonesia	142.237*	142.185*	141.371*
	[<0.001]	[<0.001]	[<0.001]
Korea	113.682*	107.842*	107.324*
	[<0.001]	[<0.001]	[<0.001]
Malaysia	138.510*	140.171*	140.646*
	[<0.001]	[<0.001]	[<0.001]
Pakistan	218.953*	219.061*	219.287*
	[<0.001]	[<0.001]	[<0.001]
Philippines	73.321*	77.337*	74.903*
	[<0.001]	[<0.001]	[<0.001]
Sri Lanka	217.698*	218.212*	218.995*
	[<0.001]	[<0.001]	[<0.001]
Taiwan	120.207*	115.760*	112.680*
	[<0.001]	[<0.001]	[<0.001]
Thailand	287.825*	286.529*	255.190*
	[<0.001]	[<0.001]	[<0.001]
Vietnam	135.923*	137.705*	134.465*
	[<0.001]	[<0.001]	[<0.001]

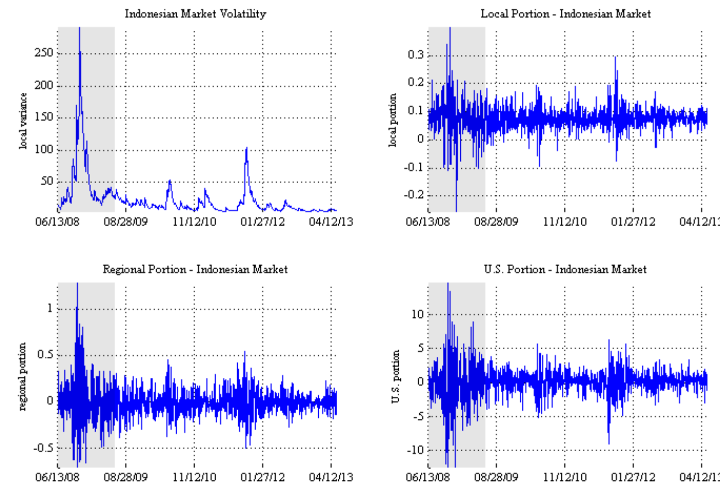
Figure A.1: Estimated Daily Market Volatility and Decomposition of Expected Daily Return with Australia as Regional Center

The estimated level of daily volatility is presented in the upper left panel of each figure. The expected daily return of local market m is decomposed into three parts: the local portion (shown in the upper right panel) is computed as $\alpha_0 + \alpha_1 R_{m,\,t-1}$, the regional portion (shown in the lower left panel) as $\alpha_3 R_{AU,\,t-1}$ and the U.S. portion (shown in the lower right panel) as $\alpha_2 R_{US,\,t-1}$.

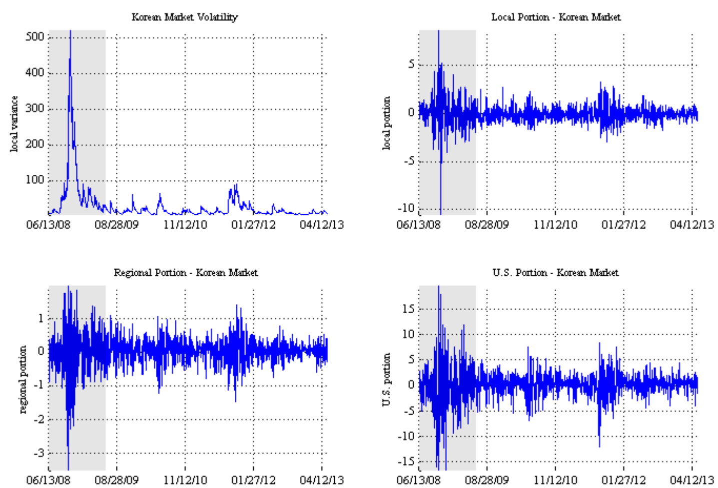
(a) India



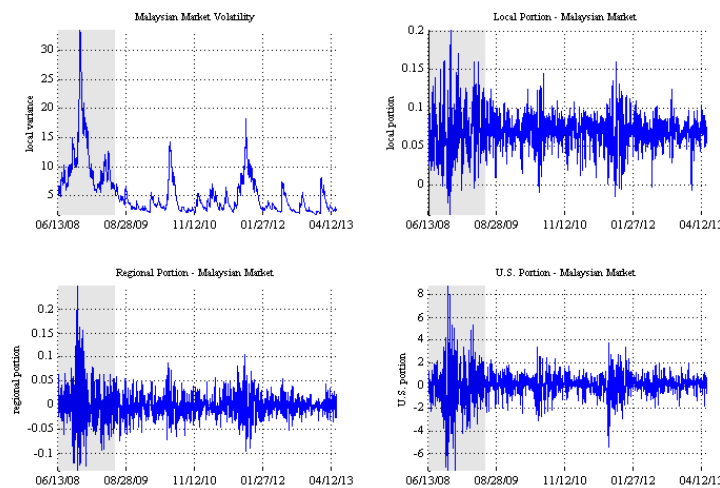
(b) Indonesia



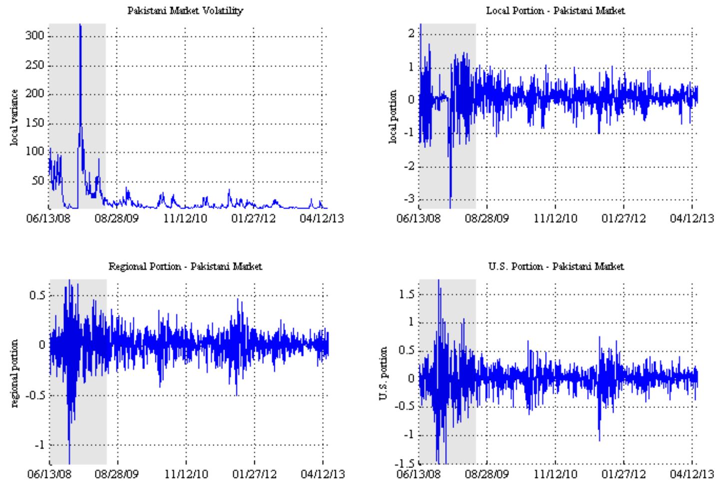
(c) Korea



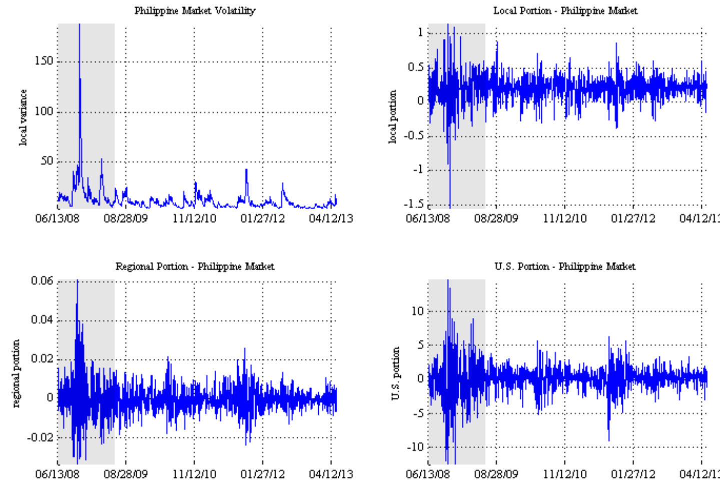
(d) Malaysia



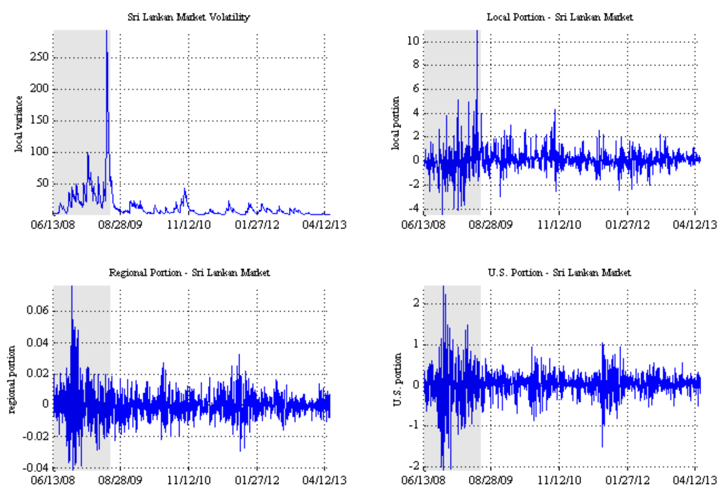
(e) Pakistan



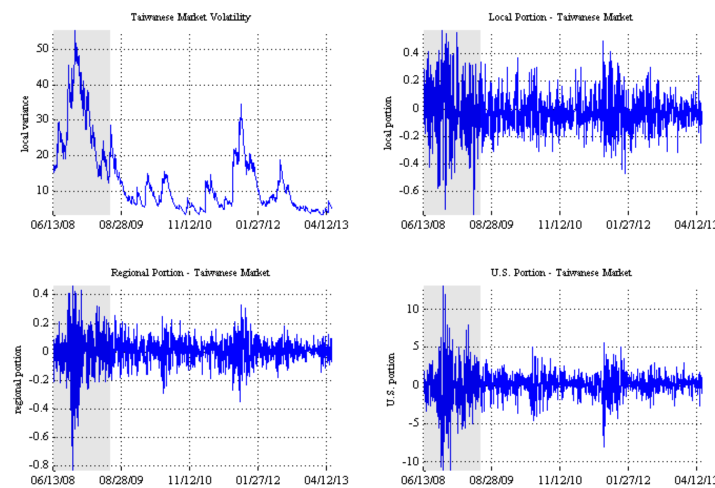
(f) The Philippines



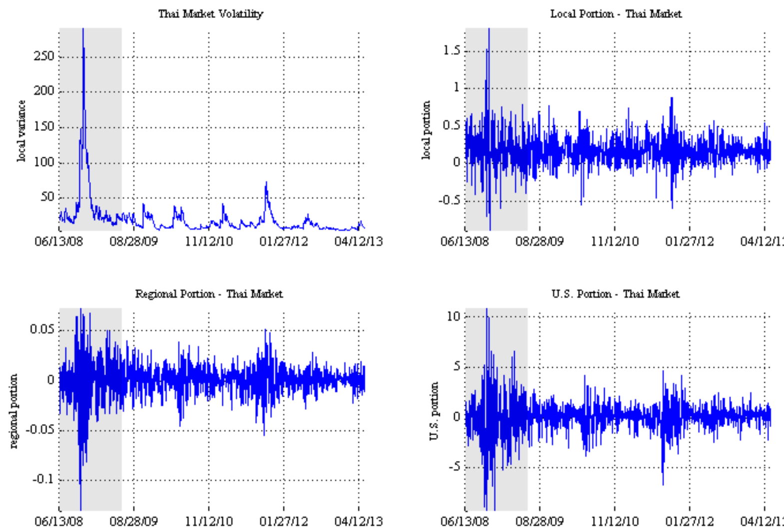
(g) Sri Lanka



(h) Taiwan



(i) Thailand



(j) Vietnam

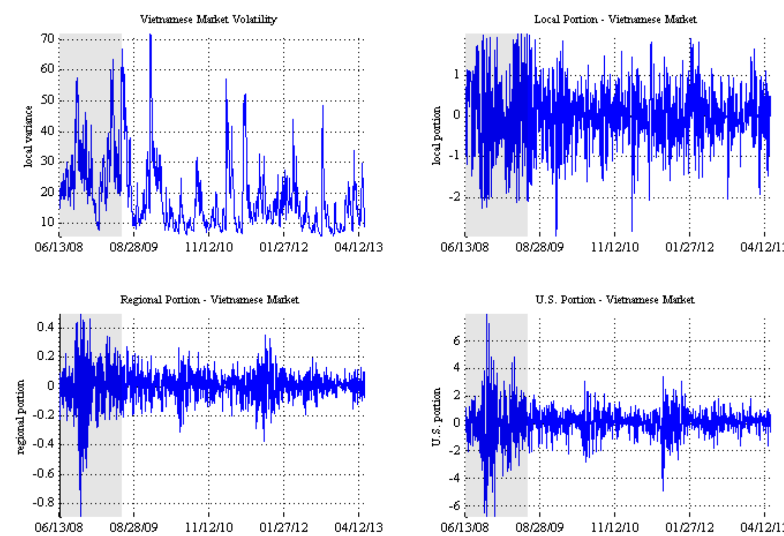
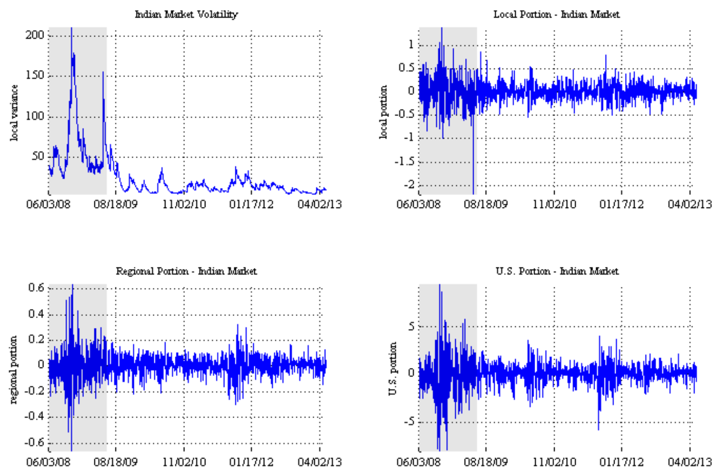


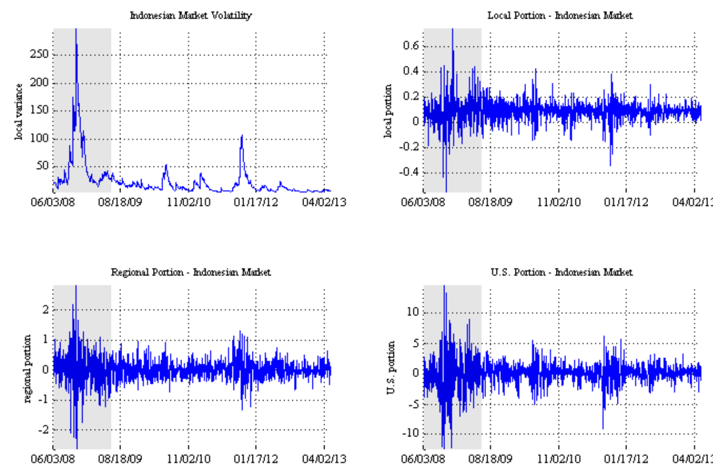
Figure A.2: Estimated Daily Market Volatility and Decomposition of Expected Daily Return with China as Regional Center

The estimated level of daily volatility is presented in the upper left panel of each figure. The expected return of local market m is decomposed into three parts: the local portion (shown in the upper right panel) is computed as $\alpha_0 + \alpha_1 R_{m,\,t-1}$, the regional portion (shown in the lower left panel) as $\alpha_3 R_{CN,\,t-1}$ and the U.S. portion (shown in the lower right panel) as $\alpha_2 R_{US,\,t-1}$.

