Dynamic Linkages and Propagation Mechanisms among Asian Stock Markets: An Analysis of the Pre-and Post 1997-98 financial crisis

by

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Abstract

This thesis analyzes dynamic interdependence, volatility transmission and market integration across eight selected Asian stock markets from 1992 to 2007. Various methodologies are applied to test such relationships. In particular, the focus is given to the impact of the 1997-98 Asian financial crisis on the dynamic linkages and propagation mechanisms among these selected Asian equity markets.

The techniques of unit root testing, cointegration, vector error correction modelling (VECM) and forecast error variance decomposition (VDC) analysis are initially performed in both whole sample period and four sub-sample periods (namely pre-crisis, crisis, post-crisis and recovery periods). The results suggest that Asian stock markets are highly integrated and the crash has brought a greater interaction amongst markets. Japan, Hong Kong and Singapore appear to play the relative leading role over other markets. Furthermore, the characteristics of stock volatility are then examined using univariate TAR-GARCH model. The results show that volatility is time-varying and bad news will generate more volatility than good news. Additionally, the empirical findings show the existence of day of week effects in returns and volatility in emerging markets before but not after the crisis. This suggests improved post-crash market efficiency in Asian emerging markets. Furthermore, using a multivariate GARCH-BEKK model, the results highlight the complex nature of volatility linkages and indicate that each market reacts to both local news and news originating in other markets. During the pre-crisis period, trading time plays an important role in the determination of volatility spillover effects. During the crisis and post-crisis periods, however, market trading time appears to become a less important determinant of volatility spillover effects, giving way to quality of markets. During the recovery period, it is found that more reciprocal volatility transmission relationships existed between markets – a finding that is strongly consistent with a growing degree of Asian equity market integration over recent years. Finally, by utilising dynamic conditional correlation (DCC) model to examine the contemporaneous interactions between the markets, the apparent higher co-movement of the sampled stock markets in times of crisis is found, which might be evidence of a 'contagion effect'. Additionally, it is also shown that bilateral correlations increase in periods of high market volatility.

***Keywords*: Dynamic interdependence, Volatility transmission, Market integration**

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Chapter 1 Introduction

1.1 Background and Motivations

The interaction of national stock markets has been an extensively researched area. This is mainly because stock prices and real economic activity are naturally correlated. According to the discounted-cash-flow valuation model, a stock market price reflects the discounted value of expected future dividends (expected future growth). From this perspective, a stock price works as a leading indicator that reflects investors' expectations of the future economic prospects of the economy. Further, interactions between stock prices provide evidence of information flows between national markets, with implications for market stability and real economic activity. Interactions between developed equity markets have been thoroughly investigated in earlier studies. For example, Grubel and Fadner (1971) focused on the interrelationships between the US, UK and Germany, Ripley (1973) investigated stock indices for 19 developed countries including the US, UK, France, Denmark, Italy and Canada, while Wasserfallen (1989) examined Germany, Switzerland and the UK.

Since the early 1990s, financial liberalization in Asian countries has fostered considerable investment interest in Asian stock markets. This is shown by the creation of various mutual funds with investment focus on Asian equity markets (Cheung, Cheung and Ng, 2003) and the explosion of equity flows into Asia (Purfield, Oura, Jobst and Kramer, 2006). The loosening of controls on foreign investor participation in equity markets has resulted in large equity inflows further stimulating increases in cross-border economic and financial activity. As well as participating in the growth prospects of the region, investors have concentrated on stock market linkages in Asia for the purpose of efficient allocation of capital and risk diversification. The financial crisis of 1997-98, which induced a collapse of stock prices throughout the entire region, has made investors recognise that financial instability in one country can be transmitted to neighbouring countries. This has reinforced investors' interest in examining the inter-relationships and volatility transmission mechanisms between Asian equity markets.

These relationships are also of interest to policymakers. This is because liberalization of Asian stock markets allows foreigners to purchase shares of Asian firms more easily, which may increase the exposure of those firms to systemic risk. Measuring stock market integration (long-term relationship) and volatility transmission across countries may provide a useful channel for policymakers to understand the sensitivity of their economies to sudden withdrawals of foreign portfolios (as in the period of financial crisis) either from their economy or from the region as whole. Accordingly, policymakers can decide whether they should create a safety net at the regional/country level. Additionally, examining regional stock market interactions could help policymakers to evaluate whether policies for improving regional cross-country economic integration are successful. The pattern of market interdependence may also provide information on cross-country flows of international portfolio investment. Such investment may strengthen a country's foreign exchange reserves, in turn affecting the exchange rate of the local currency. This means that knowledge of stock market interdependence may help policymakers to formulate policies that address macroeconomic imbalances across countries.

While a knowledge of stock market interdependence and volatility transmission has very important implications for Asian policymakers and investment practitioners, studies of Asian stock market relationships and volatility transmission mechanisms are comparatively few. Specifically, there is lack of studies investigating changes in the relationships between Asian stock markets. For example, the 1997-98 Asian financial crisis was characterized by extreme market conditions that may have signalled a change in information transmission mechanisms. After the financial crisis the pattern of interactions between markets may have been influenced by the ways in which the crisis was resolved. Furthermore, many Asian countries have initiated bilateral and multilateral trade arrangements. Japan signed a bilateral economic partnership agreement (EPA) with Singapore in November 2002. In 2007, Japan concluded agreements with Malaysia, Indonesia, the Philippines and Thailand. Korea also began a similar negotiation with ASEAN, expected to be completed by 2009 (Hashmi and Lee, 2008). In addition, Asian countries have discussed the creation of an 'Asian currency union'. All these affairs indicate that cross-border economic activity has increased significantly and that equity market interaction patterns in the region may have significantly changed (and may continue to change). Thus, it is worth investigating the dynamic evolution of linkages between Asian equity markets in order to make appropriate changes in trading strategies and regulation policies. These considerations have formed the initial motivation for this research.

1.2 Thesis Overview and Aims of the Research

The main objective of this thesis is to examine the Asian stock market linkages. This can be done by analyzing the nature of stock price, return and volatility linkages between Asian equity markets.

There are six major research interests. The first issue to be investigated is whether stock prices of Asian countries are moving together over time in the long run, indicating the presence or absence of stock market integration. The second issue is to test lead-lag (or causal) relationships between the stock returns of these markets. This provides evidence of 'return spillovers' between markets. The third issue of interest is to identify the nature of stock volatility for individual markets. This includes tracing volatility movements and examining day-of-the-week effects in stock volatilities. From an investor's point of view, analyzing volatility sheds light on asset risk (Merton, 1980), facilitating the valuation of financial products and the development of hedging techniques. Awareness of day-of-the-week effects in stock volatilities and returns allows investors to adjust their trading behaviour and increase profits. The fourth issue is to identify the nature of the volatility (risk) transmission mechanisms between different countries. Fifth, in order to examine stock market linkages in the region, it is also of interest to estimate the time-varying correlations between the stock markets. The time-varying correlation coefficients provide a quantitative assessment of the co-movements of Asian markets and provide a straightforward method of researching contemporaneous cross-market linkages. Finally, given the currency and stock market turmoil in Asia, it is of particular interest to examine whether the financial crisis has caused market interdependencies and volatility transmission mechanisms to change.

Data selection

This research is based on nearly 15 years of daily data for eight Asian equity market indices (Japan, Hong Kong, Singapore, South Korea, Malaysia, the Philippines, Indonesia and Thailand) from 08/01/1992 to 08/03/2007. This period is of great interest both because most Asian countries have experienced financial liberalization since the early 1990s and because this period covers the 1997-98 Asian financial crises. More importantly, the data are up-to-date and hence can provide recent evidence on inter-relationships between Asian stock markets.

Methodological choices

It has become routine in the literature that empirical examination of dynamic relationships between stock indices should first test for cointegration between the series. If stock indices are cointegrated, short-run lead-lag relationships (or causality-in-mean) and long-run cointegrating relationships can be represented by a vector error correction model (VECM) (Chapter 3). Having examined market relationships in terms of stock prices and stock returns, the research focus then turns to stock return volatility (risk). Given the widely documented evidence of 'volatility clustering' and 'leverage effects' in financial time series, a Threshold Autoregressive GARCH-in-mean specification (TAR-GARCH-M) is used to model time-varying volatility and to examine possible asymmetry effects in volatilities (Chapter 4). Risk-return relationships are also investigated through this model, to discover whether investors in Asian equity markets are compensated for taking higher risks. Additionally, day-of-the-week dummies are added to both return and volatility equations of the TAR-GARCH model to examine regular changes in market returns and volatility. A multivariate GARCH-BEKK model is then used to test for 'volatility spillover' effects (Chapter 5), which, together with the evidence on causality-in-mean ('return spillover'), provides a more complete and accurate picture of the dynamics between Asian stock markets. Finally, since correlation coefficients are standard measures of market co-movement, a multivariate DCC-TGARCH model (dynamic conditional correlation) is used to measure contemporaneous interactions between markets (Chapter 6).

1.3 Contributions to Knowledge

The thesis makes five major contributions to the literature. ***First***, it offers a systematic review of the theoretical and empirical modelling of stock market linkages in the existing literature. ***Second***, by examining the dynamics of Asian stock market indices over a sample period of nearly 15 years, this thesis provides new and important evidence about the behaviour of stock indices in Asia. In particular, the empirical findings are compared over four sub-samples, differentiated by different stages of the financial crisis. This allows insights into the impact of the financial crisis on Asian equity market linkages. ***Third***, this research is not confined to one methodology. Different methodologies permit the analysis to exploit the nature of stock market linkages to a much greater extent than is normally possible in such studies. For example, cointegration analysis focuses on long-run equilibrium relationships in levels of stock prices. Short-run lead-lag relationships (causality-in-mean) based on VECM framework provides evidence of market linkages in returns, while the multivariate GARCH-BEKK model investigates market volatility relationships. This provides a broader view of the interactions among Asian stock markets. ***Fourth***, instead of assuming a constant correlation between markets (as is the case in many previous studies), this thesis allows the time-variation of correlations to be studied by using an easy-to-implement multivariate DCC-TGARCH framework. The evidence of time-varying conditional correlation between equity markets has important implications for efficient cross-market portfolio diversification (of interest to fund managers). ***Last but not least***, this thesis does not only focus on the relationships between stock markets. More importantly, the work adds to the literature by finding the reasons and factors that may shape these interaction patterns.

1.4 Structure of the Thesis

There are 7 chapters in this thesis. Chapter 1 is this introduction.

Chapter 2 introduces background knowledge about stock markets, with particular attention to the development of Asian stock markets, including brief descriptions of the Asian economy, the role of stock markets in Asia and equity market microstructure. The 1997-98 Asian financial crisis is also briefly discussed, which is useful for understanding the extreme market conditions that may have induced changes in the mechanisms of information transmission between Asian stock markets.

Chapter 3 first presents the data used in this research. The sample is then divided into four sub-periods, namely pre-crisis, crisis, post-crisis and recovery periods. Long-run equilibrium relationships (examination of stock prices) and short-run lead-lag relationships (examination of stock returns) are investigated within a VECM framework [1] for both the entire sample period and sub-periods. The results are compared and some implications are drawn. However, these two methods do not allow the estimation of the relative strength of the Granger-causal chain, so forecast error variance decomposition (VDC) is used to show the overall relative importance of the various markets in generating fluctuations internally and in other markets.

Chapter 4 extends the analysis of chapter 3 by examining the time series behaviour of stock volatility. A univariate threshold autoregressive GARCH-in-mean specification (TAR-GARCH-M) is employed that models 'volatility clustering' and 'leverage effects' in the volatility of stock returns. The movement of stock volatility is analyzed to see if the major market events of financial liberalization and the financial crisis are associated with sudden changes in volatility. The relationship between stock returns and volatility is also investigated to show whether there exists a positive and significant reward-to-risk relationship. In addition, day-of-the-week effects in returns and volatility are captured through the TAR-GARCH model using dummy variables.

A multivariate GARCH-BEKK model is used in Chapter 5 to investigate volatility transmission between stock markets. There are two different types of 'volatility spillover', arising through lagged squared innovations ('news') and lagged conditional variances. Short-term 'volatility spillover' effects between two markets are measured through lagged squared innovations, while long-term effects are captured by persistence in conditional volatility through lagged conditional variances. Both types of 'volatility spillover' effect are analyzed in the thesis, in an attempt to provide a complete and accurate picture of volatility transmission between Asian stock markets.

[1] For crisis sample period, since no cointegrating relationship is found, a VAR framework is adopted.

Chapter 6 introduces another important method of measuring market linkages, namely cross-market time-varying correlation. This chapter mainly focuses on the 'contemporaneous relationships' rather than 'lead-lag' relationships (investigated in chapter 3 and chapter 4) between markets. Multivariate DCC-TGARCH methods are used to model pair-wise dynamic time-varying correlations (measurement of cross-market market co-movements). Special attention is paid to changes in cross-market co-movements, with discussion of the reasons behind these changes. A multiple dummy variable regression model is also developed, with dummies for the crisis, post-crisis and recovery periods, to analyse the evolution of market correlations. It is possible that 'contagion' effects may be associated with a significant increase in cross-market co-movement during a crisis period, so significant crisis dummies may reveal whether 'contagion effects' were present during the Asian financial crisis. Finally, conditional standard deviations of stock returns are added to the regression model in order to examine the relationships between conditional correlations and the volatilities of the underlying markets.

Chapter 7 summarizes the main findings of the thesis and suggests further possible research directions.

Chapter 2 An Introduction to Asian stock markets

This chapter provides a basic introduction to Asian stock markets. The introduction includes three major parts. The concept and economic functions of the markets are first introduced. The developments and microstructure of Asian stock markets are then discussed. Finally, the 1997-98 Asian financial crises and its impact are also briefly presented.

2.1 Definition and functions of stock markets

Concepts of stock markets and stock market indices

A stock market, or equity market, is a private or public market for the trading of company stock at an agreed price. The concept of 'stock market' that is commonly used is actually the 'stock exchange', which facilitates the exchange of securities between buyers and sellers, thus providing a marketplace (virtual or real). The exchanges provide real-time trading information on the listed securities, facilitating price discovery. The behaviour of a stock market is normally measured by the movements of prices in the market, which are captured in a price index called a stock market index. Such an index is usually market capitalization weighted, with the weights reflecting the contribution of the stock to the index. The constituents of the index should be reviewed frequently to include or exclude stocks in order to reflect the changing business environment.

Functions of stock markets

The stock market is one of the most important places for companies to raise money. It allows businesses to be publicly traded or raise additional capital for expansion by selling shares of ownership of the company in a public market. Additionally, a stock market also provides liquidity for investors, allowing them to quickly and easily sell their securities. This is an attractive feature of investing in stocks, compared to other less liquid investments such as real estate.

It has been shown that the behavior of stock markets (measured by stock prices or stock indices) plays an important role in economic activity, mainly because the performance of a country's stock market is often considered as the primary indicator of that country's economic strength and development. A rise in a stock market index (an increase in stock prices) is normally considered to be a signal of increased business investment (and vice versa for a fall). Purfield et al. (2006) suggest that the behavior of stock market (change in stock prices) may affect real activity through four main channels.

Wealth effects: stock prices can affect the wealth of households and their consumption. Under the life cycle/permanent income hypothesis[2], higher stock prices can increase an individual's lifetime wealth, leading to higher spending.

The financing or cost of capital effect: The rise or fall of stock prices also has an impact on cost of capital, which alter the requited return necessary to make a capital budgeting project, therefore spurring or decreasing investment.

Credit channel: stock price fluctuations can influence borrowing capacity by affecting borrowers' wealth and the value of assets pledged as collateral (Kiyotaki and Moore, 1997). These dynamics affect the finance premium on loans and thus influence investment and consumption.

Balance-sheet effects and financial fragility: stock price fluctuations can affect the net worth of financial institutions by affecting both the valuation of equity portfolios and the health of borrowers (potentially generating nonperforming loans). Severe stock price crashes may cause intermediaries to cut back credit, potentially dampening aggregate demand. Moreover, this may lower corporate and household income, further weakening intermediaries and prompting further declines in stock prices.

[2]The life cycle hypothesis (LCH) is an economic concept analysing individual consumption patterns. LCH assumes that individuals consume a constant percentage of the present value of their life income.

The permanent income hypothesis (PIH) states that the key determinant of consumption is an individual's real wealth (permanent income), not his current real disposal income. Permanent income is determined by a consumer's assets; both physical (shares, bonds, property) and human (education and experience). These influence the consumer's ability to earn income. The consumer can then make an estimation of anticipated lifetime income.