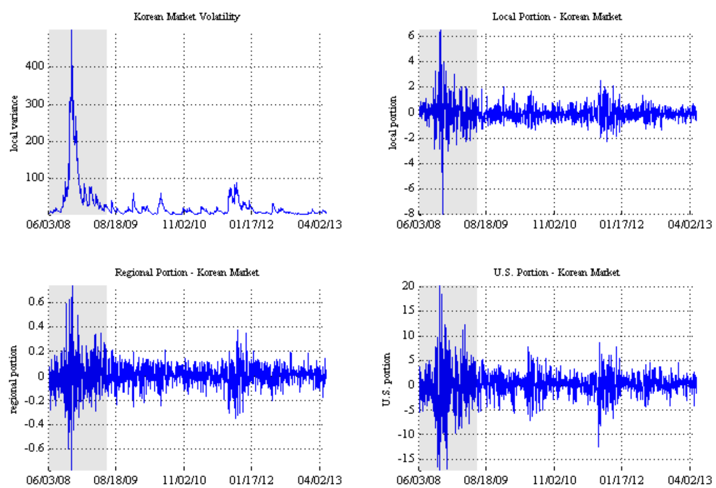
(a) India



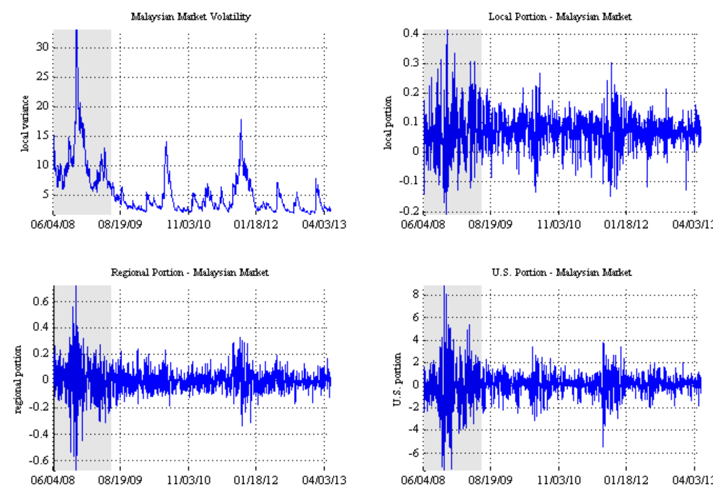
(b) Indonesia



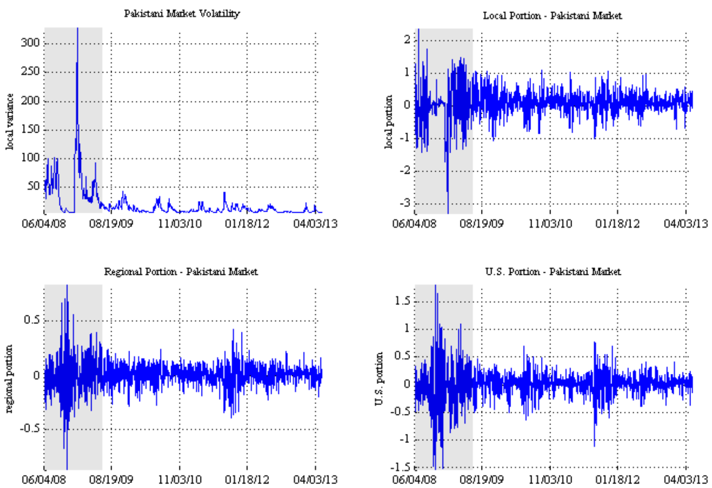
(c) Korea



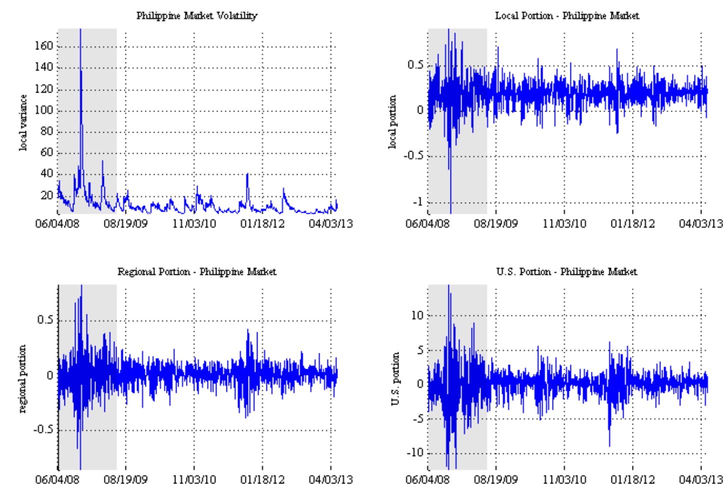
(d) Malaysia



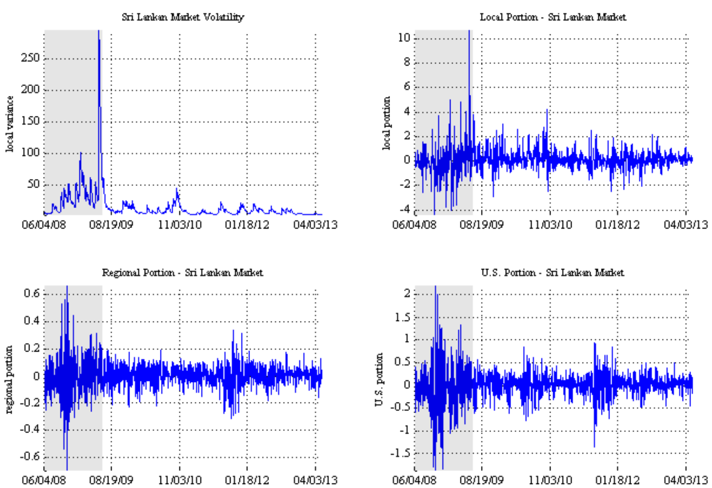
(e) Pakistan



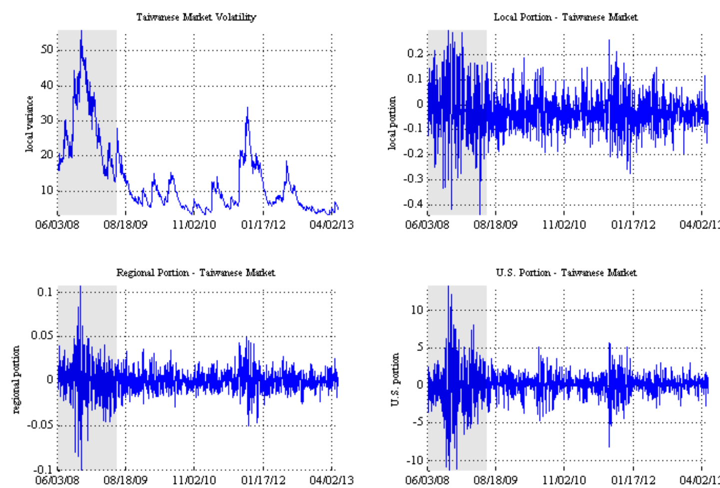
(f) The Philippines



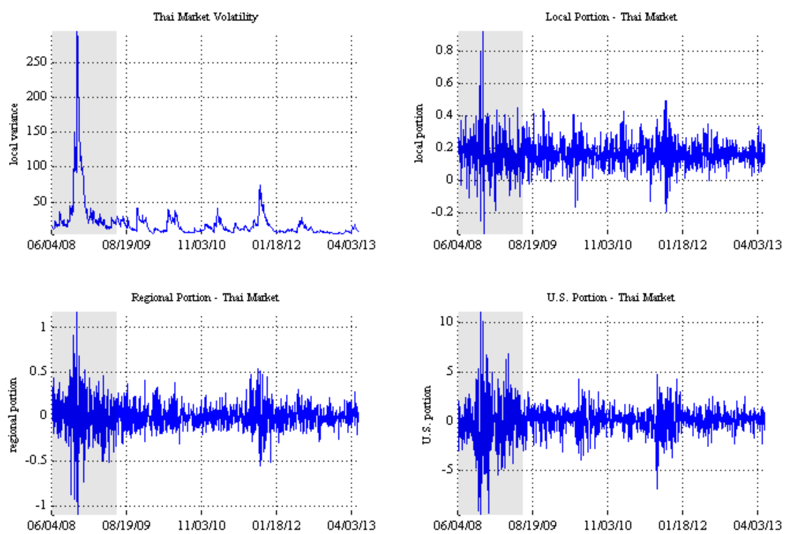
(g) Sri Lanka



(h) Taiwan



(i) Thailand



(j) Vietnam

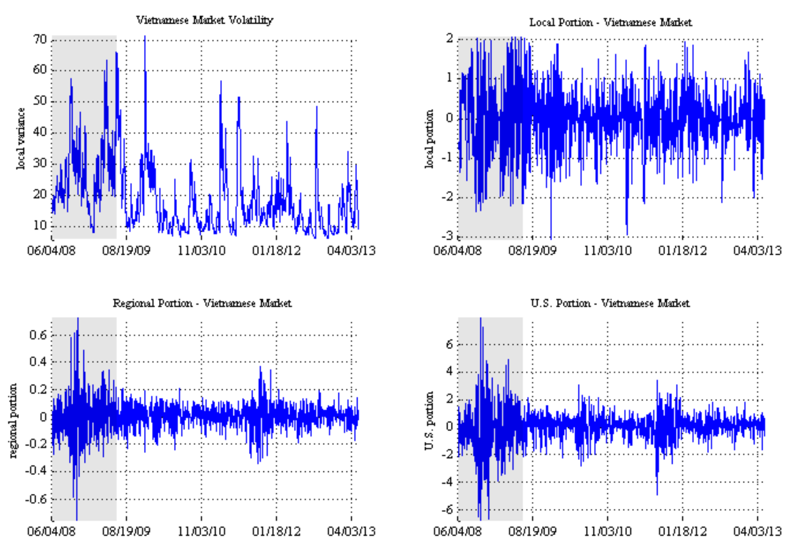
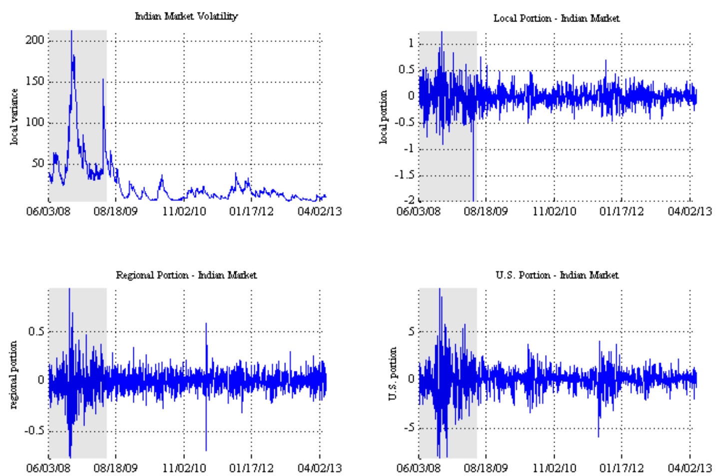


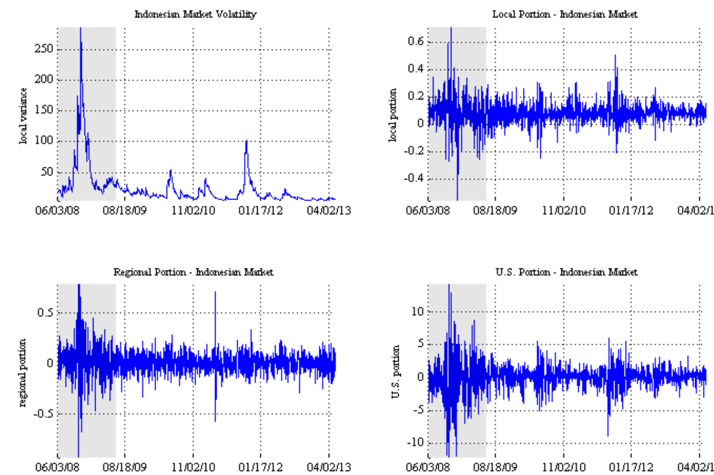
Figure A.3: Estimated Daily Market Volatility and Decomposition of Expected Daily Return with Japan as Regional Center

The estimated level of daily volatility is presented in the upper left panel of each figure. The expected return of local market m is decomposed into three parts: the local portion (the upper right panel) is computed as $\alpha_0 + \alpha_1 R_{m,\,t-1}$, the regional portion (the lower left panel) as $\alpha_3 R_{JP,\,t-1}$ and the U.S. portion (the lower right panel) as $\alpha_2 R_{US,\,t-1}$.

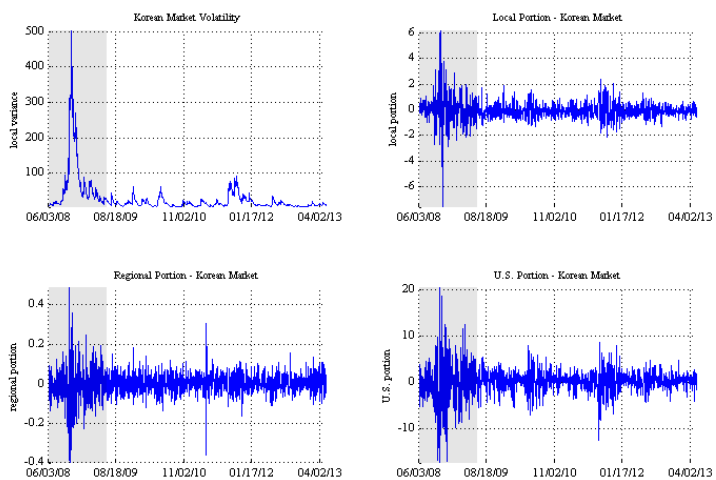
(a) India



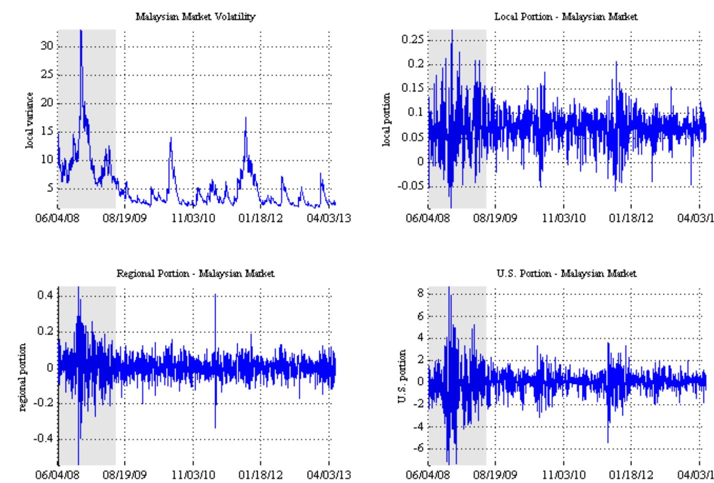
(b) Indonesia



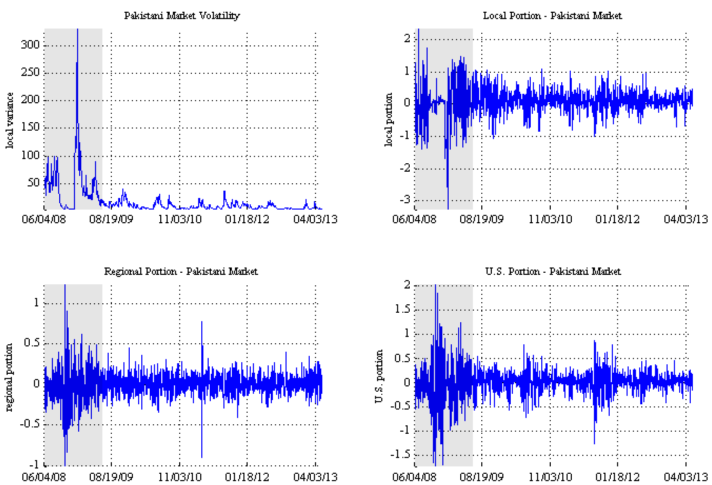
(c) Korea



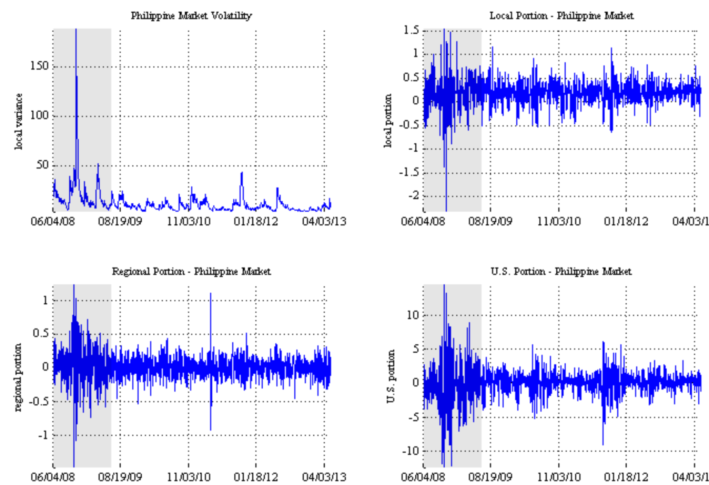
(d) Malaysia



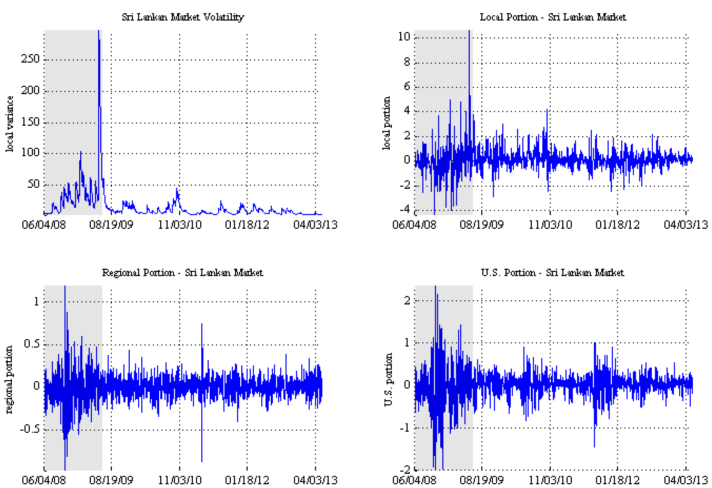
(e) Pakistan



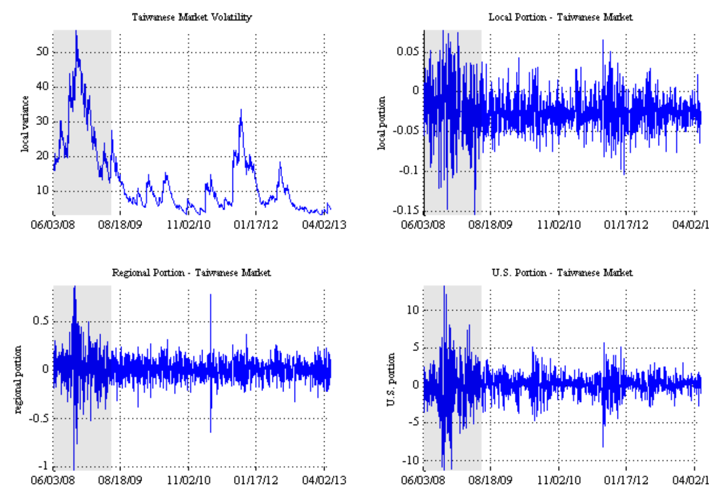
(f) The Philippines



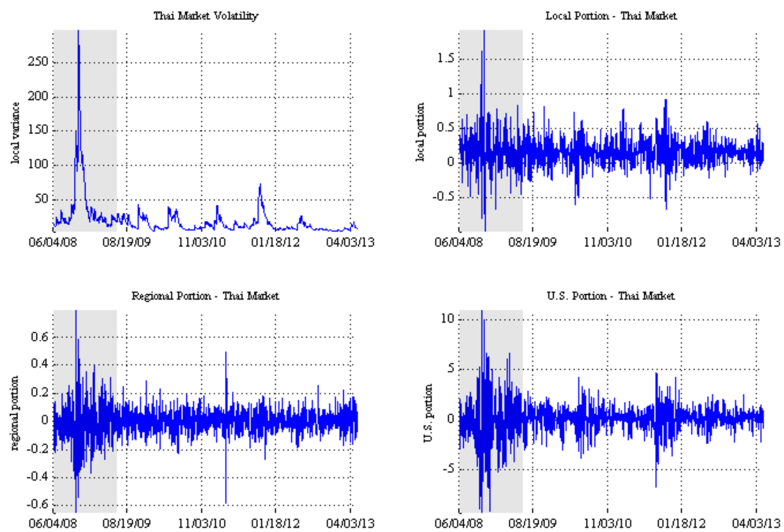
(g) Sri Lanka



(h) Taiwan



(i) Thailand



(j) Vietnam

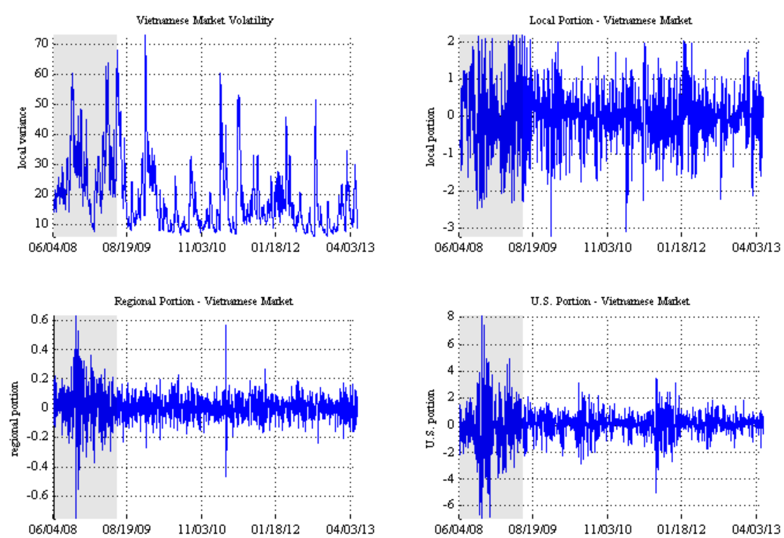
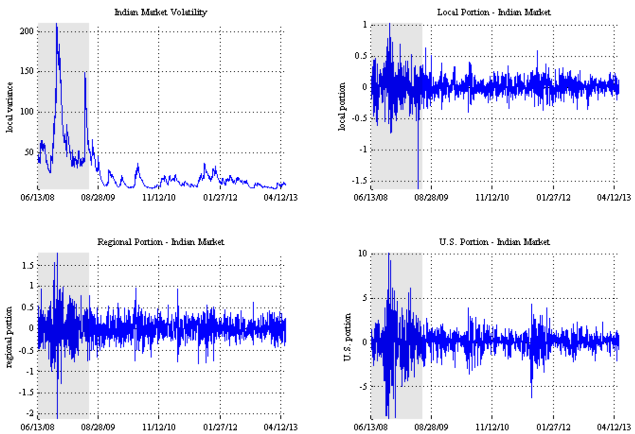


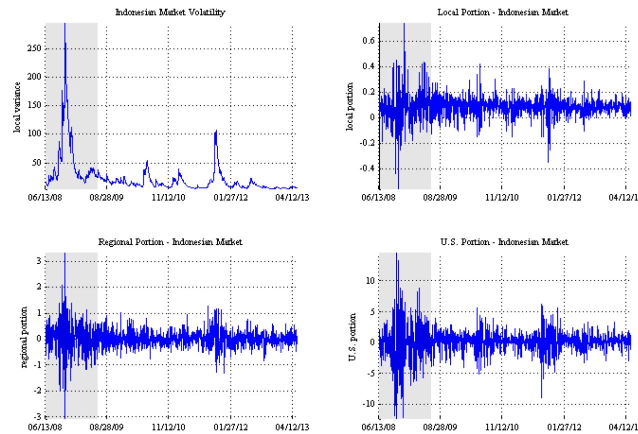
Figure A.4: Estimated Daily Market Volatility and Decomposition of Expected Daily Return with All Three Markets Incorporated in Mean Equation

The estimated level of daily volatility is presented in the upper left panel of each figure. The expected return of local market m is decomposed into three parts: the local portion (shown in the upper right panel) is computed as $\alpha_0 + \alpha_1 R_{m,\,t-1}$, the regional portion (shown in the lower left panel) as $\alpha_3 R_{AU,\,t-1} + \alpha_4 R_{CN,\,t-1} + \alpha_5 R_{JP,\,t-1}$ and the U.S. portion (shown in the lower right panel) as $\alpha_2 R_{US,\,t-1}$.