Confidence effects: stock price changes may provide entrepreneurs with information about market expectations of future demand, thus influencing investment decisions.

In summary, the stock market plays a crucial role in real activity. Stock prices (or stock indices), as measures of stock market behaviour, therefore hold interest for both investment practitioners (e.g. fund managers and individual investors, for the purpose of exploiting profits) and policy makers (e.g. central banks, for the purpose of maintaining financial stability).

2.2 Development of Asian stock markets

Overview of Asian economy

The economic rise has been truly remarkable in Asia, starting with the Japanese economic miracle. Shattered by the Second World War, Japan began rebuilding its economy with U.S aid soon after the war ended. Japan's real economy grew by an average of 9.2% per year between 1950 and 1970, before moderating to slightly less than 5% per year between 1970 and 1990 (Stewart and Andreychuk, 1998). Although Japan has been mired in a slowdown since a financial and property crash in the early 1990s, its share of world exports nonetheless increased from US $9.8 billion in 1966 (5.1% world exports) to US $443.1 billion in 1995 (8.8% of world exports) (Stewart and Andreychuk, 1998). After the United States, Japan is the world's second largest economy.

Japan plays a key role in Asia's economic development. Japan has become an increasingly important trade partner as well as a source of capital, technology and foreign aid during the course of Asia's rapid economic growth and industrialization. Meanwhile, the rest of Asia has been growing in importance as export markets for Japanese goods and services[3] (Park and Rahman, 1999). Thus, there is a close and growing economic interdependence between Japan and the rest of Asia.

3 Yamagata (1997) notes that Asia has been Japan's largest export market since 1991, surpassing the United Sates in that regard.

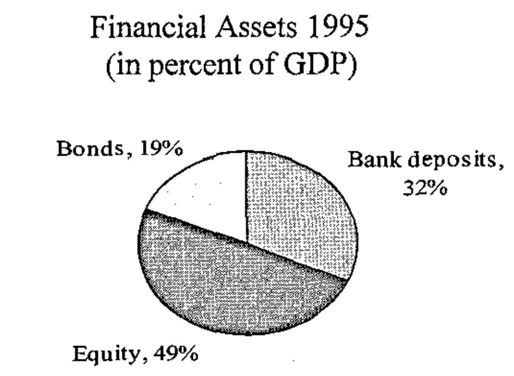
Following Japan's example of export-led growth, the newly industrialized economies (NIEs) of Hong Kong, South Korea and Singapore began developing in the 1960s. They are also well known as the 'Asian Little Dragons' since these countries maintained exceptionally high growth rates and rapid industrialization between the early 1960s and 1990s. Average real GDP growth in these countries was over 8.5% per year between 1960 and 1988. Taken together, exports from these countries reached US $528.7 billion (10.5% of world exports) (Stewart and Andreychuk, 1998). In the 21st century, all three countries have become advanced high-income economies and have been identified as models of achievement for other emerging economies.

Four of the Association of Southeast Asian Nations (ASEAN) economies-Malaysia, Thailand, Indonesia and the Philippines represent another wave of Asian industrialization since early 1990s. Like Japan and the NIEs, the ASEAN economies rely on export-led strategy to achieve high economic growth rates, with merchandise exports rising from US $3.4 billion in 1966 (1.8% of world exports) to US $193.4 billion (3.9% of world exports) in 1995 (Stewart and Andreychuk, 1998). At the same time, these economies maintained high interest rates and liberalized their financial markets to attract foreign investors looking for high rates of return. As a result, these countries received large inflows of funds and experienced a dramatic run-up in asset prices. Together with Singapore and South Korea, they experienced between 8% and 12% increase in GDP. This achievement is widely acclaimed by the IMF and the World Bank, and is known as the 'Asian economic miracle'.

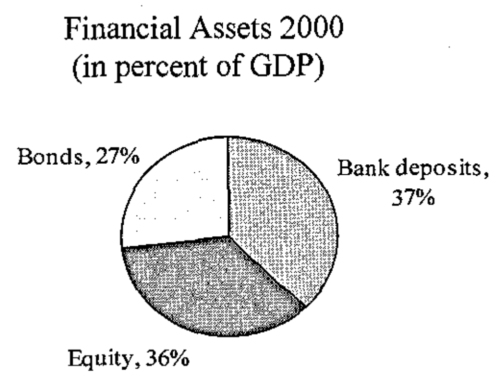
Role of stock markets in Asia

Asian equity markets are sizable and fast growing. Since 1990, Asian equity market capitalization has more than doubled in U.S. dollar to $13.7 trillion, which is 30% of world equity market capitalization (Purfield *et al.*, 2006). While the banking sector remains key to financial intermediation, the Asian countries have tried to develop their stock markets in order to achieve long-run growth and development of the financial sector (Phuan, Lim and Ooi, 2009). This greater emphasis by Asian countries on the development of stock markets means that equities have taken a large share of financial assets in the region, accounting for about half of total assets (deposits, stocks and bonds) (Figures 2.1).

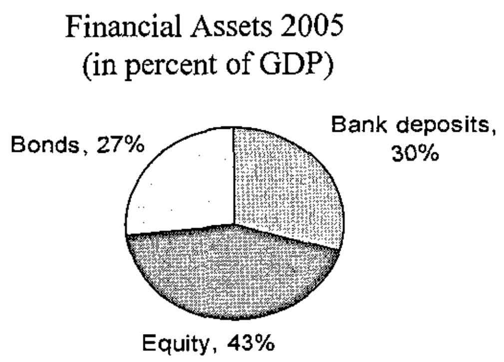
Figure 2.1 Financial Assets 1995-2005



Source: Federation of World Exchanges



Source: Federation of World Exchanges



Source: Federation of World Exchanges

Table 2.1 The evolving role of equity in the financial sector

	1995				2000				2005			
	Bank deposits	Equity market	Bond market	Total financial sector	Bank deposits	Equity market	Bond market	Total financial sector	Bank deposits	Equity market	Bond market	Total financial sector
	(In percent of GDP)											
Japan	101.9	118.4	103.7	323.9	113.3	113.3	128.7	355.3	124.5	123.2	194.1	441.9
Hong Kong	164.5	282.7	30.8	477.9	221.3	278.8	43.6	543.6	246.6	588.9	60.1	895.6
Korea	36.3	24.9	50.3	111.5	68.3	45.6	62.1	176.0	67.1	90.5	88.9	246.4
Singapore	77.9	380.6	29.7	488.2	99.9	287.3	57.3	444.4	105.6	270.0	88.1	463.7
Malaysia	72.9	315.5	81.8	470.2	88.6	133.0	100.4	322.1	98.9	140.5	111.2	350.5
Indonesia	43.8	36.0	7.1	86.9	48.2	15.0	39.1	102.4	40.3	29.5	21.8	91.6
Philippines	48.2	95.6	46.0	189.8	54.1	51.1	51.9	157.1	47.4	114.8	70.5	232.7
Thailand	73.9	54.9	16.9	145.7	93.8	36.3	36.3	166.5	83.6	73.7	51.2	208.5

Source: World Federation of Exchanges

Equity market characteristics

There are microstructure differences between Asian equity markets, especially in terms of size, share turnover and numbers of stocks (shown in Table 2.2). The Japanese market is the largest in terms of capitalization, number of listed stocks and market turnover. The Hong Kong market is the second largest market in Asia in terms of capitalization, followed by the markets of Korea, Singapore, Malaysia and Thailand in the middle, Indonesia and the Philippine markets at the bottom (statistics in 2005). Markets in the Philippines and Indonesia also tend to be at the lower end of the spectrum in terms of market turnover. The Philippine market has the lowest number of listed stocks.

Table 2.2 Equity market characteristics

1995	Japan	Hong Kong	Singapore	Korea	Malaysia	Philippines	Indonesia	Thailand
Market capitalization (in USD millions)	3,545,306.5	303,705.3	150,958.6	181,954.8	213,757.4	58,779.6	66,453.8	135,774.2
Share turnover	884,000.4	95,832.0	63,983.2	185,427.5	60,792.4	14,666.8	14,403.2	59,303.3
Number of listed companies	1,791	542	272	721	526	205	237	416
Settlement date	t+3	t+2	t+5	t+2	t+5	t+3	t+4	t+3
Trading costs (commission)	0.2-1.15%	>0.25%	up to 0.75%	n.a	up to 1%	1.5%+12%VAT	up to 1.1%	0.50%
2000	Japan	Hong Kong	Singapore	Korea	Malaysia	Philippines	Indonesia	Thailand
Market capitalization (in USD millions)	3,157,221.8	623,397.7	155,125.6	148,361.2	113,155.3	25,261.4	26,812.5	29,217.4
Share turnover	2,315,501.8	376,664.1	95,153.1	556,246.3	52,868.7	8,186.7	15,109.3	21,117.0
Number of listed companies	2,096	790	480	702	790	230	286	381
Settlement date	t+3	t+2	t+3	t+2	t+5	t+3	t+4	t+3
Trading costs (commission)	0.2-1.15%	>0.25%	up to 0.75%	n.a	up to 1%	1.5%+12%VAT	up to 1.1%	0.50%
2005	Japan	Hong Kong	Singapore	Korea	Malaysia	Philippines	Indonesia	Thailand
Market capitalization (in USD millions)	4,572,901.0	1,054,999.3	257,340.6	389,473.4	180,517.5	39,817.8	81,428.1	123,885.0
Share turnover	4,481,721.6	464,272.5	116,456.5	625,185.7	51,601.4	6,982.4	41,633.5	95,645.7
Number of listed companies	2,351	1,135	686	683	1,019	237	336	504
Settlement date	t+3	t+2	t+3	t+2	t+5	t+3	t+4	t+3
Trading costs (commission)	0.2-1.15%	>0.25%	up to 0.75%	n.a	up to 1%	1.5%+12%VAT	up to 1.1%	0.50%

Source: World Federation of Exchanges

Equity inflows

As mentioned, controls on participation by foreign investors in Asian equity markets have been loosened since the early 1990s. At the same time, equity flows into Asia have soared. According to Lane and Ferretti (2007), inflows have been especially strong in recent years. By the end of 2004, international investors had invested $638 billion in Asian equity markets - a twelvefold increase over 1990s levels. Accordingly, emerging Asian markets now capture three-quarters of global equity investments in emerging markets, up from about one half in 1992 (Purfield *et al.*, 2006). This is also supported by the evidence of the explosion of flows from dedicated Asia regional funds, whose assets have grown at rates in excess of 54% per year since 2000, with assets of $125 billion in 2006 (EPFR Global WebPages, 2008).

The quality of market infrastructure and governance

The development of stock markets relies on a well-functioning infrastructure. The quality of market infrastructure can be judged by several key factors: an effective legal framework, reliable accounting and disclosure standards, an efficient and reliable clearing and settlement process, and reliable and easily accessible information. Since most countries in the region have developed electronic clearing and settlement systems, the quality of market infrastructure is dependent on rules and regulations governing corporate governance in the region. While there is little variation across Asian economies in legal rights of shareholders, there are differences in the requirements on disclosure and transparency and board responsibilities (Cheung and Hasung, 2005). For example, Malaysia, the Philippines, Singapore and Thailand require disclosure of the top 10 shareholders plus any with stakes of 5% or more. Indonesia does not require disclosure of management shareholdings. Herring and Chatusripitak (2000) assessed the quality of market infrastructure with results that are shown in Table 2.3. The differences between markets are striking. The developing Asian markets as a whole are substantially below developed market quality. Japan, Hong Kong and Singapore stand out as high-quality markets. The Philippine market displays a lack of 'rule of law', poor 'bureaucratic quality' and weak 'accounting standards'. Indonesia is disadvantaged by its relative lack of freedom of access to information.

Table 2.3 Indicators of quality of equity market infrastructure

	Total score	Rule of law	Bureaucratic quality	Accounting standards	Press freedom
Japan	8.67	8.98	9.82	7.10	7.92
Hong Kong	7.75	8.22	6.90	7.30	6.72
Singapore	7.58	8.57	8.52	7.90	3.44
Korea	6.73	5.35	6.97	6.80	7.36
Malaysia	6.55	6.78	5.90	7.90	3.90
Thailand	6.50	6.25	7.32	6.60	6.02
Philippines	4.14	2.73	2.43	6.40	5.54
Indonesia	3.52	3.98	2.50	n.a	2.86

Source: Herring and Chatusripitak (2000)

Note: n.a = not available

1997-98 Asian financial crises

Following the collapse of the Thai Baht on July 2, 1997, the financial markets of East and Southeast Asia (in particular, Thailand, Malaysia, the Philippines and South Korea) headed in a similar downward direction during late 1997 and 1998. The regional markets faced increasing pressure in the aftermath of the devaluation of the Thai baht, reflected in the subsequent unravelling of the managed currencies of Malaysia and Indonesia. As the crises became full-blown, intense foreign exchange and stock market turmoil spread through the entire region. News of economic and political distress, particularly bank and corporate fragility, became commonplace in the affected countries. It seems that any adverse event in one market put additional pressure on the other markets. This period of economic unrest (or financial contagion) is commonly referred to as the 'Asian financial crisis'.

There is consensus on the existence of the crisis and its consequences, but the causes of the crisis, its scope and its resolution are less clear. According to Nanto (1998), the causes and factors contributing to financial crises may include:

i. private-sector debt problems and poor loan quality
ii. rising external liabilities for borrowing countries
iii. close alignment between the local currency and the US dollar
iv. weakening economic performance and balance-of-payments difficulties

v. currency speculation

vi. lack of confidence in the ability of the governments in question to resolve their problems successfully.

Whatever the disputed causes, the Asian crisis started in mid-1997 and had devastating effects on Asian economies. Several issues related to the crisis are still unsolved. What was the transmission mechanism of shocks from one country to the other? Were there 'contagion effects' during the crisis? Did some countries play a larger role in terms of cross-border impact than others? These questions provide the motivation behind the research reported in this dissertation. In the following chapters, various analyses will be carried out to tackle these issues.

Chapter 3 Cointegration and Causality in Asian Stock Markets

3.1 Introduction

Financial integration is the process by which a country's financial markets become more closely linked with those in other countries. According to Worthington and Higgs (2007), financial integration arises in two main ways. One is from formal efforts to integrate financial markets with particular partners, through sharing membership in some regional agreement. Integration in this form involves the elimination of cross-border restrictions on the activities of firms and investors within the region, as well as the harmonisation of rules, taxes and regulations between member countries. The European Union is an obvious example for this kind of integration. However, financial integration may also emerge less formally, very often without a regional agreement. This includes foreign bank entry into domestic markets, direct borrowing by firms in international markets, bilateral financial and trade agreements, strengthening finance and trade relationships between countries and the convergence of business practices. Financial integration like this is relatively more common in the developing world, especially in geographically close regions.

During the last two decades, there seems to have been an increase in the interdependence and integration of Asian financial markets, especially equity markets. There are several reasons for this. First, technological advances in trading systems have eliminated many barriers to trading, improved the flow of information and reduced transaction costs. Second, the booming economies in Asia have attracted more equity capital to assist financial development. Third, the shift to floating exchange rates, market liberalization and abolition of capital controls in Asia has led to an increase in capital flows to Asian countries. Freer capital flows improve capital allocation, with additional funds flowing to (often less-developed) Asian countries that have better productive opportunities, thereby assisting the process of financial integration and enhancing financial development.

The growing integration of Asian financial markets has attracted the attention of both investors and financial policy makers and has encouraged investors in certain markets to incorporate into their decisions not only the information generated from the domestic market but also information transmitted around the world. If markets are highly integrated, then a country's economy cannot be isolated from foreign shocks, with adverse consequences for the effectiveness of independent monetary policy. However, an integrated regional stock market is more efficient than segmented national markets. With an integrated regional stock market, investors from member countries can allocate capital to locations where it is most productive. This lowers the costs of firms seeking capital and the transaction costs of investors.

The interdependence of financial markets also has significant implications for portfolio diversification. Studies of the benefits of international portfolio diversification, particularly earlier ones, such as Agmon and Lessard (1977), Levy and Sarnat (1970) and Solnik (1974) advocate diversification of porfolios across national borders, as long as returns to stocks in these markets are less than perfectly correlated with the domestic market. They conclude that there are substantial benefits associated with risk-reduction through international diversification. Since benefits of diversification come from low cross-country correlations in asset returns, it appears that investors may benefit more from segmented than integrated markets. Closely tied to this issue is the degree of cointegration between stock prices in different national markets. If certain markets are cointegrated, then market prices will tend to move together over time and any market will be representative of the behaviour of that group of markets. The benefits of cross-border diversification will therefore be eradicated in the long-term for investors with long horizons (if there are significant deviations from this long-term equilibrium, then international investors could make short-term speculative investments based on the forecast that the market will revert to its long term relationship).