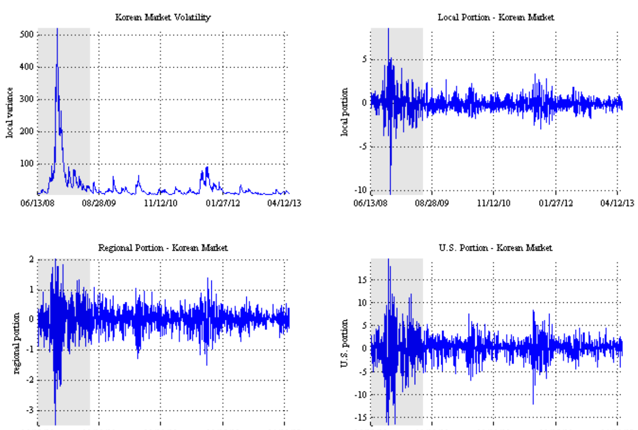
(a) India



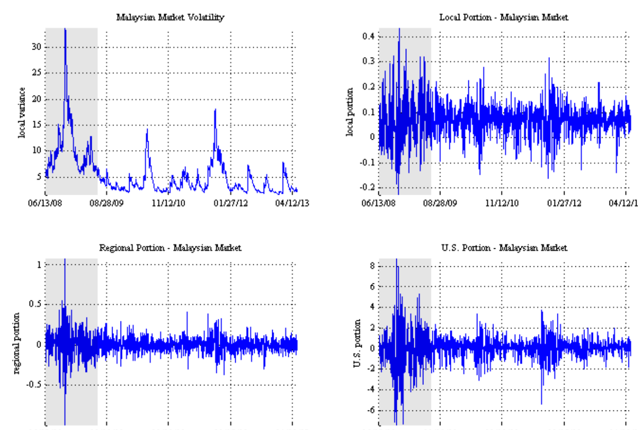
(b) Indonesia



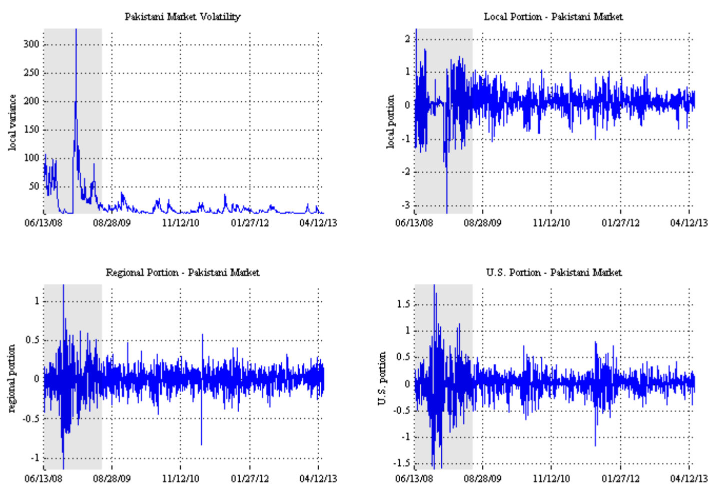
(c) Korea



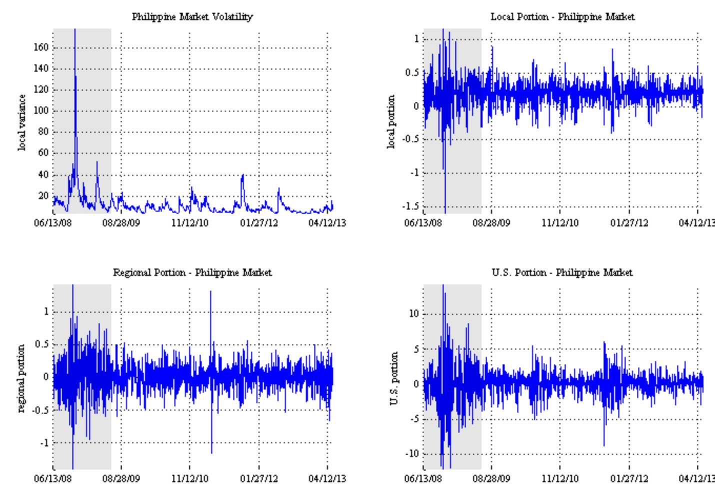
(d) Malaysia



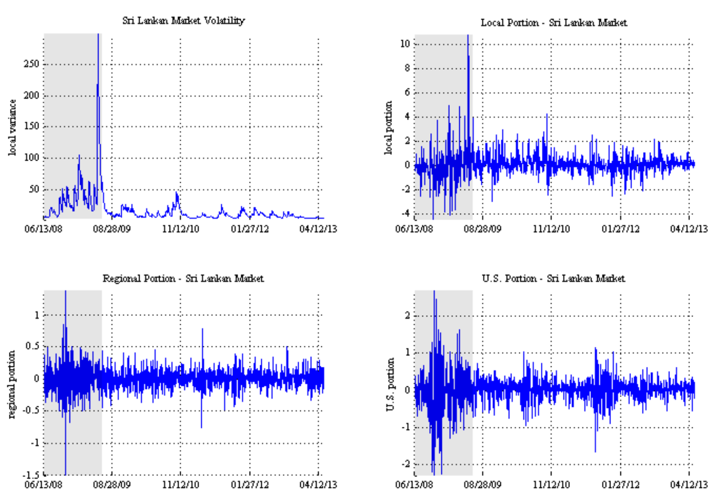
(e) Pakistan



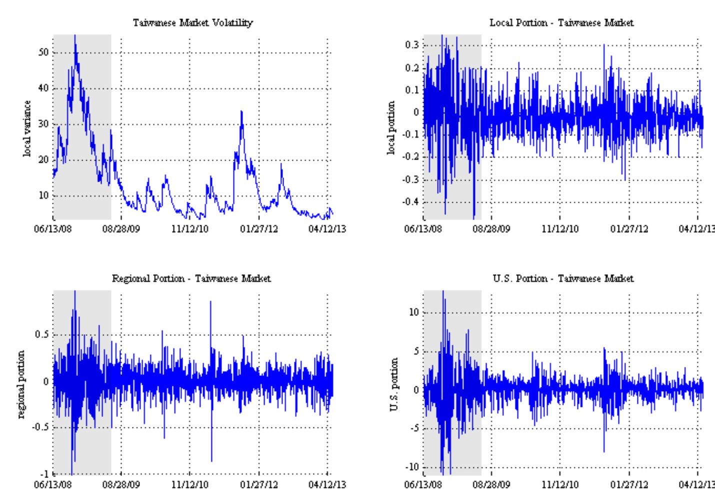
(f) The Philippines



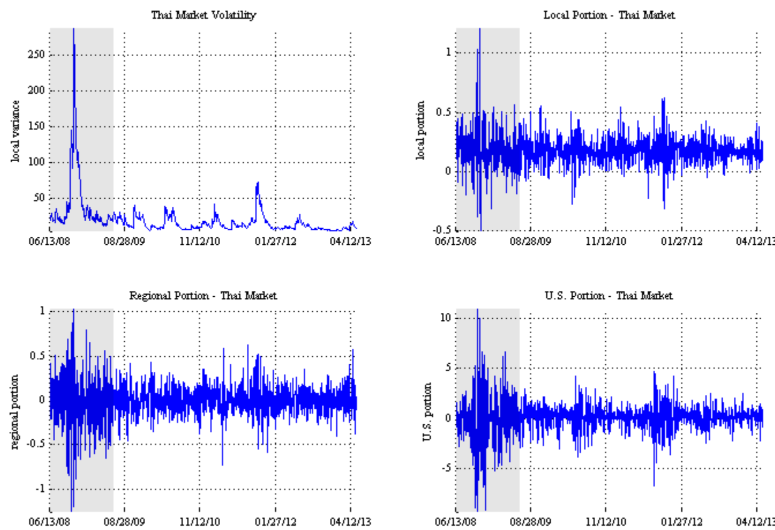
(g) Sri Lanka



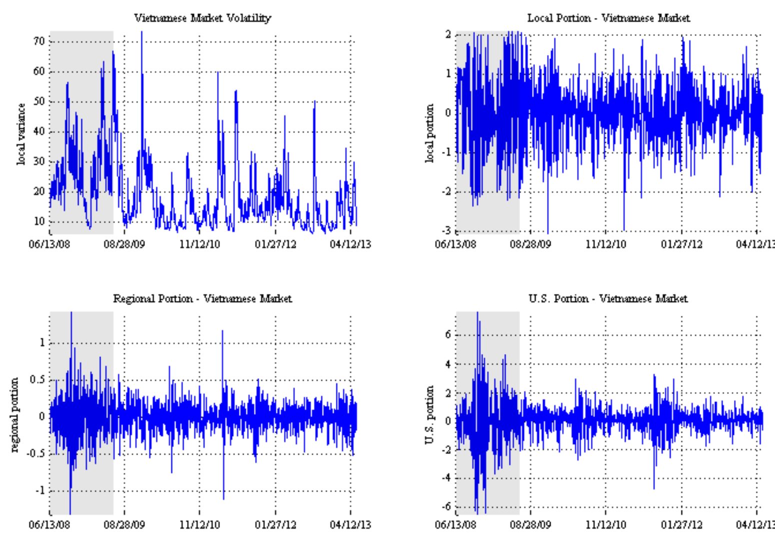
(h) Taiwan



(i) Thailand



(j) Vietnam

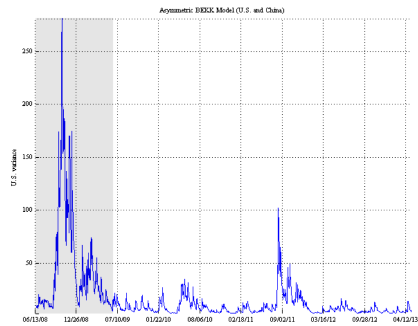


Appendices of Chapter 3

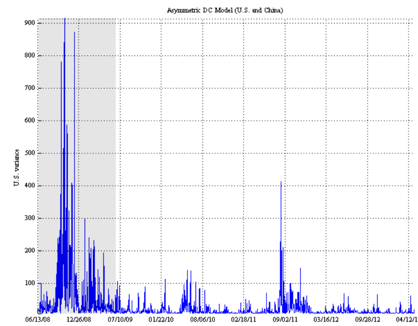
Figures A.5–A.7 on pages 123–125 present the estimated level of daily U.S. and regional variances and daily covariance and correlation between the two markets. The BEKK estimates are displayed in the left column of these figures and the DC estimates in the right. The shaded area indicates the most recent recession period reported by NBER. Figure A.8 plots the histograms (in frequency) and empirical probability density functions of the diagnostic test statistics derived from the simulations. The probability density functions of the several involved χ^2 distributions with different degrees of freedom are displayed alongside the empirical probability density functions for the purpose of comparison.

Figure A.5: Estimated U.S. Variance, Chinese Variance, Covariance and Correlation Under Two Model Specifications

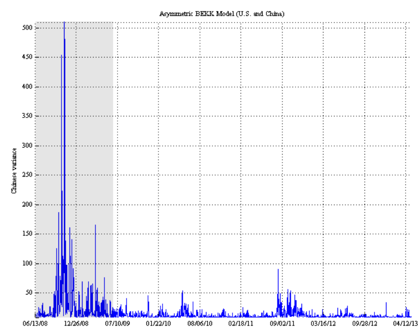
(a) U.S. Variance (BEKK model)



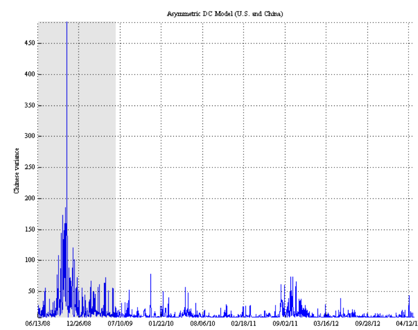
(b) U.S. Variance (DC model)



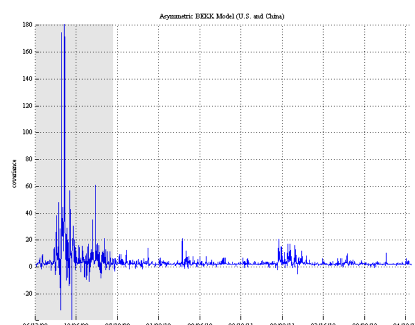
(c) Chinese Variance (BEKK model)



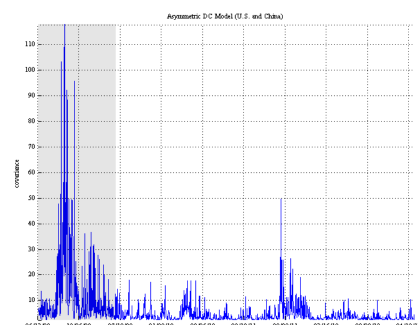
(d) Chinese Variance (DC model)



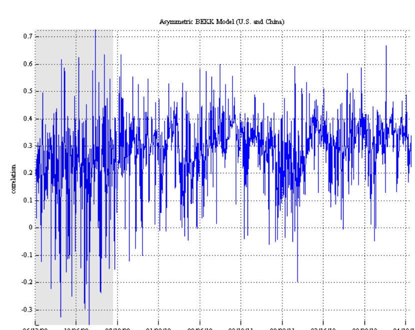
(e) U.S.–China Covariance (BEKK model)



(f) U.S.–China Covariance (DC model)



(g) U.S.–China Correlation (BEKK model)



(h) U.S.–China Correlation (DC model)

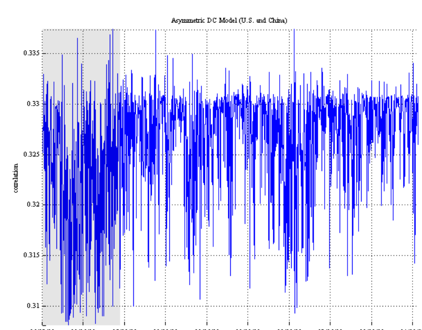
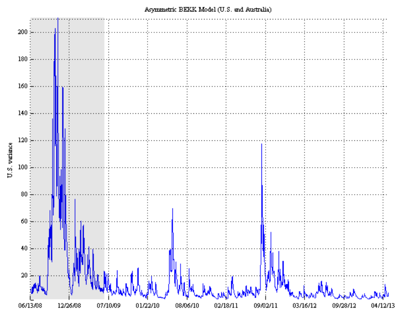
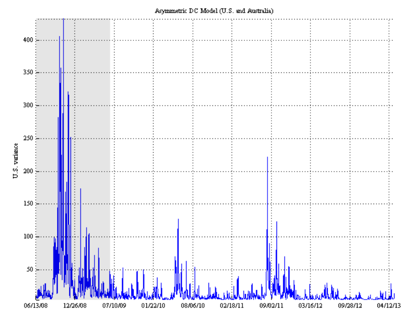


Figure A.6: Estimated U.S. Variance, Australian Variance, Covariance and Correlation Under Two Model Specifications

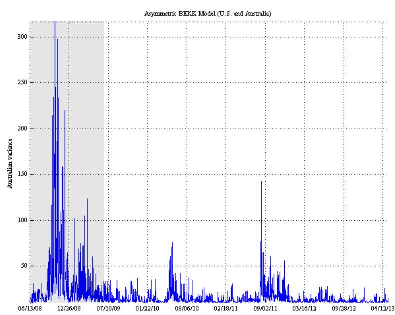
(a) U.S. Variance (BEKK model)



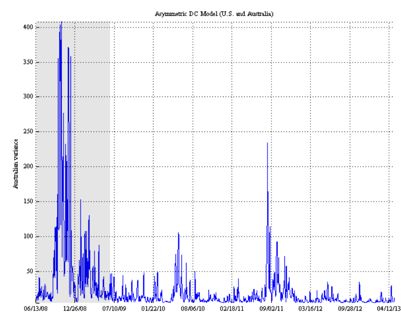
(b) U.S. Variance (DC model)



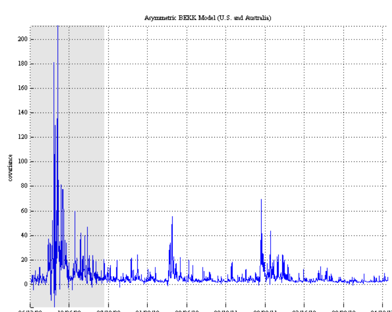
(c) Australian Variance (BEKK model)



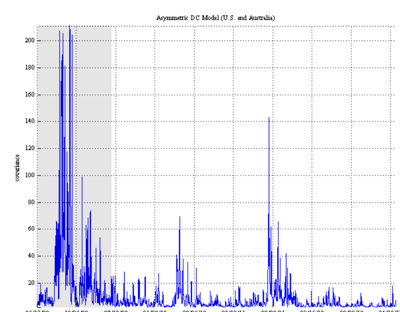
(d) Australian Variance (DC model)



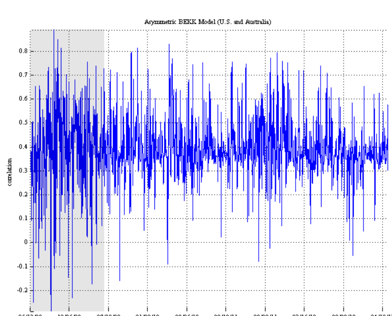
(e) U.S.–Australia Covariance (BEKK model)



(f) U.S.–Australia Covariance (DC model)



(g) U.S.–Australia Correlation (BEKK model)



(h) U.S.–Australia Correlation (DC model)

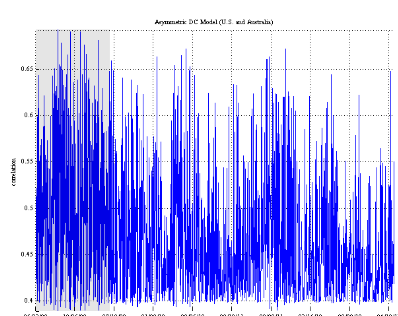
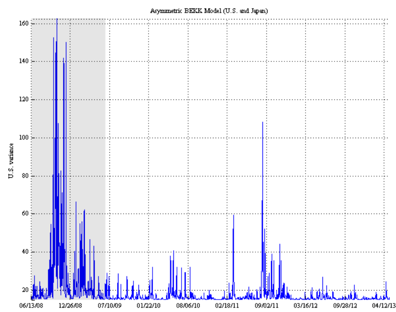
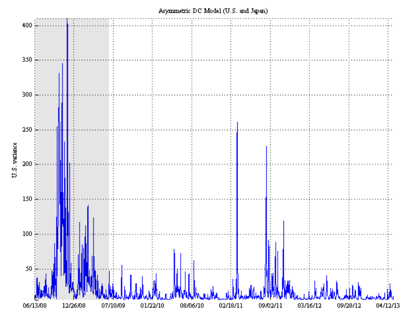


Figure A.7: Estimated U.S. Variance, Japanese Variance, Covariance and Correlation Under Two Model Specifications

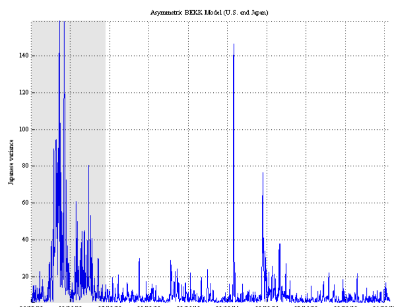
(a) U.S. Variance (BEKK model)



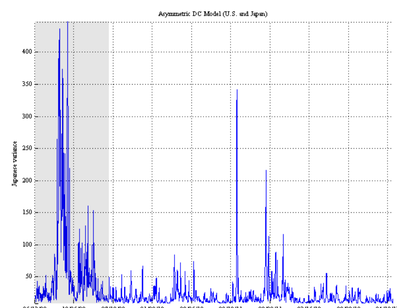
(b) U.S. Variance (DC model)



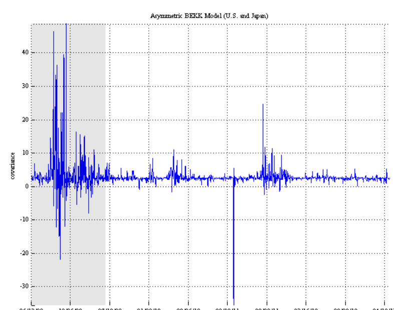
(c) Japanese Variance (BEKK model)



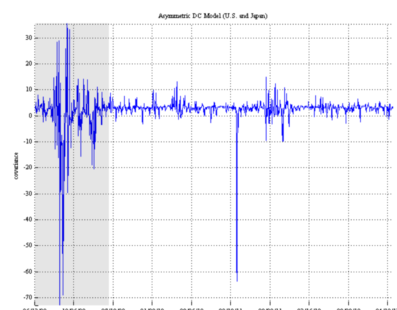
(d) Japanese Variance (DC model)



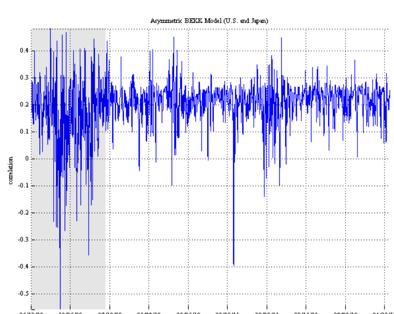
(e) U.S.–Japan Covariance (BEKK model)



(f) U.S.–Japan Covariance (DC model)



(g) U.S.–Japan Correlation (BEKK model)



(h) U.S.–Japan Correlation (DC model)

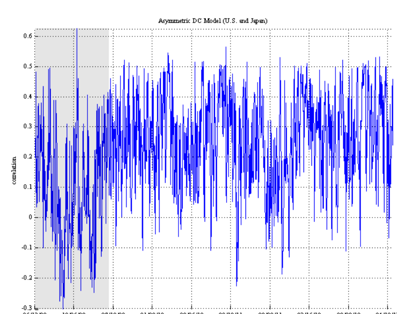
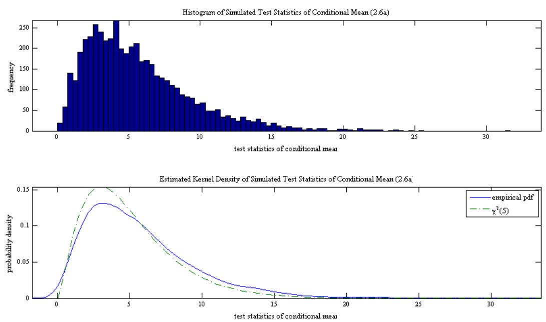
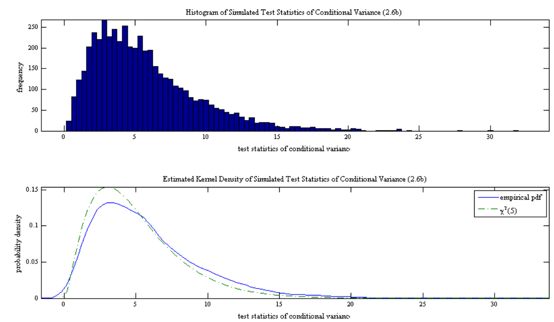


Figure A.8: Monte Carlo Simulation of Diagnostic Test Statistics

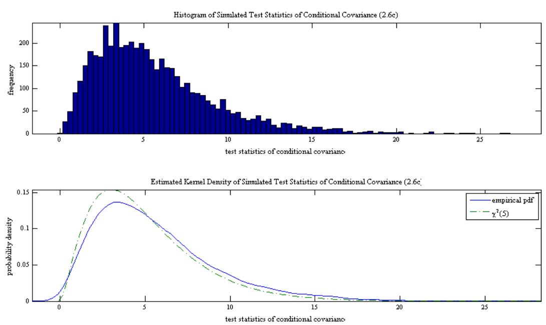
(a) Conditional Mean



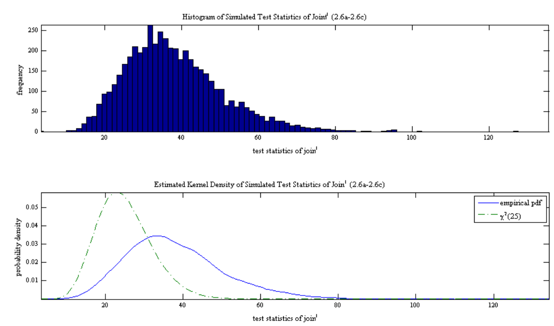
(b) Conditional Variance



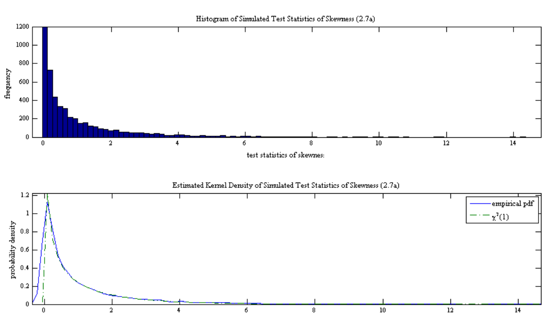
(c) Conditional Covariance



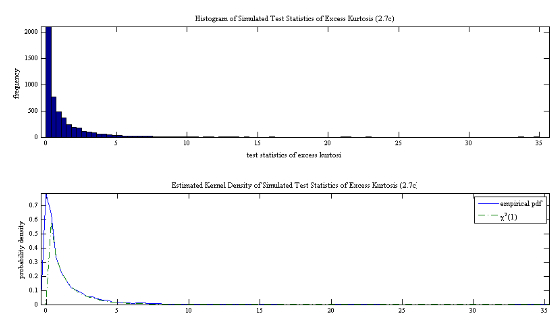
(d) Joint[1]



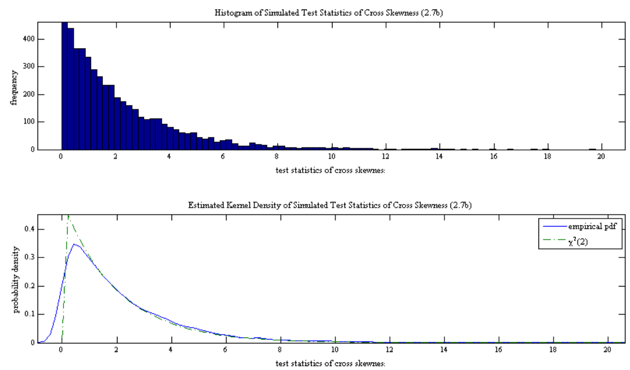
(e) Skewness



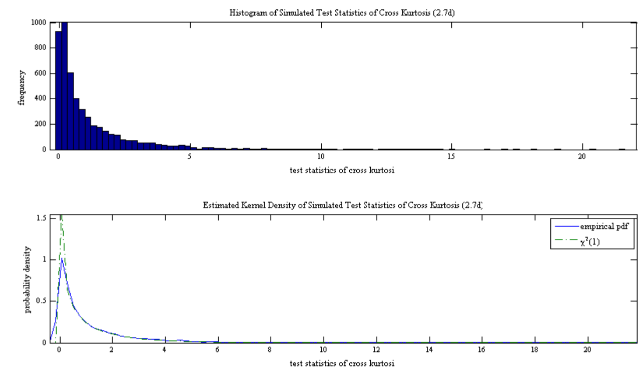
(f) Excess Kurtosis



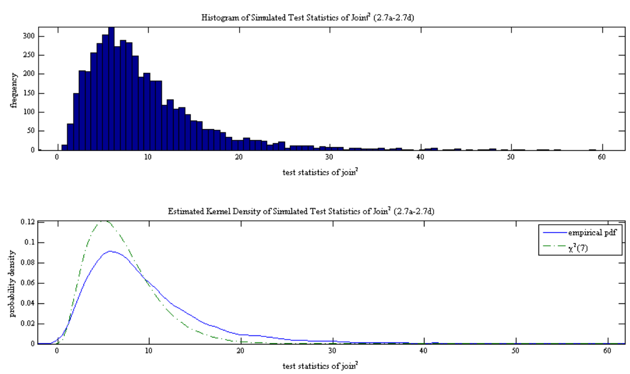
(g) Cross Skewness



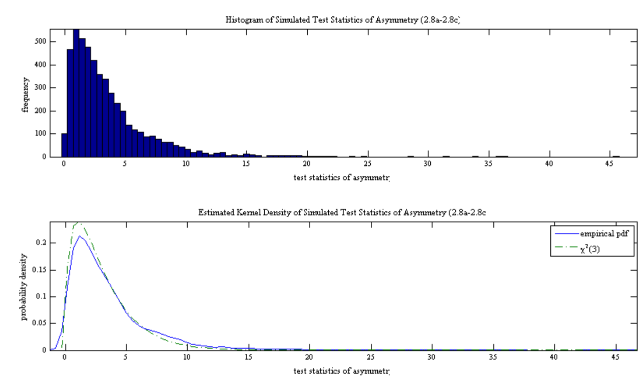
(h) Cross Kurtosis



(i) Joint^2



(j) Asymmetry



I suppose that two markets always have the same underlying stochastic process and shall discuss three separate scenarios briefly. In the first scenario, the U.S. and a local market have the same unobservable process governing the switching of the spillover intensities, which is different from that of a regional market. In other words, $S^{\dagger}_{m,\,t} \equiv S^{\ddagger}_{m,\,t}$. With $S^{\dagger}_{m,\,t}(S^{\ddagger}_{m,\,t})$ and $S^{*}_{m,\,t}$ taking their respective values, four combinations in total yield a new state variable:

$$\begin{aligned}
\mathcal{X}_{m,\,t} &= 1 \quad if \quad S^{\dagger}_{m,\,t} = S^{\ddagger}_{m,\,t} = 1, S^{*}_{m,\,t} = 1;\\
\mathcal{X}_{m,\,t} &= 2 \quad if \quad S^{\dagger}_{m,\,t} = S^{\ddagger}_{m,\,t} = 1, S^{*}_{m,\,t} = 2;\\
\mathcal{X}_{m,\,t} &= 3 \quad if \quad S^{\dagger}_{m,\,t} = S^{\ddagger}_{m,\,t} = 2, S^{*}_{m,\,t} = 1;\\
\mathcal{X}_{m,\,t} &= 4 \quad if \quad S^{\dagger}_{m,\,t} = S^{\ddagger}_{m,\,t} = 2, S^{*}_{m,\,t} = 2.
\end{aligned}$$

The corresponding transition probability matrix is

$$\begin{bmatrix}
P\left(\mathcal{X}_{m,t}=1|\mathcal{X}_{m,t-1}=1\right) & P\left(\mathcal{X}_{m,t}=1|\mathcal{X}_{m,t-1}=2\right) & P\left(\mathcal{X}_{m,t}=1|\mathcal{X}_{m,t-1}=3\right) & P\left(\mathcal{X}_{m,t}=1|\mathcal{X}_{m,t-1}=4\right)\\
P\left(\mathcal{X}_{m,t}=2|\mathcal{X}_{m,t-1}=1\right) & P\left(\mathcal{X}_{m,t}=2|\mathcal{X}_{m,t-1}=2\right) & P\left(\mathcal{X}_{m,t}=2|\mathcal{X}_{m,t-1}=3\right) & P\left(\mathcal{X}_{m,t}=2|\mathcal{X}_{m,t-1}=4\right)\\
P\left(\mathcal{X}_{m,t}=3|\mathcal{X}_{m,t-1}=1\right) & P\left(\mathcal{X}_{m,t}=3|\mathcal{X}_{m,t-1}=2\right) & P\left(\mathcal{X}_{m,t}=3|\mathcal{X}_{m,t-1}=3\right) & P\left(\mathcal{X}_{m,t}=3|\mathcal{X}_{m,t-1}=4\right)\\
P\left(\mathcal{X}_{m,t}=4|\mathcal{X}_{m,t-1}=1\right) & P\left(\mathcal{X}_{m,t}=4|\mathcal{X}_{m,t-1}=2\right) & P\left(\mathcal{X}_{m,t}=4|\mathcal{X}_{m,t-1}=3\right) & P\left(\mathcal{X}_{m,t}=4|\mathcal{X}_{m,t-1}=4\right)
\end{bmatrix}.$$