To inform policy and provide guidance for investing in Asia, empirical work is needed which reflects and appropriately measures the complex market interrelationships that exist in this globally important region. One of the key requirements is to assess the level of financial integration and indicate whether the integration is progressing, stable or regressing. Unfortunately, despite more than a decade of work, relatively little empirical evidence exists concerning the financial integration process among Asian stock markets. European markets (Corhay, Rad and Urbain, 1993; Meric and Meric, 1997) and Latin America markets (Chaudhuri, 1997) have received more attention. The few studies related to Asia have either had a multilateral focus (that is, Asian markets with European and/or American markets) or have been focused on developed Asian economies. For instance, Yuhn (1997), Francis and Leachman (1998) only incorporated Japan in their studies of international stock market integration, Ramchand and Susmel (1998) added Hong Kong.

The primary goal of this chapter is to measure the dynamic linkages between multiple stock price indexes from the Asian region, including four relatively developed markets (Japan, Hong Kong, South Korea and Singapore) and four developing markets (Malaysia, Philippines, Indonesia and Thailand). We use the Johansen methodology and an eight-dimensional vector error-correction (VECM) formulation to gain insight into the long-run and short-run relationships among these stock markets over a period of fifteen years. The dynamic VECM representation provides a framework within which to test for causal dynamics (in the Granger sense) among the stock price indexes through both short-run and error-correction channels of causation. In addition, variance decomposition analysis is used to quantify the causal interactions amongst markets. In addition, given the background of Asian financial crash in 1997, it is particularly interesting to assess the effect of the financial crisis on the integration process. In summary, several issues will be addressed in this chapter: (i) the extent to which markets in the Asian region are linked (ii) the behaviour of stock markets before, during and after the financial crisis of 1997 and the effect of the crash on the propagation mechanism of the causal responses and (iii) the efficiency with which shocks (innovations in information) in one market are transmitted to other markets in the region and the relative importance of different shocks.

This chapter is organized in the following manner: Section 3.2 reviews the literature concerning stock market integration. Section 3.3 provides a description of the data. Section 3.4 presents the econometric techniques, methodology and empirical results of the cointegration tests. Sections 3.5 discusses the method and results of Granger causality analysis. Section 3.6 discusses the variance decomposition analysis. The chapter ends with some brief concluding remarks.

3.2 Literature Review

As discussed, early studies investigating relationships among stock markets mainly focus on the equity markets of the United States, Japan, United Kingdom and European countries, and most use pairwise correlation analysis. For example, Ripley (1973) uses correlation analysis to explore interrelationships between stock prices from 19 developed countries. Panton, Lessig and Joy (1976) examine similar relationships using the same method. However, Maldonado and Saunders (1981) examine the inter-temporal patterns of correlations among international equity markets and conclude that pairwise correlation coefficients are unstable.

Since pairwise correlation analysis is unreliable, many studies focus on long-run relationships between stock markets using co-integrating techniques. Kasa (1992) examines five developed stock markets (United States, Japan, Germany, Canada and United Kingdom) using both monthly and quarterly data over the period 1974 to 1990. He found evidence of a single cointegrating relationship driving these markets. Arshanapalli and Doukas (1993) employ cointegration methodology to examine the linkages and dynamic interactions among stock price indices across the major world stock exchanges, including United States, Japan, United Kingdom, France and Germany. They use daily closing stock index time series, for the period January 1980 to May 1990. Their evidence indicates that the degree of international interdependence among world equity markets has changed significantly since the October 1987 stock market crash. In particular, they note that over the post-1987 period, three European markets (Germany, United Kingdom and France) have become strongly co-integrated with the American stock market, in contrast to pre-1987 results. Allen and Macdonald (1995) extend the sample of Arshanapalli and Doukas (1993) to include 16 developed countries using monthly index data and covering the period 1970 to 1992. Specifically, they attempt to identify the benefits from international equity diversification available to Australian investors. Employing both Engle and Granger (1987) and Johansen (1988) estimation techniques, they find evidence of cointegration between the 16 developed stock market price indices considered.

More recently, Chaudhuri (1997) and Chen, Firth and Meng (2002) have investigated the interdependence of major stock markets in Latin America, using cointegration analysis. They find that Latin American stock markets share a long-run equilibrium relationship and suggest that the potential benefits for diversifying risk by investing in different Latin American countries are quite limited.

In general, the evidence of cointegrating relationships between the world developed stock markets and Latin American markets are very clear – that is, a majority of studies show long-term relationships between these stock markets. However, the empirical findings of previous studies regarding the cointegration of Asian stock markets are quite mixed and some cases even contradictory. One of the earliest of these is by Corhay *et al.* (1995), who examined stock market linkages among East Asian and Pacific-basin markets. They found no evidence of cointegration between Japan, Hong Kong, Singapore and Australia for the period 1972 to 1992. Similar conclusions are reached by Defusco, Geppert and Tsetsekos (1996), who applied the Johansen (1988) approach to Asia-Pacific stock markets (United States, South Korea, Philippines, Taiwan, Malaysia and Thailand) sampled weekly over the period 1989 to 1993. They find no cointegrating vectors for these markets. In other words, these stock markets are segmented. Following Defusco *et al.* (1996), Pan, Liu and Roth (1999) also reported no cointegration for a sample of six equity indices from Australia, Hong Kong, Japan, Malaysia, Singapore and the US[4]. Chancharat and Valadkhani (2007) used a bivariate system to examine pairwise cointegration between Thailand and its trading partners (Australia, Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, the UK and the US). They found no evidence of long-run relationships between Thailand and its major trading partners using monthly data from December 1987 to December 2005.

While the studies cited above support the hypothesis of no cointegration for Asian stock markets, others reject this hypothesis. Janakiramanan and Lamba (1998) examined Asian markets in the broader context of the Pacific Basin (with the U.S., Australia and New Zealand). Their findings confirmed the presence of some strong linkages between these markets, particular those with close geographic proximity and strong economic relationships. Importantly, while the U.S. market was the most influential market, Janakiramanan and Lamba (1998) found that its effect had diminished over more recent years in favour of regional influences. In general, they concluded that these stock markets exhibit a high degree of integration. Dekker, Sen and Young (2001) used daily data over the period 1987 to 1998 in ten-variable VARs to examine linkages between Japan, United States and eight other Asian countries stock markets including Singapore, Malaysia, the Philippines and Thailand. Their results indicate that the Japanese market is segmented and does not exert a great deal of influence. Stock markets in Singapore, Malaysian and Hong Kong are closely linked, but in the Philippines and Thailand they are segmented. Another highly relevant study is Manning (2002). He examined both weekly and quarterly data over the period 1988 to 1999. He found two cointegrating vectors for the U.S., Japan and six other Asian countries, indicating partial convergence of the stock price indices. Sharma and Wongbangpo (2002) focused on ASEAN-5 markets using monthly data from January 1986 to December 1996. They found only one

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[4] They analyzed daily data from 1994-1999. They employed a single lag in Johansen VAR.

cointegrating vector for these markets. In particular, they found that Singapore and Malaysia move one-for-one in the cointegrating vector. They argue that this is due to the distribution of inward foreign direct investment flows, the strength of trade between the two economies, their geographical proximity and their cultural similarity.

The studies cited above investigate only the static interdependence of Asian stock markets. However, in more recent years studies have paid more attention to dynamic interdependence between Asian markets, with specific focus on the long-term impact of the 1997 Asian financial crisis. In order to achieve this goal they divide the dataset into sub-periods, to describe the behaviour of markets before and after the crisis. Sheng and Tu (2000) employ multivariate cointegration analysis (Johansen, 1988) to examine the linkages between the stock markets of 12 Asia-Pacific countries, before and during the crisis. They report no cointegration relationships in the year before the financial crisis but one cointegrating vector during the period of crisis. Similar conclusions are reached by Fan (2003) and Daly (2003). Fan (2003) investigated the United States and five Asian stock markets (Singapore, Japan, Hong Kong, Thailand and Taiwan). His sample covers the period from January 1991 to December 1999. He finds no evidence of strong pre-crisis comovement, but finds a cointegrating relationship between these indices after the crisis. Fan (2003) concludes that the degree of comovement between Asian markets increases after July 1997. Daly (2003) uses a longer period of data and increases the number of countries sampled, adding two developed stock market indices (Germany and Australia) and five Southeast Asian stock market indices (Indonesia, Singapore, Malaysia, the Philippines and Thailand). He also splits the sample into two time periods: a pre-crash period from 4 April 1990 to 1 September 1997 and a post-crash period from 1 November 1997 to 5 October 2001. Interestingly, he finds no evidence of co-integrating relationships in either the pre- or post-crisis periods between Southeast Asia and the United States, Germany and Australia, but finds one cointegrating vector for countries within Southeast Asia in the post-crisis period only.

It seems from these studies that there is cointegration between the Asian stock returns in the aftermath of the crisis, but not before. However, not all studies agree with this conclusion. For example, Climent and Meneu (2003) examine seven Asian countries (Indonesia, Malaysia, Philippines, South Korea, Hong Kong, Japan and Thailand) with United States and United Kingdom. Their sample covers the period January 1995 to May 2000. Surprisingly, they find no long-term equilibrium multivariate cointegration relationships in either the pre-crash or post-crash periods. Chatterjee *et al.* (2003) investigates similar markets for the period April 1990 to March 2001, using pre-crisis and post-crisis sub-samples. His analysis indicates a single cointegrating relationship for each of the sub-periods as well as for the total period under investigation. This is consistent with Masih and Masih (1997), who find similar results for both the pre-crisis and post-crisis periods.

The mixed and contradictory empirical findings regarding Asian stock market integration may perhaps be attributed to different research methodologies, data frequencies and sample periods. This study therefore contributes to the extant literature in several ways.

First, a multivariate framework is used for eight stock market indices, allowing the group of markets to be considered as a whole.

Second, since weekly, monthly or quarterly data could obscure interactions between stock markets that last for only a few days (e.g., Karolyi and Stulz, 1996), daily data are used to implement more powerful tests of cross-country co-movements.

Third, different findings could be due to different sample periods, especially when the data cover special periods such as stock market liberalization, stock market crashes etc.. Many studies have shown that stock market crashes (for example the the 1987 crash) may strengthen international stock market linkages (Lin, Engle and Ito, 1991). Taking the 1997 Asian financial crisis into consideration, this study extends the sample to cover the period from January 8, 1992 to March 8, 2007. The overall sampling period is also split into four sub-periods so as to capture possible time variation in stock market integration before, during and after the crisis. It appears that only a few studies (e.g. Climent and Meneu, 2003, Chatterjee *et al*, 2003) have addressed the issue of how the financial crisis changed market integration among Asian countries over time. Most work on market integration has assumed that markets are either perfectly integrated or perfectly segmented. The validity of such assumptions is examined by investigating how the Asian financial crisis affected market integration over time.

Fourth, very few studies have examined the possibility that long-run relationships among stock markets may have been subject to structural breaks. Gregory and Hansen (1996) argue that structural breaks have important implications for cointegration analysis because these breaks can reduce the power of cointegration tests and lead to the under-rejection of the null hypothesis of no cointegration. This study therefore employs Zivot and Andrews (1992) techniques to find potential structural break points.

Finally, conventional measures of market interdependence, based on increases in cross-market correlation or on the existence of cointegrating relationships, identify only the existence of integration. This study investigates changing causality patterns, which can not only explore the existence of interdependence but also identify changes of causal directions among Asian stock markets.

3.3 Data Description and Unit Root Tests

3.3.1 Data and Descriptive Statistics

The data set is sourced from Thomson Financial DataStream and consists of daily closing stock price indices from eight major Asian stock markets: the Japanese

Nikkei 225 stock average of (JP), the Hang Seng of Hong Kong (HK), the Malaysian Kuala Lumpur Composite (MA), the Singaporean Strait Times (SG), the South Korea Composite (KR), the Philippine Composite (PHI), the Indonesian Jakarta S.E. Composite (IND) and the Bangkok S.E.T of Thailand (THA). The sample is for the period from January 8, 1992 to March 8, 2007, providing data points for fifteen years. The data across markets are matched by calendar date, so that whenever national stock exchanges are closed, due to the trading restrictions such as national holidays, the index prices for all markets are removed from the analysis for that day.

Taiwan is not included in my sample, for various reasons:

(1) Taiwan is a smaller and less dominant market than other developed markets in Asia. This sample includes the Japanese and Hong Kong markets, which are two large and influential economies (not only in Asia but in the world).

(2) The main research interest is the financial crisis, for which Taiwan is clearly not the origin. The crisis started in Southeast Asian countries other than Taiwan due to the problems of these countries in particular, so these are the countries included in the sample.

(3) Another interest is the impact of the financial liberalization process since the 1990s in Asia. However, Chen (2001) observed that Taiwan was immune from financial panic because of an economy with characteristics different from those of its neighbors.

(4)Taiwan has been regularly excluded from Southeast Asia research (Climent and Meneu, 2003; Anoruo, Ramchander and Thiewes, 2003; Worthington and Higgs, 2007).

All stock price indices are denominated in local currencies and not converted to a common currency such as the US dollar. The preference for local currency denomination of individual stock prices is based on various arguments. First, the study includes domestic causes of stock price interdependence. Su and Felmingham (2003) have concluded that local economic conditions and domestic economic policy can have an impact on interdependence and this may not be captured if indices are converted to a common currency. Second, most foreign investors make investment decisions based on returns denominated in their own currencies. For example, Japanese investors think in terms of Yen denominated returns and European in Euro denominated returns. Third, weakness in the US dollar means that it has the risk of no longer being the world common currency. The difficulty with converting local stock price indices to a common currency leaves an unresolved question: which currency should be selected as common? Furthermore, SDRs (Special Drawing Rights) are not used since an SDR is not a currency held by private investors. Major international investors calculate asset values based on currency rather than SDRs. Additionally, SDRs have many other disadvantages. As discussed by Gold (1999), SDRs form a small proportion of each country's total reserves. Moreover, the proportion of SDRs in total reserves has declined significantly since their introduction by the IMF. They also suffer from an allocation problem in that the allowed proportion of reserves held in SDRs is decided by the IMF[5].

Most of the countries in the sample were directly involved in the Asian financial crisis, particularly Thailand and Hong Kong. The devaluation of the Thai Baht in July 1997, and its subsequent depreciation, and Hong Kong's speculative attack in October of the same year are considered as key crisis events. Korea, Malaysia, Indonesia, Philippine and Singapore were also crucial crisis-affected countries and they experienced large devaluations in both foreign exchange and stock markets. Japan was selected for two reasons. First, the major economic influence in Asian region comes from Japan and the influence of the Japanese stock market movements on the rest of the markets in the region is thus of importance. A number of studies report the significant impact of Japan on other Asian markets, including Cha and Cheung (1998) and Ng (2000). Second, the Japanese stock market was also not wholly immune to the crisis. For example, in the first two weeks of November 1997,

[5] The disadvantages of SDRs have been explicitly discussed by Gold (1999), "Legal and Institutional Aspects of the International Monetary System" (p210-216). Gold shows that SDRs are only a supplement to, not a replacement for existing reserve assets.

the Nikkei index outpaced all other Asian markets in declining 10.1%, led by its troubled financial sector (shown in Appendix 3.1).

Since daily data are used, it is necessary to account for differences in time zones and overlapping trading hours between stock exchanges. Table 3.1 lists the trading hours of Asian stock exchanges and shows that they trade within the same time interval. Thus, trading hours are highly overlapping. Schotman and Zalewska (2006) examined the issue of non-synchronous trading and overlapping trading hours. They argue that controlling for time differences in trading hours of stock markets is important and show that time-adjustment improves estimates of market integration. They also show that using weekly or monthly data does not sidestep the consequences of the time-match problem but leads to a significant loss of information. Furthermore, they recommend the use of higher frequency data (daily data) so as to allow for more precise estimation of variances and covariances. Booth, Martikainen and Tse (1997) examined the relationship between opening/closing price and overlapping trading times of stock exchanges. His conclusion can be summarized as follows: when trading hours do not overlap only trading time returns (open to close price) should be used, but when trading hours do overlap either trading time (open to close price) or daily returns (close to close price) can be adopted. There seem to be two drawbacks in using open to close price to calculate stock returns. First, this neglects periods of time when market is closed. For example, information may still arrive during the time of market closure. Second, it has been argued that opening price is noisier than the closing price (Amihud and Mendelson, 1987). For these reasons close to close prices are used to calculate stock returns. Hamao, Masulis and Ng (1990) compared results using open to close price and close to close price and found that the two methods generated very close empirical results.

Table 3.1 Trading hours of stock exchange

Country	Index	Abbreviation	Local Time	GMT
Japan	Nikkei 225	Nikkei 225	09:00-11:00	00:00-02:00
			12:30-15:00	03:30-06:00
Hong Kong	Hang Seng	Hang Seng	10:00-12:30	02:00-04:30
			14:30-16:00	06:30-08:00
Singapore	Straits Times Industrial	STI	10:00-12:30	02:00-04:30
			14:30-16:00	06:30-08:00
South Korea	S.E Composite	KOSPI	09:00-12:00	01:00-04:00
			13:00-15:00	05:00-07:00
Malaysia	Kuala Lumpur Composite	KLCI	09:30-12:30	01:30-04:30
			14:30-17:00	06:30-09:00
Philippine	S.E Composite	PSEi	09:30-12:00	01:30- 04:00
Indonesia	Jakarta S.E. Composite	JSX	09:30-12.00	02:30-05:00
			13:30-16:00	06:30-09:00
Thailand	BANGKOK S.E.T.	BANGKOK S.E.T.	10:00-12:30	03:00-05:30
			14:30-16:30	07:30-09:30

GMT: Greenwich Mean Time.

The daily closing indices and the stock indices are converted into continuously compounded rates of return by taking the first differences of the data in natural logarithms. Logarithms are used as most economic and financial time series follow curvilinear trends. The stock index and return series for the eight Asian stock markets are plotted in Figure 3.1 and Figure 3.2, respectively. Of particular note in Figures 3.1 and 3.2 are the simultaneous fall in all stock market indices in the second half of 1997 and the high volatility of market returns associated with the 1997-98 Asian financial crisis. It is clearly shown that the stock markets of Asia sustained an increase in volatility over this time.

The index time series plots in Figure 3.1 show that in the early 1990s all stock markets in Asia soared, with the exception of Japan. This may be due to the impact of financial liberalization in most Asian countries. However, during the period 1997-1998, all Asian stock indices were affected by the crisis, with a huge loss of value in each case. The Japanese stock market lost 29% of its market value, Korea 27% and Singapore 27%. Some markets lost even more, Hong Kong lost 33% of its value, while Malaysia, Indonesia, Philippines and Thailand lost 46%, 34% and 43% of their market values respectively. This shows that the crisis had a substantial impact on all Asian stock markets in the sample and that contagion may have existed during the crisis period. It is also noteworthy that, after a short-term recovery in 1999-2000, all Asian stock markets fell into the global market recession of 2000 to 2003. Many Asian countries (Hong Kong, Singapore, Malaysia, Korea and the Philippines) lost almost half of their market value compared to 2000. According to the annual report of the Asia Regional Integration Centre (ARIC) (2003), a decline in net capital inflows to the Asian region and domestic economic problems contributed to this decline. From 2003 until the end of the sample period there was a boom in nearly all Asian markets, with some (Hong Kong, Singapore, Korea and Indonesia) even reaching historical record values. This could be seen as a sign of an Asian economic recovery. Finally, Figure 3.1 also suggests that the index series are non-stationary, which is characteristic of stock markets.

Figure 3.2 suggests that the returns are stationary and display volatility-clustering (large (small) shocks tend to follow large (small) shocks). Several extreme values of more than 10% can be seen, most occurring during the period 1997-1998.

Figure 3.1 Stock market indices for Hong Kong, Japan, Singapore, Malaysia, Indonesia, South Korea, Philippines and Thailand

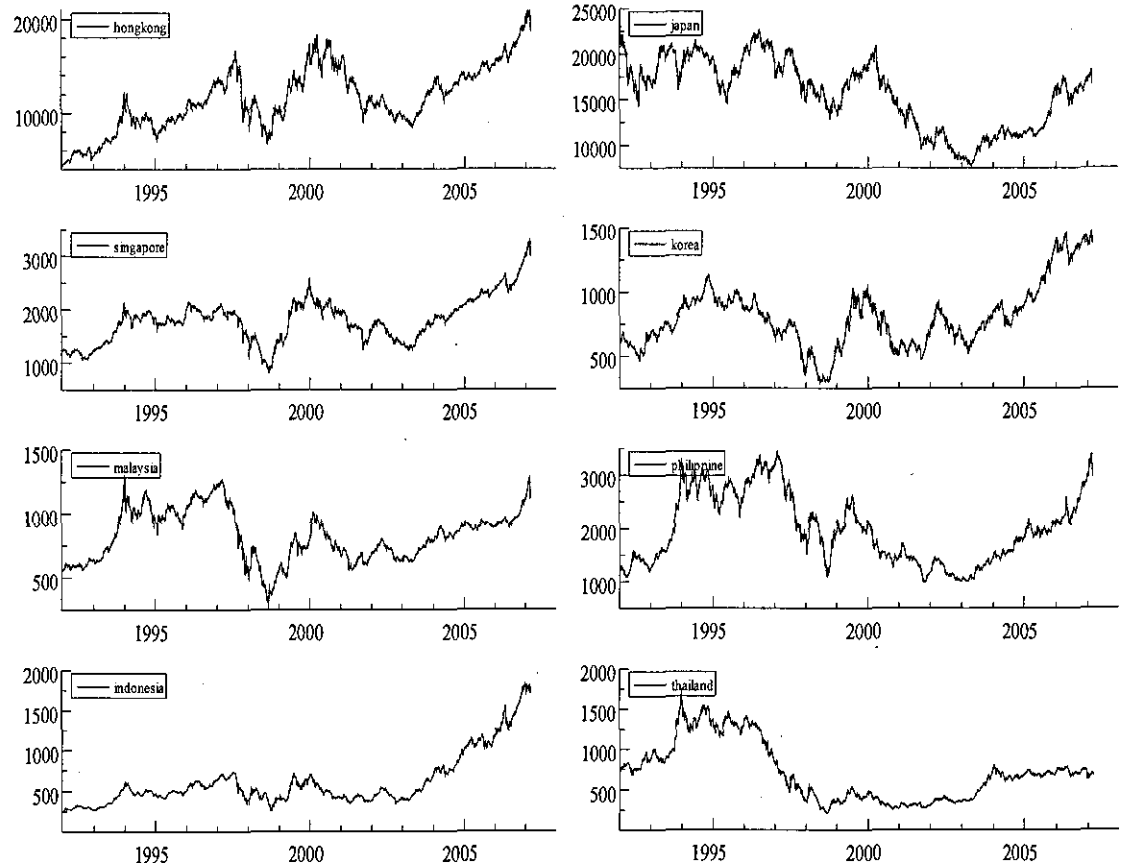
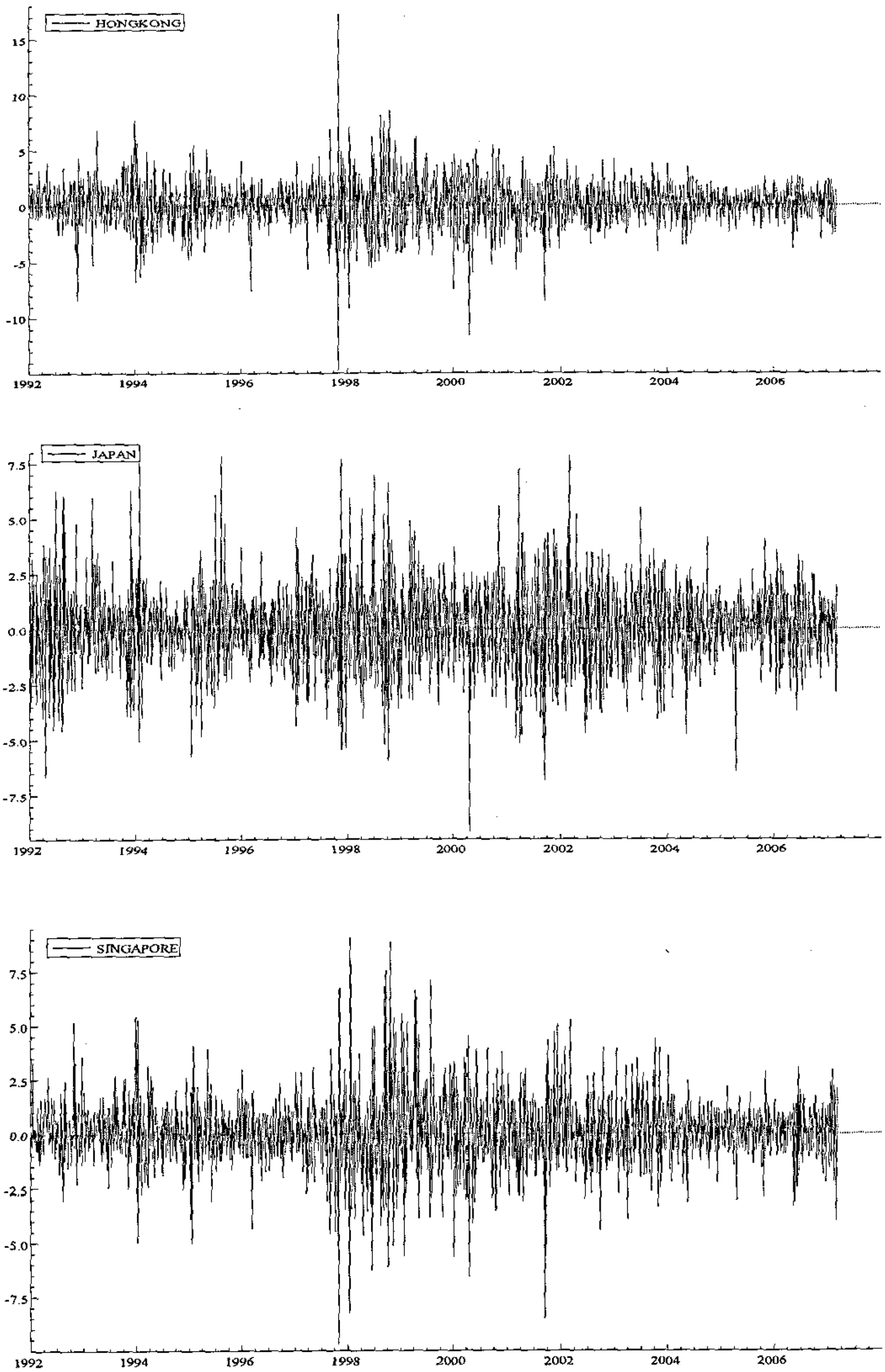
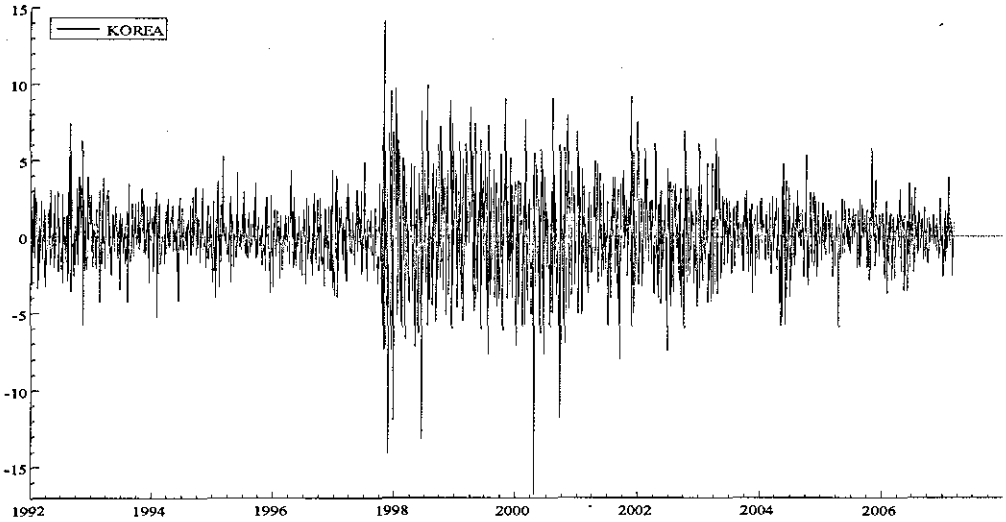


Figure 3.2 Stock returns for Hong Kong, Japan, Singapore, Malaysia, South Korea, Indonesia, Philippines and Thailand




KOREA
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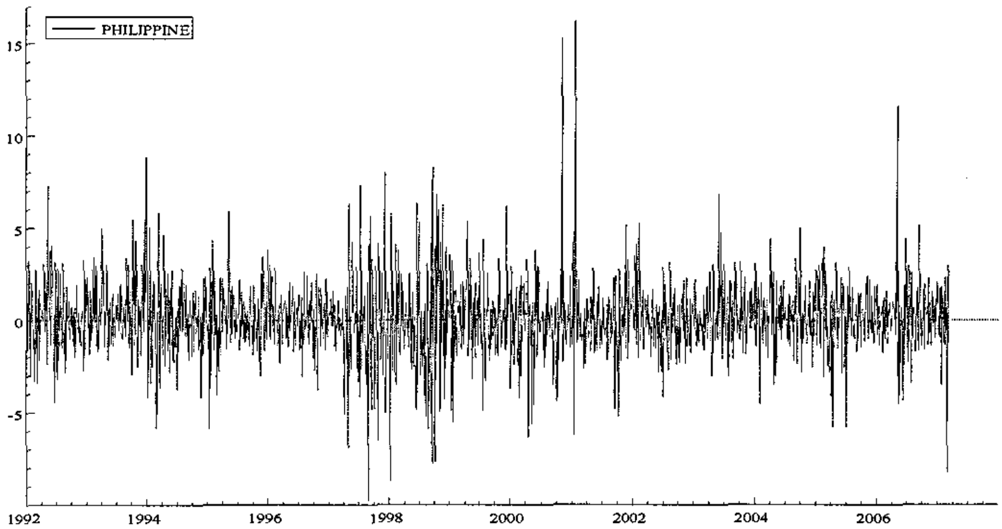
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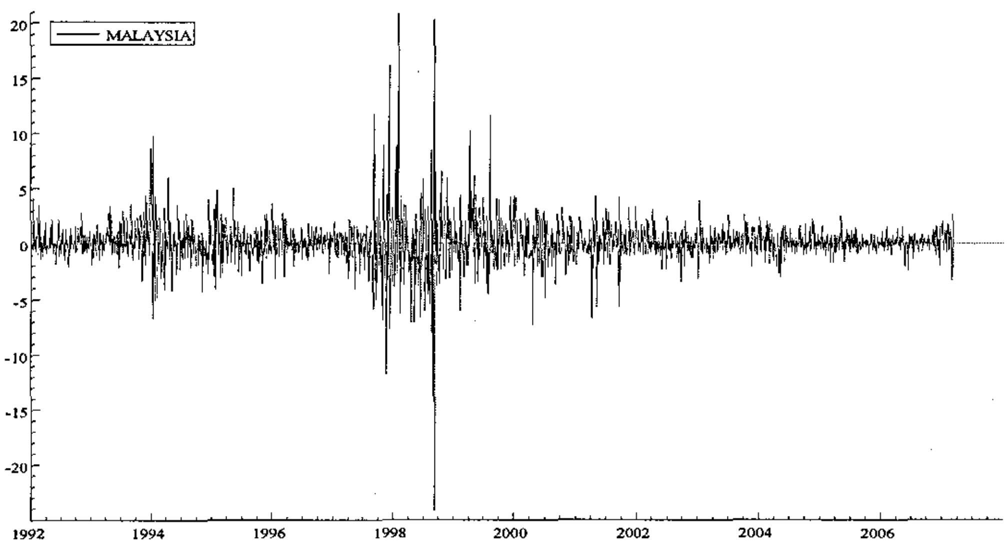
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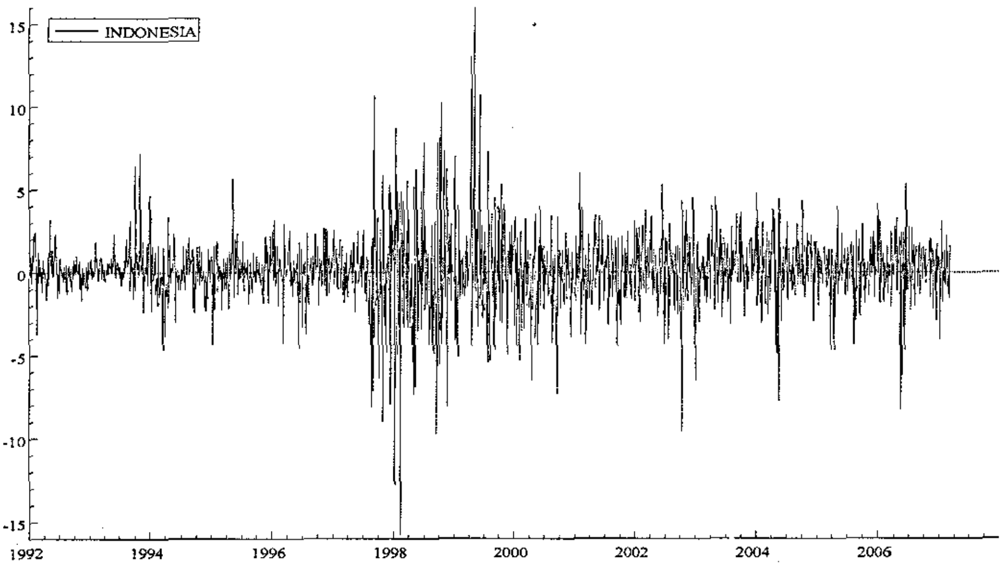
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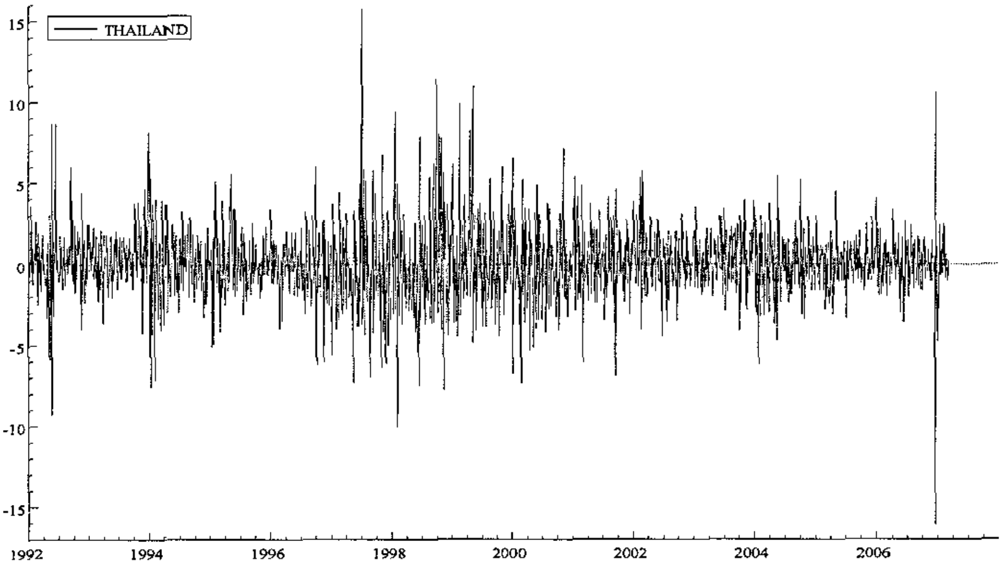
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Table 3.2 presents summary statistics of the daily return series for the eight markets. The mean ranges from -0.0105% to 0.0622%. With the exception of Japan and Thailand, returns are positive. For Malaysia, Singapore and South Korea, the daily stock returns averages about 0.02% over the total sample period. Indonesia and Hong Kong outperform other markets, with average daily returns of 0.0622% and 0.0474% respectively. Japan performs worst with a negative return of -0.0105%.