Let $P^{\dagger\,1}_{m}$, $P^{*\,1}_{m}$, $P^{\ddagger\,1}_{m}$, $P^{\dagger\,2}_{m}$, $P^{*\,2}_{m}$ and $P^{\ddagger\,2}_{m}$ denote the conditional probabilities that the underlying processes of the U.S., the regional and the local innovation for market m at time t stay in the same state as those at time $t-1$, i.e. $P^{\dagger\,1}_{m} = P(S^{\dagger}_{m,t} = 1|S^{\dagger}_{m,t-1} = 1)$, $P^{*\,1}_{m} = P(S^{*}_{m,t} = 1|S^{*}_{m,t-1} = 1)$, $P^{\ddagger\,1}_{m} = P(S^{\ddagger}_{m,t} = 1|S^{\ddagger}_{m,t-1} = 1)$, $P^{\dagger\,2}_{m} = P(S^{\dagger}_{m,t} = 2|S^{\dagger}_{m,t-1} = 2)$, $P^{*\,2}_{m} = P(S^{*}_{m,t} = 2|S^{*}_{m,t-1} = 2)$ and $P^{\ddagger\,2}_{m} = P(S^{\ddagger}_{m,t} = 2|S^{\ddagger}_{m,t-1} = 2)$. Since it is very likely that disturbance spillovers from the U.S. and the regional market are subject to their respective unrelated business cycles, the transition probability matrix can be reduced to a simpler form by assuming that $S^{\dagger}_{m,t}(S^{\ddagger}_{m,t})$ and $S^{*}_{m,t}$ are completely independent:

$$\begin{bmatrix} P_m^{\dagger 1} P_m^{*1} & P_m^{\dagger 1}\left(1-P_m^{*2}\right) & \left(1-P_m^{\dagger 2}\right) P_m^{*1} & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*2}\right) \\ P_m^{\dagger 1}\left(1-P_m^{*1}\right) & P_m^{\dagger 1} P_m^{*2} & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*1}\right) & \left(1-P_m^{\dagger 2}\right) P_m^{*2} \\ \left(1-P_m^{\dagger 1}\right) P_m^{*1} & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*2}\right) & P_m^{\dagger 2} P_m^{*1} & P_m^{\dagger 2}\left(1-P_m^{*2}\right) \\ \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*1}\right) & \left(1-P_m^{\dagger 1}\right) P_m^{*2} & P_m^{\dagger 2}\left(1-P_m^{*1}\right) & P_m^{\dagger 2} P_m^{*2} \end{bmatrix}.$$

The second scenario assumes that the random process controlling the switching of $\delta_{m,t}$ is always the same as the one determining how σ_m^2 changes with time: $S^{*}_{m,t} \equiv S^{\ddagger}_{m,t}$. In the last scenario, a local market has nothing in common with the regional or the U.S. market, though the state variables of these latter two are identical, i.e. $S^{\dagger}_{m,t} \equiv S^{*}_{m,t}$. Similarly, for the second scenario, the new latent variable is

$$\begin{aligned} \mathcal{Y}_{m,t} &= 1 \quad if \quad S^{\ddagger}_{m,t} = S^{*}_{m,t} = 1, S^{\dagger}_{m,t} = 1; \\ \mathcal{Y}_{m,t} &= 2 \quad if \quad S^{\ddagger}_{m,t} = S^{*}_{m,t} = 1, S^{\dagger}_{m,t} = 2; \\ \mathcal{Y}_{m,t} &= 3 \quad if \quad S^{\ddagger}_{m,t} = S^{*}_{m,t} = 2, S^{\dagger}_{m,t} = 1; \\ \mathcal{Y}_{m,t} &= 4 \quad if \quad S^{\ddagger}_{m,t} = S^{*}_{m,t} = 2, S^{\dagger}_{m,t} = 2, \end{aligned}$$

and the corresponding reduced-form transition probability matrix is

$$\begin{bmatrix} P_m^{\dagger 1} P_m^{\ddagger 1} & \left(1-P_m^{\dagger 2}\right) P_m^{\ddagger 1} & P_m^{\dagger 1}\left(1-P_m^{\ddagger 2}\right) & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{\ddagger 2}\right) \\ \left(1-P_m^{\dagger 1}\right) P_m^{\ddagger 1} & P_m^{\dagger 2} P_m^{\ddagger 1} & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{\ddagger 2}\right) & P_m^{\dagger 2}\left(1-P_m^{\ddagger 2}\right) \\ P_m^{\dagger 1}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 1} P_m^{\ddagger 2} & \left(1-P_m^{\dagger 2}\right) P_m^{\ddagger 2} \\ \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 2}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 1}\right) P_m^{\ddagger 2} & P_m^{\dagger 2} P_m^{\ddagger 2} \end{bmatrix}.$$

For the third scenario, the new latent variable is

$$
\begin{array}{lcccl}
\mathcal{V}_{m,t} & = & 1 & if & S^{\dagger}_{m,t} = S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 1; \\
\mathcal{V}_{m,t} & = & 2 & if & S^{\dagger}_{m,t} = S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 2; \\
\mathcal{V}_{m,t} & = & 3 & if & S^{\dagger}_{m,t} = S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 1; \\
\mathcal{V}_{m,t} & = & 4 & if & S^{\dagger}_{m,t} = S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 2,
\end{array}
$$

and the corresponding reduced-form transition probability matrix is

$$
\begin{bmatrix}
P^{\ddagger 1}_m P^{*1}_m & \left(1 - P^{\ddagger 2}_m\right) P^{*1}_m & P^{\ddagger 1}_m \left(1 - P^{*2}_m\right) & \left(1 - P^{\ddagger 2}_m\right)\left(1 - P^{*2}_m\right) \\
\left(1 - P^{\ddagger 1}_m\right) P^{*1}_m & P^{\ddagger 2}_m P^{*1}_m & \left(1 - P^{\ddagger 1}_m\right)\left(1 - P^{*2}_m\right) & P^{\ddagger 2}_m \left(1 - P^{*2}_m\right) \\
P^{\ddagger 1}_m \left(1 - P^{*1}_m\right) & \left(1 - P^{\ddagger 2}_m\right)\left(1 - P^{*1}_m\right) & P^{\ddagger 1}_m P^{*2}_m & \left(1 - P^{\ddagger 2}_m\right) P^{*2}_m \\
\left(1 - P^{\ddagger 1}_m\right)\left(1 - P^{*1}_m\right) & P^{\ddagger 2}_m \left(1 - P^{*1}_m\right) & \left(1 - P^{\ddagger 1}_m\right) P^{*2}_m & P^{\ddagger 2}_m P^{*2}_m
\end{bmatrix}.
$$

The third specification assumes that the three underlying random processes are totally independent of one another. There are eight combinations in total with $S^{\dagger}_{m,t}$, $S^{\ddagger}_{m,t}$ and $S^{*}_{m,t}$ taking their respective values:

$$
\begin{array}{lcccl}
\mathcal{W}_{m,t} & = & 1 & if & S^{\dagger}_{m,t} = 1, S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 1; \\
\mathcal{W}_{m,t} & = & 2 & if & S^{\dagger}_{m,t} = 1, S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 2; \\
\mathcal{W}_{m,t} & = & 3 & if & S^{\dagger}_{m,t} = 1, S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 1; \\
\mathcal{W}_{m,t} & = & 4 & if & S^{\dagger}_{m,t} = 1, S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 2; \\
\mathcal{W}_{m,t} & = & 5 & if & S^{\dagger}_{m,t} = 2, S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 1; \\
\mathcal{W}_{m,t} & = & 6 & if & S^{\dagger}_{m,t} = 2, S^{*}_{m,t} = 1, S^{\ddagger}_{m,t} = 2; \\
\mathcal{W}_{m,t} & = & 7 & if & S^{\dagger}_{m,t} = 2, S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 1; \\
\mathcal{W}_{m,t} & = & 8 & if & S^{\dagger}_{m,t} = 2, S^{*}_{m,t} = 2, S^{\ddagger}_{m,t} = 2.
\end{array}
$$

Columns 1–4 and columns 5–8 of the corresponding transition probability matrix are presented below:

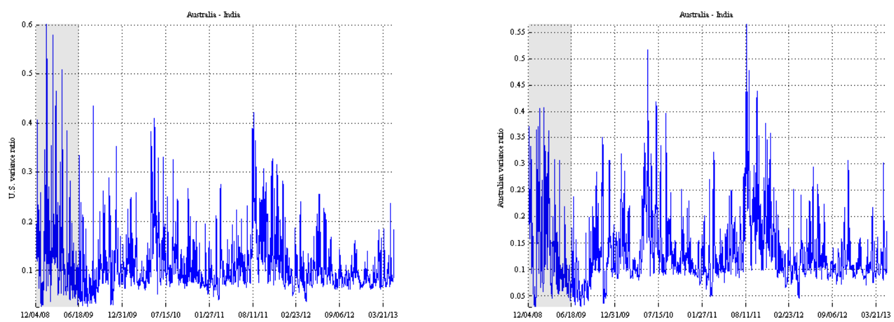
$$
\begin{bmatrix}
\underline{\textit{column 1}} & \underline{\textit{column 2}} & \underline{\textit{column 3}} & \underline{\textit{column 4}} \\
P_m^{\dagger 1}P_m^{*1}P_m^{\ddagger 1} & P_m^{\dagger 1}P_m^{*1}\left(1-P_m^{\ddagger 2}\right) & P_m^{\dagger 1}\left(1-P_m^{*2}\right)P_m^{\ddagger 1} & P_m^{\dagger 1}\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 2}\right) \\
P_m^{\dagger 1}P_m^{*1}\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 1}P_m^{*1}P_m^{\ddagger 2} & P_m^{\dagger 1}\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 1}\left(1-P_m^{*2}\right)P_m^{\ddagger 2} \\
P_m^{\dagger 1}\left(1-P_m^{*1}\right)P_m^{\ddagger 1} & P_m^{\dagger 1}\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 2}\right) & P_m^{\dagger 1}P_m^{*2}P_m^{\ddagger 1} & P_m^{\dagger 1}P_m^{*2}\left(1-P_m^{\ddagger 2}\right) \\
P_m^{\dagger 1}\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 1}\left(1-P_m^{*1}\right)P_m^{\ddagger 2} & P_m^{\dagger 1}P_m^{*2}\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 1}P_m^{*2}P_m^{\ddagger 2} \\
\left(1-P_m^{\dagger 1}\right)P_m^{*1}P_m^{\ddagger 1} & \left(1-P_m^{\dagger 1}\right)P_m^{*1}\left(1-P_m^{\ddagger 2}\right) & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*2}\right)P_m^{\ddagger 1} & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 2}\right) \\
\left(1-P_m^{\dagger 1}\right)P_m^{*1}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 1}\right)P_m^{*1}P_m^{\ddagger 2} & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*2}\right)\left(1-P^{\ddagger 1}\right) & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*2}\right)P_m^{\ddagger 2} \\
\left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*1}\right)P_m^{\ddagger 1} & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 2}\right) & \left(1-P_m^{\dagger 1}\right)P_m^{*2}P_m^{\ddagger 1} & \left(1-P_m^{\dagger 1}\right)P_m^{*2}\left(1-P_m^{\ddagger 2}\right) \\
\left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 1}\right)\left(1-P_m^{*1}\right)P_m^{\ddagger 2} & \left(1-P_m^{\dagger 1}\right)P_m^{*2}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 1}\right)P_m^{*2}P_m^{\ddagger 2} \\
\underline{\textit{column 5}} & \underline{\textit{column 6}} & \underline{\textit{column 7}} & \underline{\textit{column 8}} \\
\left(1-P_m^{\dagger 2}\right)P_m^{*1}P_m^{\ddagger 1} & \left(1-P_m^{\dagger 2}\right)P_m^{*1}\left(1-P_m^{\ddagger 2}\right) & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*2}\right)P_m^{\ddagger 1} & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 2}\right) \\
\left(1-P_m^{\dagger 2}\right)P_m^{*1}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 2}\right)P_m^{*1}P_m^{\ddagger 2} & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*2}\right)P_m^{\ddagger 2} \\
\left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*1}\right)P_m^{\ddagger 1} & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 2}\right) & \left(1-P_m^{\dagger 2}\right)P_m^{*2}P_m^{\ddagger 1} & \left(1-P_m^{\dagger 2}\right)P_m^{*2}\left(1-P_m^{\ddagger 2}\right) \\
\left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 2}\right)\left(1-P_m^{*1}\right)P_m^{\ddagger 2} & \left(1-P_m^{\dagger 2}\right)P_m^{*2}\left(1-P_m^{\ddagger 1}\right) & \left(1-P_m^{\dagger 2}\right)P_m^{*2}P_m^{\ddagger 2} \\
P_m^{\dagger 2}P_m^{*1}P_m^{\ddagger 1} & P_m^{\dagger 2}P_m^{*1}\left(1-P_m^{\ddagger 2}\right) & P_m^{\dagger 2}\left(1-P_m^{*2}\right)P_m^{\ddagger 1} & P_m^{\dagger 2}\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 2}\right) \\
P_m^{\dagger 2}P_m^{*1}\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 2}P_m^{*1}P_m^{\ddagger 2} & P_m^{\dagger 2}\left(1-P_m^{*2}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 2}\left(1-P_m^{*2}\right)P_m^{\ddagger 2} \\
P_m^{\dagger 2}\left(1-P_m^{*1}\right)P_m^{\ddagger 1} & P_m^{\dagger 2}\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 2}\right) & P_m^{\dagger 2}P_m^{*2}P_m^{\ddagger 1} & P_m^{\dagger 2}P_m^{*2}\left(1-P_m^{\ddagger 2}\right) \\
P_m^{\dagger 2}\left(1-P_m^{*1}\right)\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 2}\left(1-P_m^{*1}\right)P_m^{\ddagger 2} & P_m^{\dagger 2}P_m^{*2}\left(1-P_m^{\ddagger 1}\right) & P_m^{\dagger 2}P_m^{*2}P_m^{\ddagger 2}
\end{bmatrix}
$$

Figure A.9 displays the proportions of local variance attributable to shocks to the U.S. and the Australian/Chinese/Japanese markets during the period 4 December 2008–3 May 2013. When RS–I is chosen for a certain local market, I apply the probability-weighted switching spillover coefficients to formulae (4.13a) and (4.13b) to calculate the variance ratios. The shaded area covers the recent U.S. recession and financial crisis.