The maximum and minimum values and standard deviations for the eight series differ somewhat. Specifically, Singapore and Japan show signs of lower volatility, with standard deviations of 1.4157% and 1.5607% per day, respectively. The standard deviations for Hong Kong, Malaysia, the Philippines and Indonesia are all moderate, at just over 1.7% per day, while South Korea and Thailand show higher volatility with standard deviations of 2% per day on average. These features are also supported by the minimum and maximum values. Japan has the lowest maximum value of 7.8304%. Singapore also has a fairly small gap between maximum and minimum values, with a maximum value of 15.15465% and a minimum value of -9.6719%. The largest single-day drop is Malaysia's -24.1534%, while the largest single-day gain is Thailand's 26.7582%. Overall, these Asian stock markets tend to show some volatility in their market returns. The markets of Singapore and Japan stock are much more tranquil than the others, especially South Korea and Thailand.

The observed skewness statistics are non-zero for the return series for all countries, indicating skewed returns distribution for all markets. In general, the market returns exhibit positive skewness, with the exception of South Korea. The positive skewness seems mainly due to some extreme positive returns in these markets. The kurtosis statistics for all index returns are large and positive. The excess kurtosis statistics indicate that the distributions are leptokurtic relative to the normal distribution. The Jarque-Bera test statistic rejects the null hypothesis of normality at the one percent level of significance for all series. The rejection of normality for the unconditional distributions of returns (common to almost all returns of speculative assets) suggests intertemporal dependencies in returns (that is, the observations are not independent and identically distributed). The Ljung-Box statistic for up to six lags, calculated for both returns and squared returns, indicates the presence of significant linear and non-linear serial dependence, respectively, for all Asian stock markets. Linear dependence for the first moment of the distribution of returns may be due to non-synchronous trading of stocks. On the other hand, non-linear dependence can be attributed to autoregressive conditional heteroscedasticity. The Ljung-Box statistics calculated for the squared returns are several times higher than those of the returns, implying that the higher moment dependence is much more pronounced. This is consistent with the volatility clustering phenomenon observed in many stock markets. These general features of the sampled stock markets need to be taken into consideration in formulating the volatility model. Overall, the initial descriptive statistics are in favour of a model that incorporates both a mean equation that takes serial correlation into account and a volatility equation that acknowledges the strong heteroscedastic features in the data.

Table 3.2: Summary Statistics for Daily Equity Market Returns

	Hong Kong	Japan	Malaysia	Singapore	Philippine	Indonesia	Korea	Thailand
Mean	0.0474	-0.0105	0.0240	0.0296	0.0286	0.0622	0.0249	-0.0022
Median	0.0560	0.0009	0.0166	0.0211	0.0000	0.0395	0.0472	-0.0400
Maximum	17.2471	7.8304	20.8174	15.1546	21.4871	15.9581	14.1094	26.7582
Minimum	-14.7347	-9.1655	-24.1534	-9.6719	-9.7442	-15.7434	-16.7787	-16.0633
Std. Dev.	1.7457	1.5607	1.7293	1.4157	1.7038	1.7490	2.1413	1.9476
Skewness	0.1871	0.0822	0.7738	0.4794	1.1843	0.1922	-0.1684	1.1020
Kurtosis	12.8640	5.7720	38.3368	12.6496	18.7274	15.3613	8.1491	19.9642
Jarque-Bera	12792.89*	1012.361*	164256.4*	12345.83*	33211.59*	20080.85*	3495.86*	38421.43*
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ljung-Box(6)	22.789*	16.811*	56.991*	55.489*	45.228*	106.1*	24.421*	32.029*
P-value	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.000
Ljung-Box^2(6)	374.97*	198.67*	1217.0*	535.96*	37.752*	183.42*	366.55*	118.69*
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: The * indicates significance at the 1% level.

The sample summary statistics-means, standard deviations, minima and maxima are quoted in percent.

Jarque-Bera is a test statistic for testing the normality of the return series.

Ljung-Box (6) and Ljung-Box^2 (6) are the Ljung-Box statistic for returns and squared returns with six lags, respectively.

3.3.2 Unit-root and Structural change

3.3.2.1 Unit Root Test

Prior to testing for cointegration, the time series properties of the stock index series are investigated. Tests for cointegration require nonstationary time series to be integrated of the same order. In other words, if two series are cointegrated of order *d*, or *I(d)*, then each series has to be differenced *d* times to restore stationarity. For $d=1$, first differencing is needed to obtain stationarity. It is important to convert non-stationary into stationary variables or they will not drift toward a long-term equilibrium.

The augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Zivot-Andrews (ZA) tests are commonly used to examine the stationary property of market prices. The ADF test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR(k) process and adding lagged difference terms of the dependent variable to the right-hand side of the test regression:

$$\Delta y_t = \mu + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \tag{3.1}$$

Equation (3.1) tests for the null of a unit root against a stationary alternative. Here y_t denotes the time series being tested, the term Δy_{t-i} is first difference lagged to accommodate serial correlation in the errors and k denotes the optimal lag length. In this study, the lowest value of the Akaike information criterion (AIC) is used to determine the optimal lag length in the ADF regression.

The Phillips-Perron (PP) test is used as an alternative nonparametric model to control for serial correlation. Using the PP test ensures that higher-order serial correlation in the ADF equation is handled properly. That is, the ADF test corrects for higher-order autocorrelation by including lagged differenced terms on the right-hand side of the ADF equation; while the PP test corrects the ADF *t*-statistic by removing the serial correlation that it contains. The PP nonparametric *t*-test adopts the Newey-West heteroscedasticity autocorrelation consistent estimate and is robust to heteroscedasticity and autocorrelation of unknown form.

The most common criticism of the ADF and PP tests is their inability to adjust for structural breaks. Figure 3.1 indicates that the Asian financial crisis most probably resulted in a break for all market index series. Additional unit root tests are therefore used that allow for a possible structural break. The Zivot and Andrews (1992) test, which allows for an endogenous one-time (or single) break in the intercept, is also used to detect a unit root. Its regression equation is

$$\Delta y_t = \mu + \beta t + \alpha y_{t-1} + \theta DU_t(\lambda) + \sum_{i=1}^{k} c_i \Delta y_{t-i} + \varepsilon_t \tag{3.2}$$

Here $DU_t(\lambda) = 1$ for $t > T\lambda$ and $DU_t(\lambda) = 0$ otherwise, $\lambda = T_B / T$ represents the location of the structural break, T is the sample size and T_B is the date when the structural break occurred. Following Chaudhuri and Wu (2001) and Narayan and Smyth (2005), the selection of break point T_B is based on the minimum value of the t statistic for α.

The unit root tests are applied both to levels of the series and to first differences. The results are presented in Table 3.3. All three tests show strongly that the series are non-stationary in levels but stationary in first differences, suggesting that national stock index series in Asia are individually integrated of order one, $I(1)$.

Table 3.3 Unit root tests

Market Index	ADF t-stat.		PP adjusted t-stat.		Zivot-Andrews minimum t-stat.	
	Level	Difference	Level	Difference	Level	Difference
Hong Kong	-2.52	-53.66*	-2.97	-53.66*	-4.14	-19.82*
Japan	-1.76	-58.41*	-1.65	-58.44*	-3.27	-20.41*
Malaysia	-1.94	-25.17*	-1.92	-53.63*	-4.21	-20.03*
Singapore	-1.82	-49.82*	-1.75	-49.69*	-2.04	-20.29*
Philippine	-1.53	-49.93*	-1.63	-50.07*	-2.88	-18.79*
Indonesia	-1.43	-47.20*	-1.28	-46.95*	-3.19	-19.88*
Korea	-1.74	-53.98*	-1.72	-53.94*	-2.84	-19.85*
Thailand	-1.15	-51.36*	-1.21	-51.48*	-4.49	-19.22*

Note: The critical values for the Augmented Dickey Fuller (ADF) and Philips and Perron (PP) tests of the null hypothesis of a unit root are -2.56 (10%), -2.86 (5%) and -3.43 (1%). The critical values for the Zivot-Andrews unit root test are -5.34 (1%) and -4.80 (5%).
* denotes the rejection of the null hypothesis of a unit root at the 1% significance level.

3.3.2.2 Structural change and sample division

There is a considerable econometric literature on issues related to structural change. Structural changes can lead to erroneous conclusions if they are not properly treated. Piehl, Cooper, Braga and Kennedy (1999) stress that knowledge of break points is important for accurate evaluation of any program that is likely to bring about structural change, such as financial reforms, tax reforms and regime changes. In addition, the major objective here is to examine the trend of interdependence between Asian stock markets and to investigate the impact of the Asian financial crisis. To fulfil the purpose of research, the whole sample is divided into four sub-sample periods according to different stages of the financial crisis, namely pre-crisis period, crisis period, post-crisis period and recovery period. 'Economic' evidence (news reports etc) and 'Statistical' evidence (Zivot and Andrews test for structural break) will both be used for determining the breaks. Since four sub-samples are needed, three potential structural break dates are examined in this section.

One of the classical tests for structural change is by Chow (1960), but a limitation of this test is that it only has meaning in the context of a model and the 'break date' has to be known in advance. While the Zivot and Andrews (1992) test can be used to find unknown structural break dates, it can only find a single structural break point. It is therefore used recursively here to identify multiple structural break dates, as follows. First, a single potential structural breakpoint is identified for the entire period, splitting the sample into two. Second, the test is reapplied to each sub-sample to find two further potential breakpoints. This identifies three important potential breakpoints for the whole sample period.

Evidence identifying three important potential structural break points is given in Table 3.4 for every time series (Also note that that the Zivot and Andrews (1992) test may choose different breaks for different countries). This evidence, used in conjunction with key economic and political events (exogenous events) in Asia, allows the whole sample period to be partitioned into four sub-periods. However, it should be noted that if the break points recognized by the Zivot and Andrews (1992) test are inconsistent with major events, it becomes necessary to choose one criterion over the other, because different endogenous methods of choosing structural breaks may produce different results. It was decided to rely on exogenous events in any case of inconsistency.

Table 3.4 Potential structural break points

Market Index	break date of full sample	min t-stat.	break date of sub-sample	min t-stat.	break date of sub-sample	min t-stat.
Hong Kong	12/3/2003	-4.14	30/9/1997	-4.34	18/7/2006	-3.45
Japan	4/12/2000	-3.27	28/7/1997	-3.99	28/4/2003	-2.96
Malaysia	3/7/1997	-4.21	15/7/1993	-3.47	25/10/2000	-3.44
Singapore	6/8/1997	-2.04	30/7/1993	-4.02	20/2/2001	-3.45
Philippines	19/6/1997	-2.88	27/8/1993	-3.97	2/6/2003	-3.29
Indonesia	29/8/2003	-3.19	4/8/1997	-4.54	25/8/2006	-3.63
Korea	7/5/1996	-2.84	22/12/1994	-3.48	18/9/1997	-3.16
Thailand	3/7/1996	-4.49	27/9/1993	-4.39	6/3/2003	-4.21

The break points suggested above find some support from an analysis of economic events. Baur and Fry (2008) argue that the beginning of the crisis is usually defined by an extreme event. This suggests that the Thai baht devaluation on July 2, 1997 can be used as the crisis trigger event (see Appendix 3.1, page 73). This is supported by the existence of structural break points in 1997 in all Asian stock markets. The first sub-period (pre-crisis) is therefore determined as January 8, 1992 to July 2, 1997.

The end of 1998 is defined as the end of the crisis period, since this corresponds to the reversal of the net selling activity in Asian stock markets (Karolyi, 2002) and the largest fluctuations in exchange rates and stock indices (Nagayasu, 2000). Since other studies (Lin, 2006)[6] also support this date as the end of the financial crisis, the crisis period is defined as July 2, 1997 to December 31, 1998.

After the financial crisis there is a further potential break point in 2003, applying to many Asian countries, including Hong Kong, Japan, Philippines, Indonesia and Thailand (shown in Table 3.4), corresponding to the beginning of economic recovery in Asia. This is confirmed by a report of the Asian Development Bank which states "There are tentative signs that investment, after subdued for sometime,

[6] Lin (2006) also checked whether changing the crisis period changes the empirical result, choosing additional crisis periods covering July 2, 1997 to August 31, 1998 and July 1997 to October 1998. They concluded that the results are not drastically affected by the selection of crisis periods.

is starting to pick up in the crisis-affected countries in general and Thailand in particular" (*Asia Economic Monitor*, 2003). The Asian Economic Outlook (2003) also support this finding and states that 2003 is momentum for a recovery of the Asian economy, owing to an improving external environment. The earliest potential break point in 2003 (corresponding to Thailand in Table 3.4, March 6, 2003) is therefore used as the start of Asian economic recovery period.