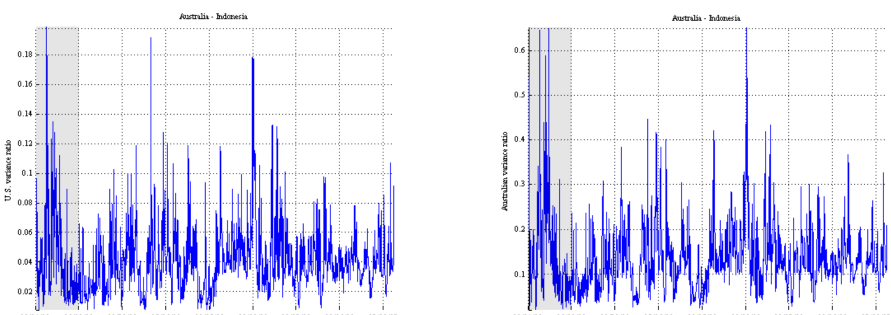
Figure A.9: U.S. and Regional Variance Ratio from 4 December 2008 to 3 May 2013

A. Australian Market as Regional Center

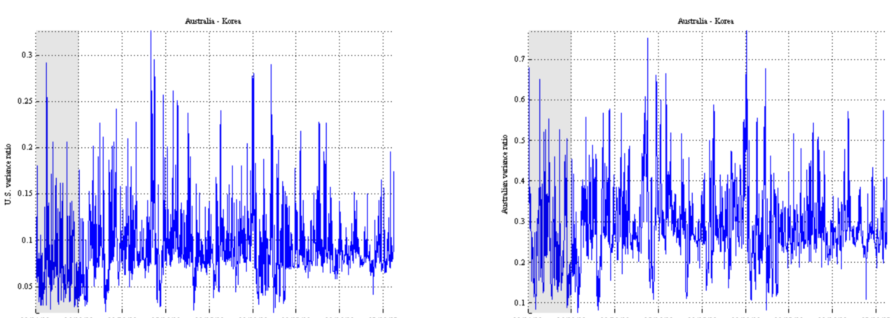
a. India



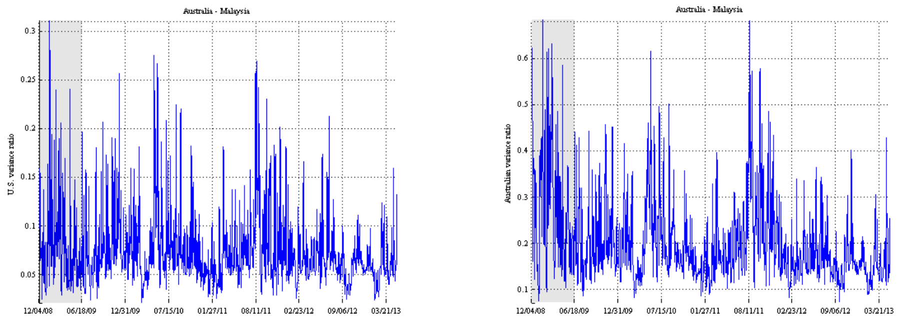
b. Indonesia



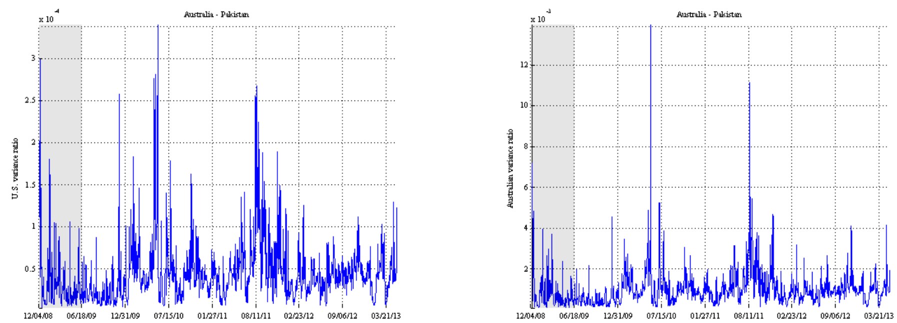
c. Korea



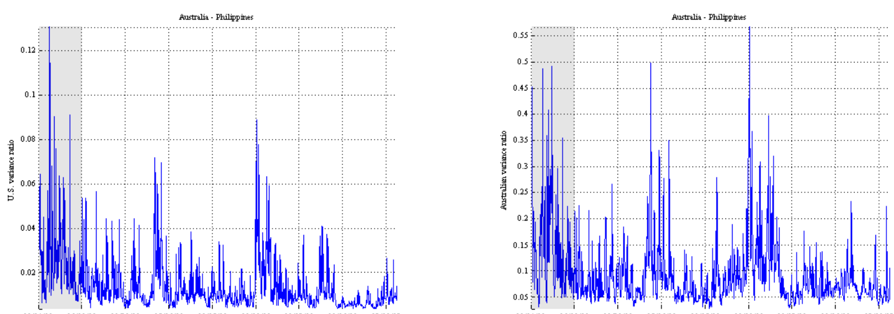
d. Malaysia



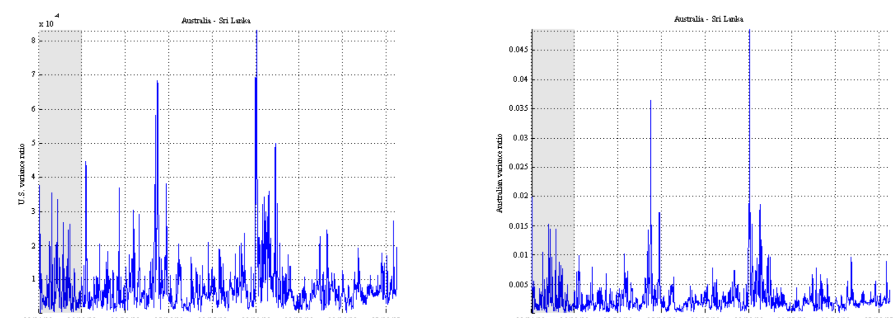
e. Pakistan



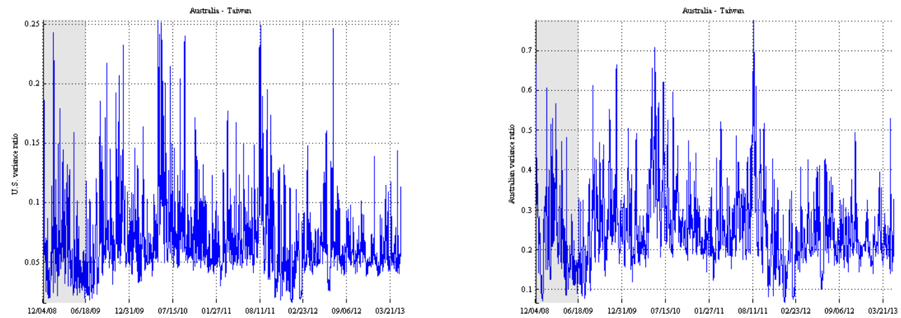
f. The Philippines



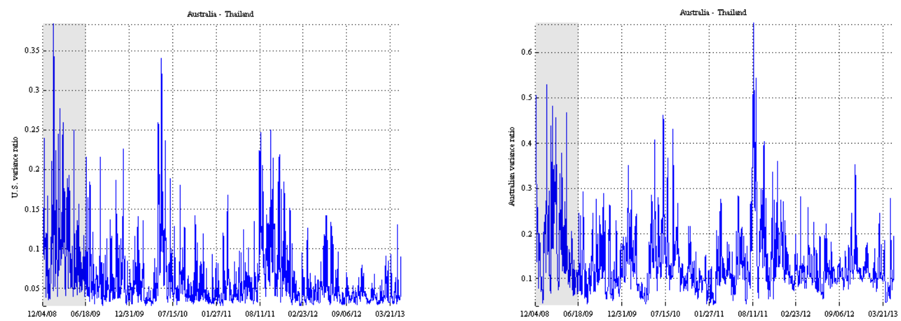
g. Sri Lanka



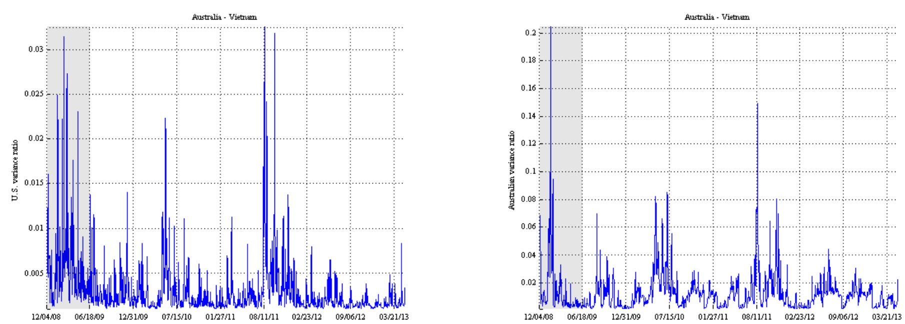
h. Taiwan



i. Thailand

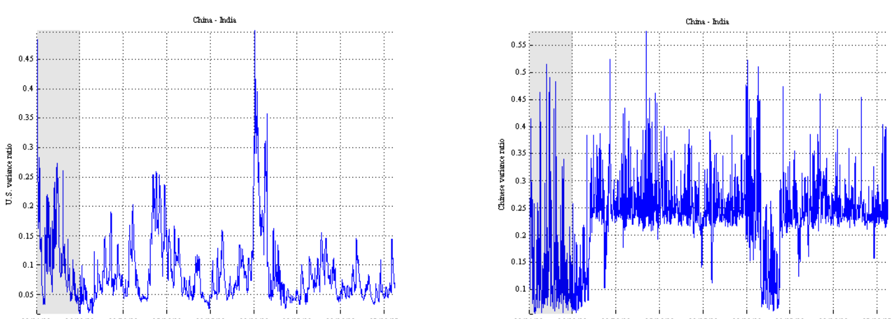


j. Vietnam

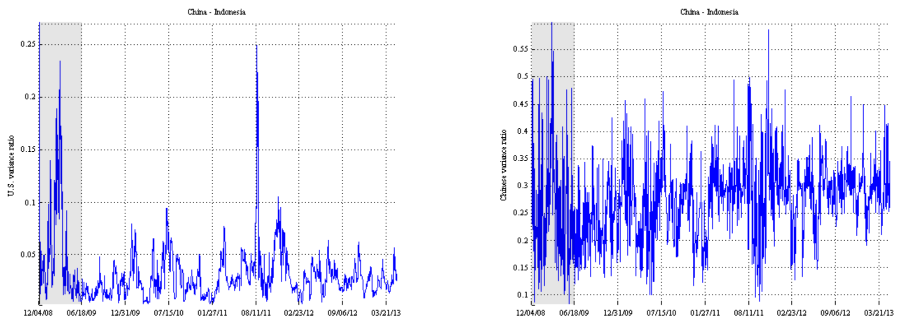


B. Chinese Market as Regional Center

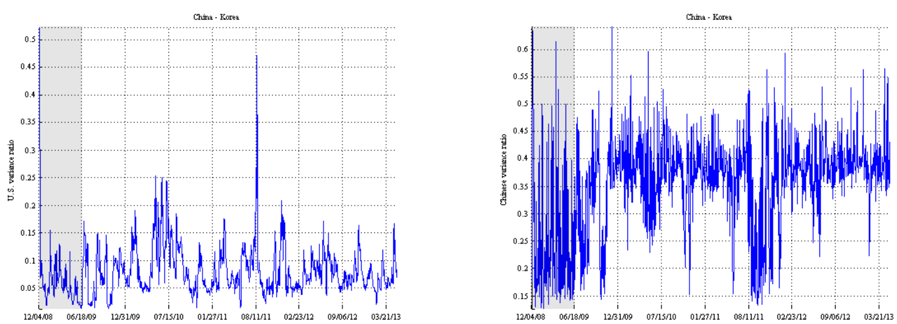
a. India



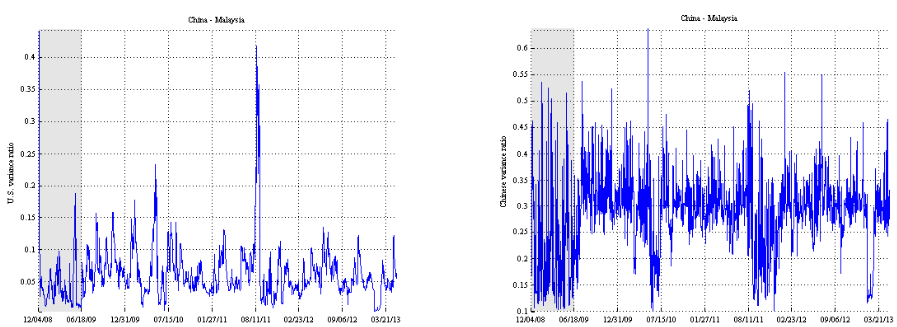
b. Indonesia



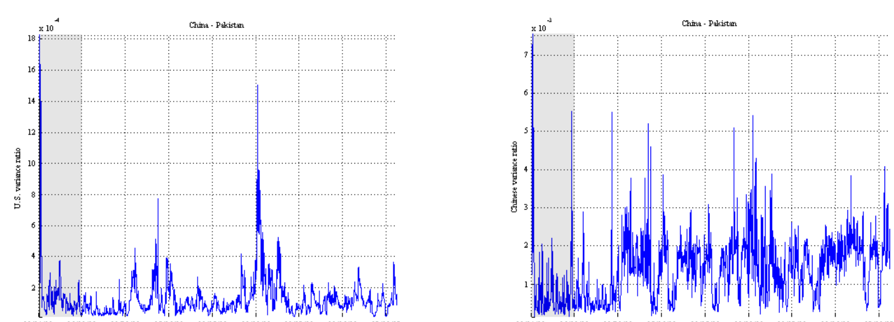
c. Korea



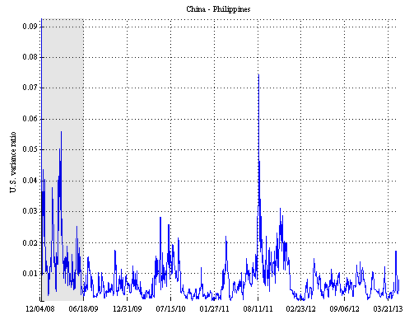
d. Malaysia

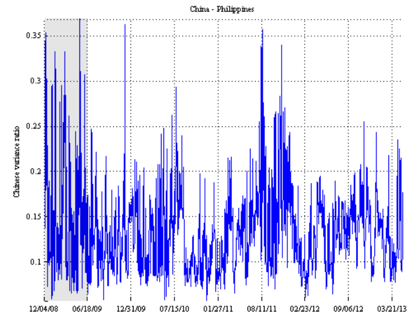


e. Pakistan

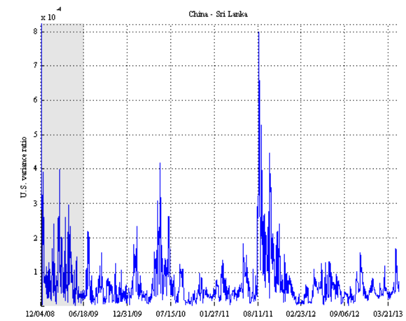


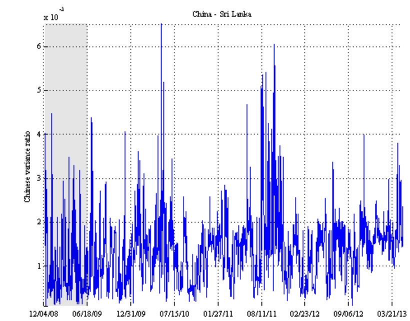
f. The Philippines



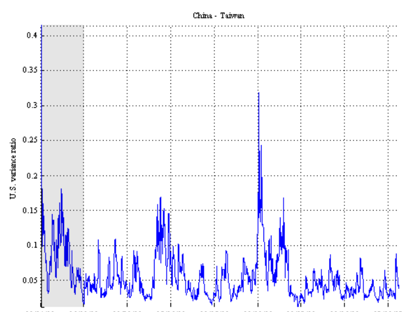


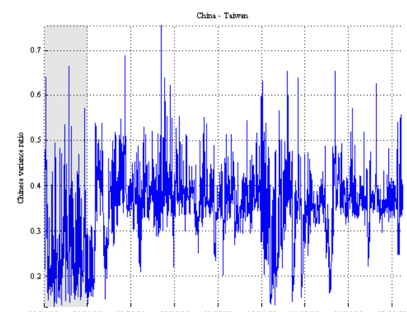
g. Sri Lanka



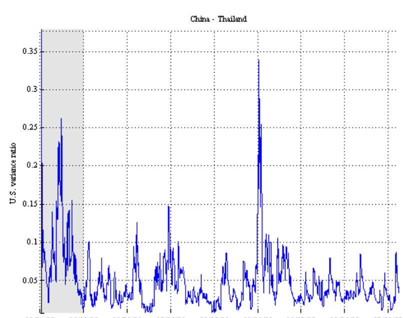


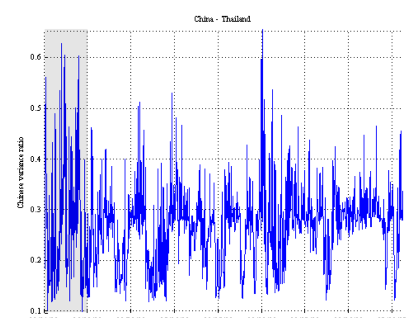
h. Taiwan



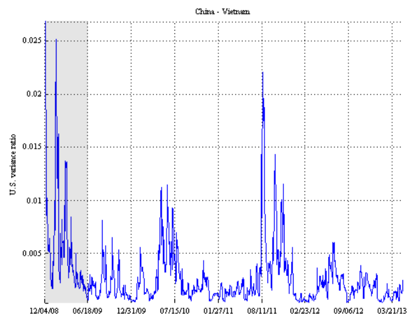


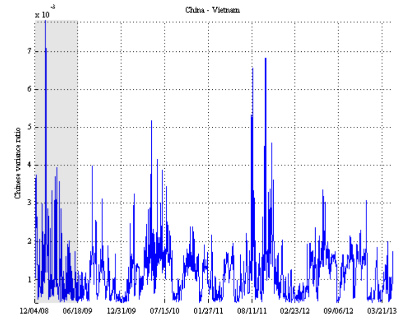
i. Thailand





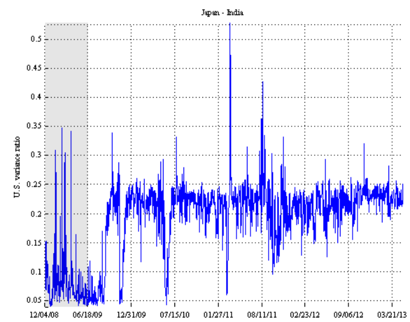
j. Vietnam

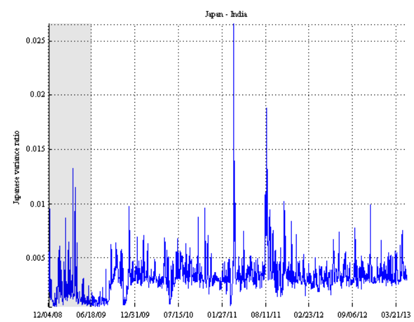




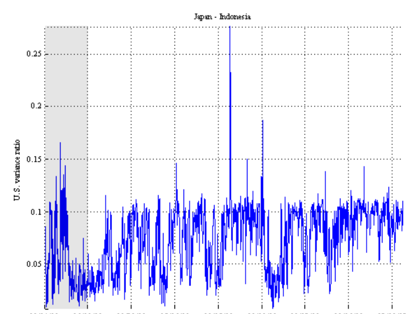
C. Japanese Market as Regional Center

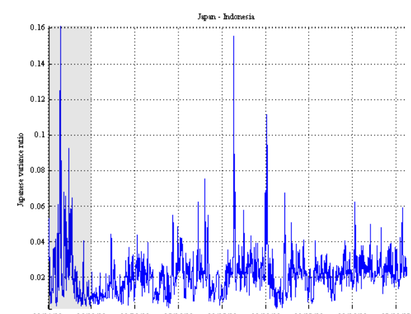
a. India



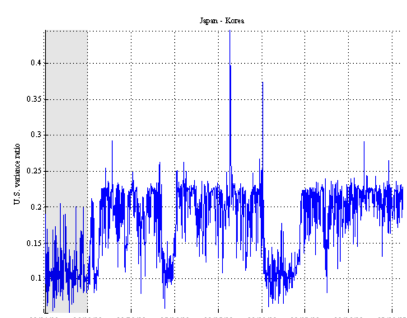


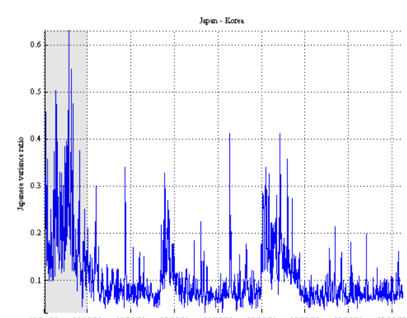
b. Indonesia



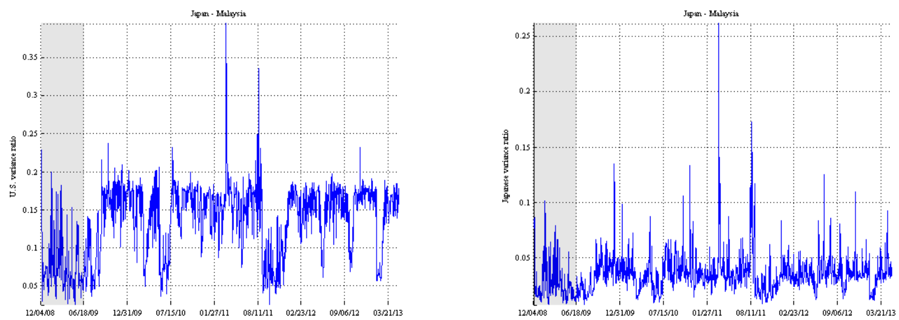


c. Korea

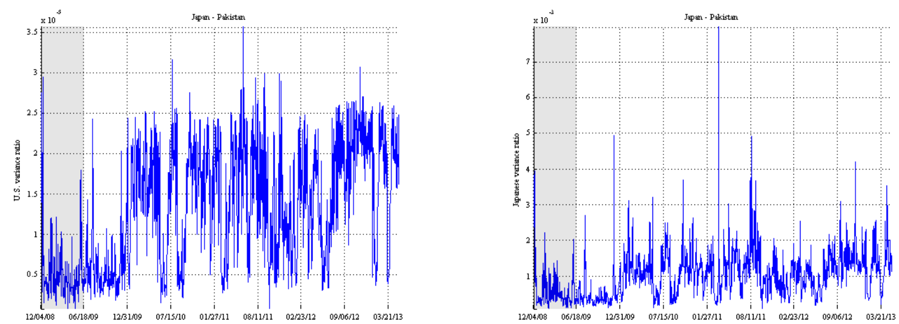




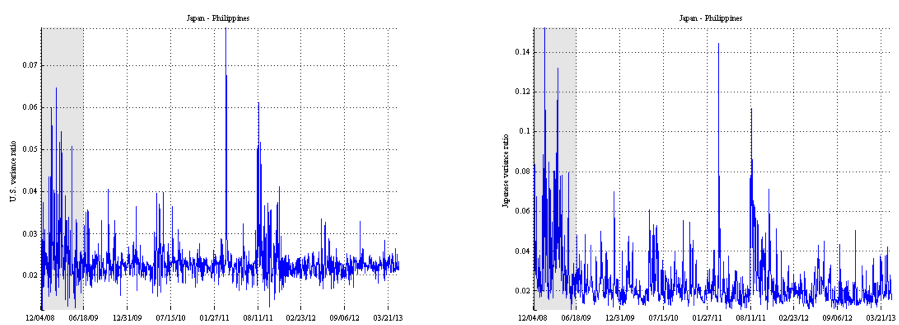
d. Malaysia



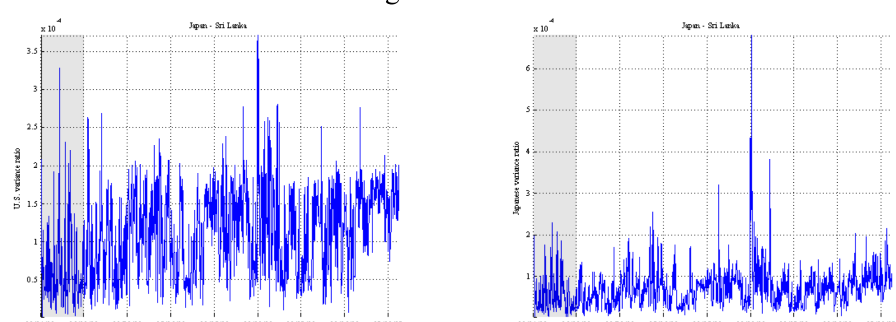
e. Pakistan



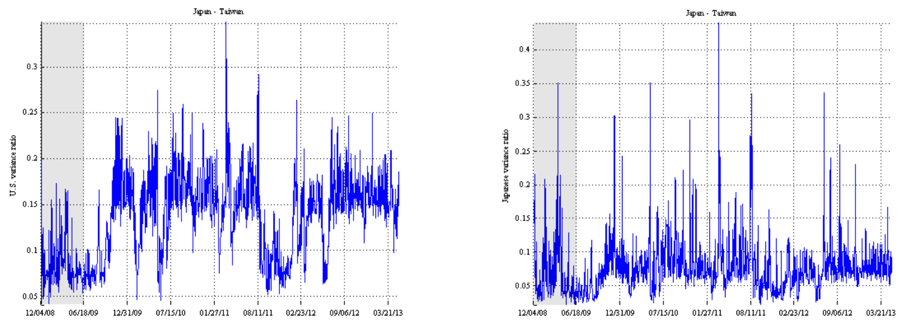
f. The Philippines



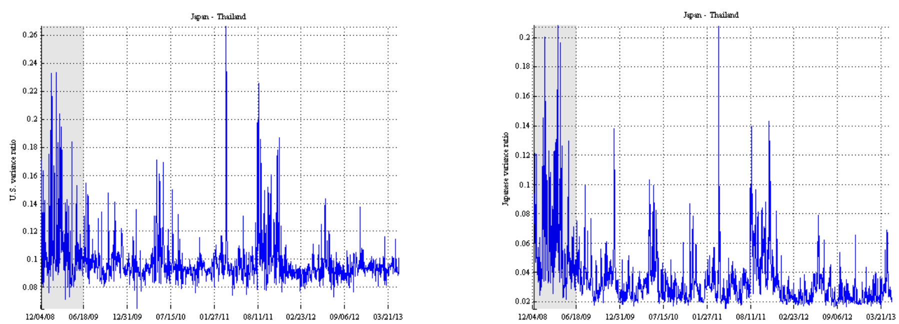
g. Sri Lanka



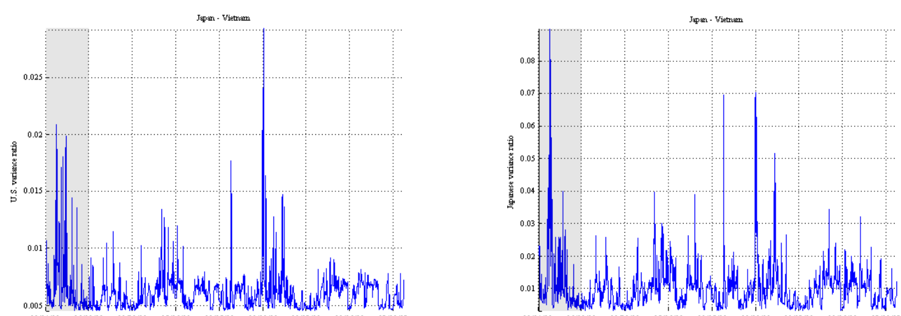
h. Taiwan



i. Thailand



j. Vietnam



VITA

LI XU

2009	B.A., Finance Shanghai International Studies University Shanghai, China
2010	M.A., Economics Florida International University Miami, Florida
2012	Doctoral Candidate in Economics Florida International University Miami, Florida