In summary, based on the above analysis, the whole sample period is split into four sub-periods:

- *pre-crisis period*: 8th January 1992 to 1st July 1997
- *crisis period*: 2nd July 1997 to 31thDecember 1998
- *post-crisis period*: 1st January 1999 to 6th March 2003
- *recovery period*: 7th March 2003 to 8th March 2007

3.4 Long-run Equilibrium: Cointegration Analysis

3.4.1 Johansen-Juselius cointegration test

After examining the characteristics of data, the next step is to check if there are any common forces driving the long-run movement of data series or whether each individual stock index is solely driven by its own fundamentals. This is done by using a test for cointegration. Granger (1981) showed that the existence of cointegration should be determined by first testing the hypothesis that each series is integrated of the same order and then testing for cointegration between these series. The seminal test for cointegration is by Engle and Granger (1987). They point out that a linear combination of two or more variables is stationary even though each of the variables is non-stationary, and that some long-run equilibrium relation ties the individual series together.

There are several tests for cointegration, including the Engle and Granger (1987) and Johansen (Johansen and Juselius, 1990) tests. Of the two, the Johansen test is preferred in this dissertation, for the following reasons: (i) unlike the Engle-Granger approach, which is sensitive to the choice of the dependent variable in the cointegrating regression, the JJ procedure assumes all variables to be endogenous; (ii) when extracting residuals from the cointegrating vector, the JJ approach is insensitive to the variable being normalized and avoids the arbitrary choice of dependent variable in the Engle-Granger approach (iii) the JJ procedure provides a unified framework for estimating and testing cointegrating relations within VECM formulation. (iv) Engle-Granger approach allows for only one cointegrating vector, while JJ approach allows more than one cointegrating vector.

Johansen-Juselius (JJ)'s method can be illustrated by considering the following vector autoregression or VAR model:

$$Y_t = \mu + A_1 Y_{t-1} + A_2 Y_{t-2} + \dots\dots\dots A_k Y_{t-k} + \varepsilon_t \tag{3.3}$$

Here Y_t is a vector of non-stationary variables, μ is a $(N\ x\ 1)$ vector of constants, k is the maximum lag, ε_t is assumed to be a $(N\ x1)$ vector of Gaussian error terms, and A is a $(N\ x\ N)$ matrix of coefficients.

The above VAR can be reparameterized in error correction form:

$$\Delta Y_t = \mu + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \dots\dots\dots \Gamma_{k-1} \Delta Y_{t-k-1} + \Pi Y_{t-k} + \varepsilon_t \tag{3.4}$$

Here Γ is a short-run coefficient. The matrix Π represents a long-run response matrix which has reduced rank if there is cointegration. The Johansen test for the number of cointegrating vectors is based on the rank of matrix Π. Denoting rank (Π) by r, there are three possibilities:

(1) $r=N$ (full rank): all elements/variables are stationary. If all variables are I(0), the issue of cointegration is not relevant.

(2) $r=0$: the variables in Π are not cointegrated, there are no combinations of the variables in Π which are stationary and there is no long-run relationship between the variables in Y_t. Equation (3.3) in this case reduces the to simple VAR model in first differences:

$$\Delta Y_t = \mu + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \dots\dots\dots \Gamma_{k-1} \Delta Y_{t-k-1} + \varepsilon_t \tag{3.5}$$

(3) $0 < r < N$: there are r possible linear combinations of non-stationary variables that are stationary (r cointegrating vectors).

When cointegration is present, the long run response matrix can be decomposed into $\Pi = \alpha\beta'$, where α and β are $N \times r$ matrices. In this decomposition, $\beta' Y_{t-k}$ represents the cointegrating vectors and α is the adjustment vector, measuring the response of the variable to the cointegrating vectors.

Johansen suggest two methods that can be used to estimate the number of cointegrating vectors: the trace test and the maximal eigenvalue test. The trace statistic provides a test of the null hypothesis of r cointegrating relations against the alternative of m cointegrating relations, $r=0,1....m-1$. The maximal eigenvalue test is for at most r cointegrating relations against the alternative of $r+1$ cointegrating relations. These statistics may yield conflicting results but here the number of cointegrating vectors is based on the results of the trace statistics tests.

3.4.2 Long-Run Cointegrating Relations

This section addresses four issues: (i) the optimal lag length chosen to estimate the cointegrating relationship (likelihood-ratio statistics); (ii) whether the cointegration occurs and how many cointegrating relationships there are (λ_{trace} and λ_{max} statistics); (iii) the relative weights of countries within the cointegrating vector (zero-loading restriction tests of the null hypothesis that the coefficient on a variable in the cointegrating vector is zero) and (iv) whether the financial crisis changes the cointegrating relationships (determined by comparing results before and after the financial crisis).

3.4.2.1 Determining the optimal Lag Length

The number of lags in the vector autoregression (VAR) used to estimate the cointegrating relationship is an important issue because this has been shown to affect the number of cointegrating vectors detected (Richards, 1996a). The optimal lag length must therefore be specified before implementing the cointegration test.

There are three common used tests to choose optimal lag length, the Akaike information criterion (AIC), the Schwarz Bayesian criterion (SBC) and likelihood-ratio test. The Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC) in my case suggest a shorter number of lags than the likelihood-ratio test, including too few lags in VAR models may make it impossible to capture any delayed generalised adjustment to market movements. Considering a relatively large number of lags is likely to generate more robust conclusions. The selection of optimal number of lags is therefore based on the sequential modified likelihood-ratio (LR) test[7].

Table 3.5 reports the lag-length specification results for the total period and sub-periods. The likelihood ratio tests suggest that 13 lags should be appropriate for the

[7] The sequential modified likelihood-ratio (LR) test for optimal lag length selection is carried out as follows. Starting from the maximum lag, test the hypothesis that the coefficients are jointly zero using the χ^2 statistics. Then comparing the modified LR statistics to the 5% critical values starting from the maximum lag, and decreasing the lag one at a time until first getting a rejection. The alternative lag order from the first rejected test is marked with an asterisk.

total sample period. It also indicates that 9 lags, 4 lags, 11 lags and 14 lags are appropriate for the pre-crisis period, crisis period, post-crisis period and recovery period respectively.

Table 3.5 Lag Length Selection

Lag	Total period	Pre-crisis period	Crisis period	Post-crisis period	Recovery period
	LR test				
0	NA	NA	NA	NA	NA
1	121034.4	34986.9	8240.1	32919.8	31893.2
2	299.82	216.39	150.16	160.76	167.10
3	111.05	65.78	74.80	67.68	67.09
4	108.68	76.03	84.69*	87.68	64.97
5	150.43	65.87	62.77	76.16	75.90
6	108.16	67.63	68.65	108.87	83.19
7	109.06	60.71	47.14	58.90	82.99
8	100.69	62.77	78.06	69.10	61.74
9	112.17	92.72*	68.68	76.09	64.86
10	124.36	74.15	74.40	71.16	71.62
11	117.30	74.29	82.86	95.66*	61.02
12	132.41	65.04	52.06	76.72	66.33
13	104.21*	83.27	72.25	62.19	56.67
14	83.30	77.63	74.42	72.72	88.83*
15	76.63	61.17	47.04	57.15	75.16

Note: * indicates lag order selected by the criterion.
chi-square with 64 degrees of freedom.
LR: sequential modified LR test statistic (each test at 5% level)

3.4.2.2 Are the Asian stock markets cointegrated?

Johansen's multivariate cointegration test is used here, since it provides insight into the cointegration of all Asian stock markets as a group, covering all markets simultaneously rather than in simple bivariate combinations. Compared to pairwise combinations, this both determines a wider range of portfolio diversification options available to investors and identifies a scope of financial integration.

Results from the Johansen multivariate cointegration test are reported in Table 3.6. The analysis is conducted for the total period under investigation as well as for the sub-periods. Both the trace and maximum eigenvalue test statistics reject the null hypothesis of no cointegrating vector for the full period (one cointegrating vector exists). However, this result might not be robust because the 1997 financial crisis is included in the full sample period. Hence, the results for the sub-periods give a better insight.

Table 3.6 Johansen-Juselius's Test for Multiple Cointegrating Vectors

H_0	H_1	λ_{trace}	Critical Value	λ_{max}	Critical Value
Panel A: Total period: 08/01/1992-08/03/2007					
r=0	r > 0	175.56*	159.52	59.40*	52.36
r≤1	r > 1	116.16	125.61	42.15	46.23
r≤2	r > 2	74.01	95.75	26.04	40.07
r≤3	r > 3	47.97	69.81	19.91	33.87
r≤4	r > 4	28.06	47.85	12.62	27.58
Panel B: Pre-crisis period: 08/01/1992-01/07/1997					
r=0	r > 0	163.52*	159.52	54.01*	52.36
r≤1	r > 1	109.51	125.61	37.75	46.23
r≤2	r > 2	71.76	95.75	25.07	40.07
r≤3	r > 3	46.69	69.81	20.72	33.87
r≤4	r > 4	25.96	47.85	11.59	27.58
Panel C: Crisis period: 02/07/1997-31/12/1998					
r=0	r > 0	128.36	159.52	38.62	52.36
r≤1	r > 1	89.75	125.61	27.02	46.23
r≤2	r > 2	62.73	95.75	22.12	40.07
r≤3	r > 3	40.60	69.81	19.93	33.87
r≤4	r > 4	20.67	47.85	8.96	27.58
Panel D: Post-crisis period: 01/01/1999-06/03/2003					
r=0	r > 0	174.78*	159.52	53.69*	52.36
r≤1	r > 1	125.39	125.61	36.90	46.23
r≤2	r > 2	88.49	95.75	29.05	40.07
r≤3	r > 3	59.44	69.81	22.45	33.87
r≤4	r > 4	36.99	47.85	18.04	27.58
Panel E: Recovery period: 07/03/2003-08/03/2007					
r=0	r > 0	164.76*	159.52	55.58*	52.36
r≤1	r > 1	109.18	125.61	30.31	46.23
r≤2	r > 2	78.87	95.75	30.18	40.07
r≤3	r > 3	48.69	69.81	20.79	33.87
r≤4	r > 4	27.90	47.85	12.04	27.58

Note: * indicates rejection of null hypothesis at 5% significance level.

An examination of individual sub-period results suggests that a single cointegrating relationship exists before and after the financial crisis. However, no cointegrating vector is observed among the Asian stock markets during the financial crisis period itself.

The finding of the existence of cointegration during the pre-crisis period further demonstrates that market oriented reforms and restructuring in the 1990s are likely to have brought the equity markets of the Asian countries closer together, resulting in comovements of stock prices even beyond the crisis. It is important to note that an absence of cointegrating vectors during the crisis period does not necessarily indicate markets are segmented during that period. For the sake of completeness, a test for cointegration is performed during the crisis. This involves a small number of observations compared to the non-crisis period, so the results should be treated with considerable caution. Additionally, some literature also emphasize the weakness of using the results of the crisis period in interpreting cointegrating relations. For example, Brouwer (1999) argues that cointegration analysis is not well identified over short sample periods and is more useful with longer time frames. Hesse (2007) concluded that high volatility during the crisis could have distorted the cointegrating relations and he suggested that the crisis periods should be excluded from sub-sample analysis. Click and Plummer (2005) suggest that five years should be a long enough time span to uncover long-run equilibrium relationships, and since all the sub-periods used here except the crisis period meet this standard, the results should therefore be reliable.

3.4.2.3 Coefficients of cointegrating vectors and tests of zero loading restrictions

The results discussed above clearly show that there is a single cointegrating vector for the eight Asian stock markets in the sample. However, the presence of this cointegrating relationship does not guarantee that all countries exert an influence on the cointegrating vector in the long run. The Johansen and Juselius (1990) procedure allows a test of whether a particular market has influence by imposing restrictions on the cointegrating vectors and using likelihood ratio tests. This method provides a measure of the importance of each component, in terms of its relative weight, in comparison to the other components. The significance levels associated with the test results of zero-loading restrictions appear in Table 3.7 for full sample period and each of the sub-periods.

For the full period model, normalized on Hong Kong, the restrictions are significantly rejected for all countries except Japan and the Philippines. This implies that all markets except Japan and the Philippines enter the cointegrating vectors at a statistically significant level. However, as stated earlier, this result may not be robust because of the inclusion of the financial crisis period. Thus, sub-period results provide more useful information.

The sub-period results show a very interesting phenomenon. In the pre-crisis model only four markets enter the cointegrating vector at a statistically significant level (Hong Kong, Singapore, Korea and Indonesia). In the post-crisis model all markets except Japan enter the cointegrating vector significantly. This is also the case for the recovery period model. These results indicate that the long-run linkage between the Asian stock markets was weak during the pre-crisis period, with many countries not participating in the long-run cointegrating vector. However, the situation is reversed after the financial crisis. All countries except Japan participate significantly in the long-run cointegrating vector to clear short-run disequilibrium. Hence, the long-run linkages among the Asian stock markets become stronger after the crisis. Two other findings deserve special comment. First, the fact that the Japanese stock market never enters the cointegrating vectors at a statistically significant level suggests that the Japanese stock market is not closely linked to other East Asian markets in the long-run. Huff (2007) examines financial systems of Japan and six Southeast Asian countries (Burma, Thailand, Malaya, Indonesia, Indonesia and the Philippines). He finds that Japan has a modern financial system and ranks in the same class as Western countries, but Southeast Asian countries lack 'modern financial institutions' and can not be comparable to Japan. This could partially explain why there is lack of long-run equilibrium relationship between Japan and other Asian countries. Additionally, Hong Kong, Singapore and Korea always have significant impact on the cointegrating vectors. This implies that in the long-run these three stock markets play a persistent and important role in the Asian region.

Table 3.7 Coefficients of cointegrating vectors and tests of zero-loading restrictions

Panel A: Full period model: 08/01/1992-08/03/2007			
Variable	Coefficient	Test statistic	*P*-Value
Hong Kong	1.00		
Japan	0.02	0.03	0.87
Malaysia	-0.34	2.88*	0.09
Singapore	-1.22	9.97***	0.00
Philippines	0.04	0.19	0.66
Korea	0.52	10.79***	0.00
Indonesia	-0.20	6.56***	0.01
Thailand	0.23	4.28**	0.04
Panel B: Pre-crisis period model: 08/01/1992-01/07/1997			
Variable	Coefficient	Test statistic	*P*-Value
Hong Kong	1.00		
Japan	-0.04	0.05	0.83
Malaysia	0.17	0.08	0.78
Singapore	2.47	11.43***	0.00
Philippines	-0.41	1.46	0.23
Korea	-0.72	9.39***	0.00
Indonesia	-2.08	16.26***	0.00
Thailand	0.03	0.04	0.83
Panel C: Post-crisis period model: 01/01/1999-06/03/2003			
Variable	Coefficient	Test statistic	*P*-Value
Hong Kong	1.00		
Japan	-0.14	0.15	0.70
Malaysia	-0.44	2.81*	0.08
Singapore	-2.50	10.90***	0.00
Philippines	0.71	3.84**	0.05
Korea	1.02	10.54***	0.00
Indonesia	0.89	3.53*	0.06
Thailand	-1.49	8.49***	0.00
Panel D: Recovery period model: 07/03/2003-08/03/2007			
Variable	Coefficient	Test statistic	*P*-Value
Hong Kong	1.00		
Japan	0.01	0.00	0.96
Malaysia	-1.84	15.87***	0.00
Singapore	2.07	13.2***	0.00
Philippines	-0.69	4.17**	0.04
Korea	-0.77	9.52***	0.00
Indonesia	0.43	4.02**	0.04
Thailand	-0.26	5.43**	0.02

Notes: The test statistic is associated with a null hypothesis that each coefficient is statistically equivalent to zero, asymptotically distributed chi-squared with 1 *df*.
***, **and * indicates rejection of null hypothesis at 1%, 5% and 10% significance level.

3.4.3 Discussion of the Economic Implications of Cointegration Results

The observed cointegration of Asian stock markets has several economic implications. First, since each price series contains information on the cointegrating vector (which binds all Asian markets together) the fluctuations of stock prices in one market can be influenced by movements in the other Asian stock price indexes in combination.

Second, the presence of cointegrating relationships implies that, once new information on prices is available in one market, prices in other markets will deviate from trend only by a transitory component. In other words, individual indices cannot wander too far away from each other over time.

Third, since Asian markets are interdependent, the possibility of gaining benefits in these markets through diversifying portfolios across national borders may be limited in the long-term. However, two additional points should be noted. First, cointegration does not rule out the possibility of arbitrage profits through diversifying portfolios across markets in the short-term or even medium term. Second, since different securities in countries will have varying financial risks, it is highly unlikely that the existence of cointegrating relationships between countries will remove the benefits of international diversification altogether. That is, covariation may be lower between stocks traded in different countries, implying that optimal selection will pick an international portfolio.

Fourth, the existence of cointegration in Asian markets has important financial policy implications for both Asian government and multinational corporations. This is because the effectiveness of financial policy in each country depends very much on the formulation of financial policy in other countries, in so far as it works through the stock market.

3.5 Lead-Lag Relations: Granger Causality

3.5.1 Granger Causality and Vector Error-Correction Models

Granger (1988) has shown that a cointegrating relationship between variables entails a causal relationship among those variables in at least one direction. In view of this, Granger causality tests are performed through an vector error correction model (VECM) or unrestricted VAR.

In the presence of cointegration, there always exists a corresponding error-correction representation. This implies that changes in the dependent stock indices are a function of the level of disequilibrium in the cointegrating relationship captured by the error-correction term as well as changes in other explanatory stock indices. Through the error-correction term, the error correction models (ECM) open up an additional channel for Granger causality to emerge. Therefore, if the time series are found to be $I(1)$ and cointegrated, Granger (1988) suggests that the error correction term (ECT) derived from the cointegrating relationship should be added when testing for causality to avoid model misspecification. In this case, the Granger causality test should base on the following:

$$\Delta X_t = \alpha_0 + \sum_{i=1}^{k} \beta_{X,i} \Delta X_{t-i} + \sum_{i=1}^{k} \gamma_{X,i} \Delta Y_{t-i} + \phi_X ECT_{X,t-i} + \varepsilon_{X,t} \tag{3.6}$$

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{k} \beta_{Y,i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{Y,i} \Delta X_{t-i} + \phi_Y ECT_{Y,t-i} + \varepsilon_{Y,t} \tag{3.7}$$

F-tests of the 'differenced' explanatory stock indices indicate 'short-term' causal effects. Failure to reject the null hypothesis, $H_0: \gamma_{X1} = \gamma_{X2} = ... = \gamma_{Xk} = 0$, implies that stock price of country Y does not 'Granger-cause' the stock price of country X, while failing to reject $H_0: \gamma_{Y1} = \gamma_{Y2} = ... = \gamma_{Yk} = 0$ implies that the stock price of country X does not 'Granger-cause' the stock price of country Y. The 'long-term' causal relationship is implied through the significance of the t-test of the lagged error-correction term (*ECT*), which contains the long-term information since it is derived from the long-term cointegrating relationships. The coefficients of the lagged error-correction terms, ϕ_X and ϕ_Y, are short-term adjustment coefficients representing the proportion of long-term disequilibrium in the dependent variable that is corrected in each short period. The non-significance of both t-test and F-test in the VECM indicates econometric exogeneity of the dependent variable.

For non-cointegrating series, Granger causality is examined through the Vector Autoregressive (VAR) model. The standard Granger causality test is applied:

$$\Delta X_t = \alpha_0 + \sum_{i=1}^{k} \beta_{x,i} \Delta X_{t-i} + \sum_{i=1}^{k} \gamma_{x,i} \Delta Y_{t-i} + \varepsilon_{x,t} \tag{3.8}$$

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{k} \beta_{y,i} \Delta Y_{t-i} + \sum_{i=1}^{k} \gamma_{y,i} \Delta X_{t-i} + \varepsilon_{y,t} \tag{3.9}$$

Here ΔX_t is the first difference at time t of the logarithm of a country's stock index, where the series is non-stationary, and ΔY_t is the first difference at time t of the logarithm of the stock index for another country. Failure to reject the null hypothesis $H_0 : \gamma_{x1} = \gamma_{x2} = ... = \gamma_{xk} = 0$ implies that stock price of country Y does not Granger-cause the stock price of country X. Likewise, failure to reject $H_0 : \gamma_{y1} = \gamma_{y2} = ... = \gamma_{yk} = 0$ suggests that stock price of country X does not Granger-cause the stock price of country Y.

It should be noted that Baek and Brock (1992), Terasvirta et al. (1994) and Granger and Terasvirta (1999) extend the analysis using nonlinear Granger causality methods. In this chapter, the focus of interest is on the behaviour of stock markets within each regime, rather than on switches from one regime to another, so a linear causal model with regime dummies would seem to be suitable. In addition, according to Baek and Brock (1992), there are many practical problems in implementing tests and estimation of nonlinear Granger causality. One particularly serious issue is that the asymptotic distribution of the test statistics under the null hypothesis will typically be distorted and cause errors in the estimation of parameters. Furthermore, Baek and Brock (1992) and Terasvirta et al. (1994) all point out that the choice of lag order has still to be determined, potentially leading to model specification problems[8]. They suggest that these are all important but unresolved issues which need further investigation before testing and estimation can proceed in a reliable way.

In sum, based on the purposes of the research and the current limitations and state of knowledge regarding nonlinear Granger causality tests, these have not been used in this work. In this thesis, the focus is on linear Granger causality tests, but nonlinear tests are a natural extension of the work and undoubtedly a subject for future research.

[8] Baek and Brock (1992) state that the optimal choice of lags is beyond the scope of their paper. Terasvirta et al. (1994) argue that lag structure could be chosen using a model selection criterion but little is known about the success of such a procedure.

Table 3.8 Multivariate Granger Causality Results

Dep Variable	Short-run lagged differences F- statistics								Lagged ECT
	ΔHK	ΔJP	ΔSG	ΔKR	ΔMA	ΔPHI	ΔIND	ΔTHA	ECTt-1
Panel A: Total period: 08/01/1992-08/03/2007									t-statistics
ΔHK		1.67*	1.73*	2.03***	2.42***	1.22	1.98**		2.02**
ΔJP	1.88**		2.26***	1.55	1.65*	0.98	1.29	1.54	0.64
ΔSG	2.69***	1.60*		1.60*	1.98**	1.79**	1.15	2.57***	3.86***
ΔKR	3.71***	1.06	2.97***		0.71	0.99	1.72*	2.58***	1.18
ΔMA	6.87***	0.72	6.13***	2.04**		2.93***	6.61***	3.88***	2.75***
ΔPHI	5.14***	1.56	8.35***	4.21***	6.97***		4.90***	8.24***	0.19
ΔIND	2.71***	2.01**	1.76**	5.33***	1.25	2.70***		4.84***	-0.12
ΔTHA	2.98***	0.81	2.47***	2.92***	2.70***	1.36	4.38***		0.41
Panel B: Pre-crisis period: 08/01/1992-01/07/1997									t-statistics
ΔHK		1.33	0.52	2.17**	1.24	0.63	1.43	0.47	-0.67
ΔJP	0.44		0.87	2.11**	1.32	0.92	1.5	0.98	-0.24
ΔSG	1.69*	0.46		1.51	1.93**	1.53	2.10**	1.4	0.61
ΔKR	1.84*	1.41	1.83*		1.71*	0.49	0.61	1.15	0.63
ΔMA	1.83*	0.51	2.11**	0.44		3.50**	0.99	1.86*	0.76
ΔPHI	2.09**	1.12	3.59***	0.57	3.35***		1.39	2.65***	3.31***
ΔIND	3.64***	0.78	2.77***	0.65	4.04***	3.50***		2.67***	5.98***
ΔTHA	1.42	0.27	0.83	0.61	1.83*	0.613	1.34		-0.62
Panel C: Crisis period: 02/07/1997-31/12/1998									
ΔHK		0.75	0.76	3.45**	1.43	4.59**	3.94**	4.72***	
ΔJP	0.69		0.89	3.11**	1.11	1.05	2.97*	2.65*	
ΔSG	4.83***	0.31		2.64*	2.48*	6.37***	3.91**	1.16	
ΔKR	1.58	1.88	1.72		0.49	0.27	0.48	4.07**	
ΔMA	3.96**	0.03	3.10**	4.07**		5.55***	10.98***	4.39***	
ΔPHI	6.45***	1.97	9.23***	3.38**	5.98***		6.65***	9.64***	
ΔIND	3.11**	0.91	1.64	8.61***	0.21	1.68		2.49*	
ΔTHA	0.60	1.35	3.55**	7.41***	0.72	1.74	3.04**		
Panel D: Post-crisis period: 01/01/1999-06/03/2003									
ΔHK		1.61*	1.46	1.16	1.06	0.58	1.34	2.08**	2.71***
ΔJP	2.08**		1.61*	1.48	0.54	0.86	0.68	0.87	1.38
ΔSG	2.02**	1.93**		0.31	1.55	1.42	0.46	2.41**	4.42***
ΔKR	2.75***	1.02	3.07***		0.58	1.35	0.23	3.32***	-1.15
ΔMA	0.97	1.37	1.52	0.85		1.47	1.09	1.61*	0.37
ΔPHI	1.32	0.98	2.62**	1.71*	1.31		0.97	4.51***	-0.66
ΔIND	2.28**	1.65*	1.91**	2.30**	1.46	1.89**		2.64**	0.83
ΔTHA	1.51	1.75*	2.78***	1.33	1.71*	1.74*	1.83*		2.87***
Panel E: Recovery period: 07/03/2003-08/03/2007									
ΔHK		1.45	2.05**	0.48	0.71	0.69	0.88	0.78	2.30**
ΔJP	2.87***		4.48***	1.44	1.36	0.99	1.47	0.55	-0.05
ΔSG	0.15	1.93*		0.92	1.11	0.93	0.83	0.49	1.86*
ΔKR	0.96	0.69	2.52***		0.33	1.01	2.38**	1.74*	2.93***
ΔMA	1.24	0.73	3.02***	0.86		0.55	2.06**	1.03	5.01***
ΔPHI	4.69***	1.70*	4.93***	2.54***	2.65***		4.36***	4.44***	2.20**
ΔIND	1.80*	1.44	1.27	1.76*	1.82*	1.65*		1.91*	0.85
ΔTHA	0.96	1.41	0.92	2.44**	1.70*	1.43	1.69*		2.33**

Note: Panels A, C, and D are estimated using a VECM model based on Equations 3.6 and 3.7. Panel B uses an unrestricted VAR model based on Equations 3.8 and 3.9. The ECT was derived by normalising the cointegrating vector on Hong Kong.

*** ,** and * indicate significance at 1% ,5% and 10% levels.

3.5.2 Causal relationships among Asian stock markets

Since cointegration exists between the stock markets for the entire sample period, the pre-crisis, post-crisis and recovery periods, Granger causality tests are performed on the basis of Equations (3.6) and (3.7) for these periods. In addition, for the crisis period an unrestricted VAR model is adopted with the Granger causality test based on Equations (3.8) and (3.9). It should be noted that the hypothesis ($H_0 : \gamma_{X1} = \gamma_{X2} = ... = \gamma_{Xk} = 0$) in (3.6) only measures the existence of 'short-run causality' ('long-run causality' may also be examined if cointegration is present)[9]. Testing for 'long-run causality' in VECMs may present difficulties, since various restrictions need to be satisfied for the test statistic to be distributed as χ^2. (Mills and Markellos, 2008, p374). In this thesis, 'short-run' causality only is analyzed and a summary of test results is presented in Table 3.8, which reveals some interesting findings.

An examination of the entire sample period (Table 3.8, panel A) reveals significant bi-directional causality between pairs of Asian stock markets. In particular, the stock index movements of Hong Kong and Singapore exert the strongest causal influence on all Asian economies. The other countries also exert some one-way and bi-directional causality relationships between themselves. No country is totally insulated from market movements that emanate from the other countries in the group. The high number of bi-directional causality relationships among Asian stock markets indicates a close relationship among the returns of these markets.

An examination of the sub-periods reveals some interesting contrasts. In the pre-crisis model (Table 3.8, panel B), with the Asian countries experiencing steady stock market growth in the first half of the 1990s, Hong Kong exhibits strong causality on all Asian markets with the exception of Japan and Thailand. Although many causal relationships exist, Japan and Hong Kong are not subject to much influence from the other countries with the exception of Korea, this is probably because the economies of both are more closely tied to the developed nations of the West. Singapore shows causality toward Korea, Malaysia, Philippines and Indonesia. Malaysia shows similar

[9] See Mills and Markellos (2008), pp 373-374 for the details of 'short-run and long-run' causality.

causal relationships with Singapore. Thailand exerts strong causal influence on the Philippines and Indonesia. Thailand also shows a significant bi-directional causality (feedback) relationship with Malaysia, albeit to a lesser degree. Furthermore, it is interesting to note that Korea exhibits a causal relationship on both Hong Kong and Japan during the pre-crisis period. This interesting result may be related to the balance of payments condition that was prevailing in Korea during the 1990s. The early 1990s saw huge capital flows into the Korean market and GDP growth rate was over 7 percent on average. Korea was able to maintain large current account deficits of as much as $23 billion in 1996. This deficit was offset by a $24 billion financial account surplus, of which $21 billion was foreign portfolio investment (Anoruo, Ramchander and Thiewes, 2003). Further, over 50 percent of the investment flows emanated from Japan and Hong Kong. However, there is no presumption that capital inflows from Hong Kong and Japan imply direct causal influences from Hong Kong and Japan stock markets on the Korean market. The evidence is that stock market causal linkages run from Korea to Hong Kong and Japan. Thus, in the period of economic and stock market growth in the early 1990s, Korea exhibits a causal relationship on both Hong Kong and Japan.

Over the crisis period, characteristics of market linkages, as indicated by the unrestricted VAR formulation, changed significantly. This result indicates that relationships between Asian stock markets grew closer following the onset of the financial crisis. In this period the numbers of short-run channels of causality dramatically increase, with a large amount of bi-directional causality: Hong Kong - Philippines, Hong Kong - Indonesia, Singapore - Malaysia, Singapore - Philippines, Korea - Thailand, Malaysia - Philippines, Indonesia - Thailand. The increase in feedback causality during the months of crash suggests that the crash started more or less simultaneously in all Asian countries. Moreover, it can be seen that the most severely crisis-affected countries, Korea, Indonesia and Thailand, exert the strongest causal influence on almost all of the Asian stock markets. Thus, it appears that events such as the announcement on 2nd July 1997 by the Bank of Thailand of a managed float of the baht, Indonesia abandoning its defence of its exchange rate system on 14th August 1997, and South Korea abandoning its defence of the won on 17th November 1997 created an environment in which stock markets reacted more closely to movements elsewhere in the region. Finally, it is noticeable that the

Japanese stock market exerts no causal influence on other stock markets before and during the period of crash. Given Japan's large market size and its economic influence, this result is surprising. However, Japan's economic recession in the early 1990s could be an important factor in explaining its less dominant role (Roubini, 1996)[10].

Over the post-crisis period Thailand and Singapore have the two most interactive markets, compared with the other countries in the region, since they have the greatest causal influence on other markets. Both countries Granger-cause stock market returns in Korea, the Philippines and Indonesia, with Thailand also having marginal impact on the Hong Kong market. During the post-crisis period, The Philippine and Indonesian stock markets are largely dependent markets, as they are fundamentally affected by other Asian markets but do not have much reverse impact. In addition, Malaysia has the most isolated market as it exhibits a bi-directional causality only with Thailand, at the 10% significance level. The low number of causal relationships between Malaysia and the other markets may be attributed to its policy of capital control after the financial crisis. With such restrictions in place the amount of trade and capital flows between Malaysia and other Asian markets was relatively low. Thus the degree of integration of Malaysia with other Asian markets is not strong in this sub-period and it is not surprising that no significant causal relationships are observed.

Unlike the pre-crisis and crisis periods, in the post-crisis period Korea exhibits no causal influence on the more developed countries of Hong Kong and Japan. As stated earlier, Korea shows a causal influence on both Hong Kong and Japan before and during the financial crisis, while Hong Kong and Japan fail to exhibit a strong causal influence on Korea. It was concluded that this phenomenon could be attributed to a large investment flows from Hong Kong and Japan in the early 1990s. However, when the financial crisis occurred, Korea abandoned its commitment to exchange rate pegs and foreign investors quickly withdrew their funds from the Korean market, contributing to a collapse of the country's asset values and

[10] Roubini (1996) investigated Japanese macroeconomic problems and found serious economic recession and turmoil in Japan in the 1992-1995 period. GDP growth was close to zero on average during that period. He stated that Japan was "the fall of great power" due to economic mismanagement and poor economic performance.

necessitating the massive IMF bailout. By 1998, the austerity measures imposed by the IMF resulted in a financial account deficit of $8.4 billion and a $31 billion reduction of Korean reserve assets. Therefore, the Asian financial crisis and IMF bailouts over 1997 and 1998 resulted in the elimination of the Korean market influence on Hong Kong and Japan. Furthermore, instead of lacking causal linkages with other Asian stock markets during the post-crisis period, the Japanese stock market started exerting its influence on other Asian countries. It can be seen that the Japanese market shares feedback relationships with markets in Hong Kong and Singapore and has unidirectional relationships with the Thai and Indonesian stock markets. The increasingly influential role of Japan can be attributed to the following reasons. First, since Japan was a relatively isolated market before and during the crisis, it may have been considered as a safe harbour by foreign investors for portfolio diversification and hence more funds flowed to Japan after the crisis. Second, many Asian countries were severely affected by the financial crisis and Japan, as the economic leader, provided a large amount of financial aid to these crisis-hit countries. Hence financial cooperation between Japan and other Asian countries was enhanced after the crisis. Third, because the regulatory structures of Hong Kong and Singapore are more closely related to those of Japan, it is more likely that these two markets will share two-way causal relationships with Japan. Lastly, according to Wong, Penm, Terrel and Lim (2004) and Hiratsuka (2007) in 1997-2002 there was a substantial increasing in Japanese foreign direct investment (FDI) into Asian countries, thus strengthening the economic and financial links between Japan and other Asian countries. This perhaps partially explains the causal influence from Japan on Indonesia and Thailand during the post-crisis period.

Panel E of Table 3.8 reveals that the dominant role of the Hong Kong market in the region is greatly diminished during the recovery period. It only influences Japan, the Philippines (significant at the 0.01 level) and Indonesia (significant at the 0.10 level). Singapore exhibits the strongest causal influence on all countries (significant at the 0.01 level) with the exception of Indonesia and Thailand. This finding suggests that Singapore has developed into a regional financial centre, at least in respect of the countries studied here. There are two further pieces of evidence for this. First, the market capitalization of Singapore has significantly increased in recent years (see Table 2.2, page14) becoming the largest equity market in ASEAN-

5 (Singapore, Malaysia, Philippines, Indonesia, Thailand). Second, the Milken Institute's *Capital Access Index* (Appendix 3.3, page 75)[11] shows that the financial environment for investors provided by Singapore has ranked very high among world markets in very recent years. Furthermore, panel E of Table 3.8 reveals an increase in feedback relations and comovement between the emerging markets of the sample during the recovery period. For example, there are two-way causal relationships between the pairs Malaysia-Indonesia, Philippines-Indonesia, Indonesia-Thailand, Korea-Indonesia and Thailand-Korea. The increased comovement could be due to the recovery of the emerging markets from the crisis, a reduction in capital controls and a consequent increase in cross-border activity.

[11] This index is an indicator measuring how well a country compares to others in providing access to capital to both domestic and foreign investors.

3.5.3 Summary and Implications for the Granger causality results

Various important Granger causality results are summarized in this section, with specific focus on implications for investors and policy makers.

The first important finding is the isolation of the Japanese stock market before and during the crisis. During the pre-crisis period there was no observable relationship between Japan and other Asian markets, with the exception of Korea. The absence of comovements between Japan and the other markets suggests that including Japan in their portfolio would have been advantageous to investors wanting to diversify into Asia. Investors with emerging country portfolios (Malaysia, Indonesia, Philippines and Thailand) must consider the political and economic situations of these countries because of the vulnerability of their stock markets to shocks from all sources and might therefore also have wished to include Japan. One possibility is that over the crisis period Japan remained a relatively safe harbour for such investors because there were only few causal relationships between Japan and other countries. Finally, the results here show that the influence of Japan increased after the crisis, implying that portfolio managers should be prepared to re-adjust their portfolios that include Japanese assets.

Second, it appears that the Philippine and Indonesian stock markets are subject to external influence under normal market conditions. This indicates that the smaller size markets tend to be influenced by larger markets. This finding implies that optimal portfolio asset weights may depend on the size of each stock market.

Third, in more recent years, the influence of Hong Kong has greatly diminished. while other countries, most notably Singapore, have played a more dominant role. This could be attributed to the restructuring of the Singapore stock market after the financial crisis. This is clearly relevant to managers making portfolio allocation decisions.

Fourth, the Granger causality results show that relationships are intensified during the 1997 Asian financial crisis. More bi-directional (feedback) relationships can be found during this period, which means that a speculative attack in the stock market of one country may trigger simultaneous impact in the stock markets of other countries. The increasing number of causal relationships is not good news for investors or portfolio managers since this may reduce the benefits from portfolio diversification. On the other hand, this could lower both the search costs for firms seeking capital and transaction costs for investors.

In general, one plausible implication of the Granger causality results is that there may be fewer gains from pair-wise portfolio diversification between those Asian countries where significant casual relationships exist.

Finally, it must be noted that Granger causality only indicates the most significant direct causal relationship. For example, it may be the case that markets of Japan influence non-Granger caused markets indirectly through other markets.

3.6 Short-run Dynamics: Forecast Error Variance Decomposition

Although the VECM and VAR provide an indication of the dynamic properties of the Granger-causality test, they are strictly within-sample tests. They do not allow any estimation of the relative strength of the Granger-causal chain beyond the sample period. To overcome this problem, and to obtain additional insights into the dynamic pattern and transmission mechanism of stock market linkages, it is necessary to shock the system of stock prices and partition the forecast error variance of each market. This process is called 'forecast error variance decomposition' (VDC).

The variance decomposition analysis illustrates the system dynamics by decomposing the variation in the endogenous variable into component shocks to the VAR. This gives an indication of the relative importance of each random innovation as it affects the variables in the VAR, thus showing the overall relative importance of the markets in generating fluctuations in their own and other markets. If, for example, shocks to one variable fail to explain the forecast error variances of another variable (at all horizons), the second variable is said to be exogenous with respect to the first one. The other extreme case is if the shocks to one variable explain all the forecast error variances of the second variable at all horizons, so that the second variable is entirely endogenous with respect to the first. In this study, since a cointegrating relationship has been found, a VECM framework is adopted for analyzing variance decomposition.

A vector autoregression (VAR) model has the following structure:

$$A_0 y_t = \sum_{j=1}^{J} A_j y_{t-j} + \varepsilon_t , \quad t = 1,...,T \tag{3.10}$$

Here y_{t-j} are k-dimensional vectors of endogenous variables at time t-j, A_0, A_j are the $k \times k$ parameter matrices, ε_t is a vector of disturbances and J is the lag length.

Because multiplication of equation (3.10) with any non-singular $k \times k$ matrix results in an equivalent representation of the process generating y_t, we can estimate the so-called *reduced* form of the model. The reduced form of the system is obtained by pre-multiplying equation (3.10) with A_0^{-1}, which gives:

$$B(L)y_t = u_t, \quad t = 1,...,T \tag{3.11}$$

Here $B(L)$ is a matrix polynomial with lag operator L:

$$B(L) = I - B_1L - B_2L^2 - ... - B_pL^P, \quad t = 1,...,T \tag{3.12}$$

And $B_p = A_0^{-1}A_p$, $j = 1,...,P$, $u_t = A_0^{-1}\varepsilon_t$. Equation (3.11) can be transformed into a vector moving average (VMA) representation:

$$y_t = \Pi(L)u_t = \sum_{j=0}^{\infty}\Pi_j u_{t-j}, \quad t = 1,...,T, \tag{3.13}$$

Here $\Pi(L) = B(L)^{-1}$ and $\Pi_0 = I$. A sufficient condition is that the variables in the system are stationary. The forecast error variance decomposition (VDC) can be derived from the VMA representation of the model described in equation (3.13). The τ -period forecast error is equal to:

$$y_{t+\tau} - E_t y_{t+\tau} = \sum_{i=0}^{\tau-1}\Pi_i u_{t+\tau-i} \quad t = 1,...,T \tag{3.14}$$

Here Π_i are the $k \times k$ parameter matrices of the VMA representation in equation (3.13), E_t denotes expectations formulated at time *t*, based on the estimated VAR model. Focusing, for example, on $y_{1,t}$, the first element of vector y_t, the forecast error can be written as:

$$y_{1,t+\tau} - E_t y_{1,t+\tau} = \sum_{r=1}^{k}\sum_{i=0}^{\tau-1}\pi_{1r,i}u_{r,t+\tau-i} \quad t = 1,...,T \tag{3.15}$$

Here $\pi_{1r,i}$ is the element of the Π_i matrix in the 1st row and *r*th column and $u_{r,t+\tau-i}$ is the *r*th element of the $u_{t+\tau-i}$ vector. Since the variances of the disturbance terms are all equal to one, the τ -step ahead forecast error variance of $y_{1,t}$ can be derived from the following expression:

$$\sigma_{y1}^2(\tau) = \sum_{r=1}^{k} \sum_{i=0}^{\tau-1} \pi_{1r,i}^2 , \quad t = 1,...,T \tag{3.16}$$

Here $\sigma_{y1}^2(\tau)$ denotes the forecast error variance of variable y_1 at step τ . The forecast error variance can be decomposed into the contributions of each of the variables in the system. The proportions of $\sigma_{y1}^2(\tau)$ that can be attributed to shocks in each variable y_r, $r = 1,...,k$ at step τ are :

$$\frac{\sum_{i=0}^{\tau-1} \pi_{1r,i}^2}{\sigma_{y1}^2(\tau)}, \quad t = 1,...,T \tag{3.17}$$

According to the Cholesky decomposition, the order of the series is important because changing the order may alter the dynamics of the VAR system and change the interpretation of the results[12]. In this study, since the closing price index is used, the countries are ordered according to stock market closing time. That is, the Philippine market is first and the Thai market last. The order is therefore: Philippines, Japan, Korea, Hong Kong, Singapore, Malaysia, Indonesia, Thailand[13].

[12] McMillin and Koray (1990) report that the pattern of response in VAR analysis is sensitive to different orderings. However, Mathur and Subrahmanyam (1990) found that the change in ordering had a negligible impact on the VDCs.

[13] Orderings of these variables based on the opening time were tried. However, this did not alter the results to a substantial degree.

Table 3.9 Decomposition of Variance for Pre-crisis Model

		Percentage of Forecast Variance Explained by Innovations in							
		PHI	JP	KR	HK	SG	MA	IND	THA
Days	Variables Explained								
5	PHI	95.12	0.42	0.08	2.38	0.87	0.46	0.04	0.64
10		90.89	0.26	0.21	5.51	2.04	0.27	0.29	0.52
15		83.67	0.61	0.17	10.18	3.53	0.30	0.89	0.66
Days									
5	JP	0.22	98.00	0.84	0.03	0.09	0.03	0.14	0.65
10		0.16	95.15	1.13	0.11	0.17	0.60	0.84	1.83
15		0.15	92.45	1.48	0.26	0.70	0.83	1.99	2.14
Days									
5	KR	0.01	0.53	98.41	0.55	0.17	0.03	0.04	0.25
10		0.02	0.96	96.98	0.87	0.23	0.41	0.16	0.35
15		0.07	0.75	96.52	1.51	0.22	0.39	0.20	0.34
Days									
5	HK	8.00	1.59	0.87	88.81	0.16	0.29	0.23	0.06
10		8.21	1.14	1.20	85.54	0.25	2.27	1.33	0.05
15		8.27	0.93	1.52	84.66	0.17	3.03	1.38	0.05
Days									
5	SG	8.38	4.15	1.98	21.95	62.76	0.09	0.62	0.08
10		10.71	3.46	3.19	24.63	56.17	0.77	1.00	0.08
15		10.57	3.56	3.34	28.35	51.22	0.61	2.30	0.06
Days									
5	MA	7.50	2.82	0.79	19.48	23.41	45.47	0.21	0.33
10		12.00	2.23	1.28	22.02	24.35	37.61	0.16	0.35
15		13.44	1.83	1.81	25.50	24.13	32.86	0.20	0.24
Days									
5	IND	12.50	1.94	0.48	10.52	6.65	1.62	65.30	0.99
10		15.29	2.70	0.68	15.00	6.52	0.93	57.49	1.41
15		17.86	2.57	0.51	20.52	7.60	0.54	49.03	1.36
Days									
5	THA	6.28	0.12	0.44	9.02	4.91	1.38	1.09	76.76
10		9.36	0.07	0.31	8.65	5.01	1.00	1.49	74.10
15		9.66	0.06	0.96	8.72	5.12	0.86	1.28	73.35

Note: Each entry in the tables denotes the percentage of forecast error variance of markets on the left-hand side explained by the markets at the top.
The VDC estimated based on VECM.

Table 3.10 Decomposition of Variance for Crisis Model

Days	Variables Explained	PHI	JP	KR	HK	SG	MA	IND	THA
		Percentage of Forecast Variance Explained by Innovations in							
5	PHI	87.88	0.77	1.68	1.73	1.96	1.56	2.01	2.41
10		87.44	0.79	1.70	1.78	2.02	1.76	2.03	2.48
15		87.43	0.79	1.70	1.78	2.02	1.76	2.04	2.48
Days									
5	JP	3.65	90.06	1.97	0.45	0.22	0.98	1.94	0.74
10		3.73	89.54	2.07	0.58	0.30	0.99	2.01	0.78
15		3.73	89.52	2.07	0.58	0.31	1.00	2.01	0.78
Days									
5	KR	2.49	3.54	88.00	2.30	0.98	0.30	0.15	2.24
10		2.66	3.61	87.40	2.41	1.07	0.34	0.25	2.27
15		2.66	3.61	87.36	2.41	1.08	0.34	0.25	2.27
Days									
5	HK	19.56	7.65	3.92	61.82	2.20	0.77	2.54	1.54
10		19.51	7.70	3.97	61.23	2.57	0.86	2.57	1.59
15		19.50	7.71	3.98	61.20	2.57	0.86	2.57	1.60
Days									
5	SG	32.30	4.37	2.28	18.25	37.85	2.10	2.70	0.16
10		32.06	4.39	2.37	18.15	37.79	2.26	2.71	0.27
15		32.05	4.39	2.38	18.14	37.78	2.27	2.71	0.27
Days									
5	MA	5.49	2.70	4.65	5.83	3.65	73.37	3.06	1.25
10		5.59	2.72	4.66	5.87	3.82	72.94	3.12	1.28
15		5.59	2.73	4.66	5.87	3.83	72.92	3.12	1.28
Days									
5	IND	12.06	4.03	7.80	4.28	6.99	1.57	62.52	0.75
10		12.17	4.05	7.80	4.32	7.10	1.73	61.98	0.85
15		12.17	4.05	7.81	4.32	7.09	1.74	61.97	0.85
Days									
5	THA	15.73	3.62	7.97	4.47	6.18	2.04	3.10	56.90
10		15.82	3.62	8.05	4.46	6.39	2.09	3.10	56.50
15		15.82	3.62	8.05	4.46	6.39	2.09	3.10	56.49

Note: Each entry in the tables denotes the percentage of forecast error variance of markets on the left-hand side explained by the markets at the top.
The VDC estimated based on unrestricted VAR

Table 3.11 Decomposition of Variance for Post-crisis Model

		Percentage of Forecast Variance Explained by Innovations in							
		PHI	JP	KR	HK	SG	MA	IND	THA
Days	Variables Explained								
5	PHI	95.18	0.31	1.51	0.58	1.02	0.33	0.06	1.01
10		89.59	0.49	2.48	1.63	1.80	0.24	0.11	3.65
15		85.84	0.75	3.91	2.57	2.25	0.29	0.07	4.33
Days									
5	JP	2.29	96.41	0.23	0.45	0.12	0.08	0.18	0.25
10		2.86	94.75	0.25	0.64	0.47	0.05	0.72	0.26
15		3.09	93.00	0.51	0.70	1.13	0.23	0.88	0.46
Days									
5	KR	5.17	16.52	74.59	1.67	0.68	0.97	0.23	0.16
10		6.74	18.49	66.37	4.95	0.70	1.40	0.75	0.60
15		6.61	17.88	66.83	5.17	0.56	1.15	0.95	0.86
Days									
5	HK	5.01	14.86	13.45	64.83	0.38	0.52	0.55	0.40
10		5.67	14.58	13.95	63.39	0.35	0.39	1.19	0.49
15		5.35	13.13	15.46	62.59	1.22	0.35	0.99	0.92
Days									
5	SG	5.30	10.77	12.01	14.70	56.90	0.04	0.05	0.23
10		9.19	9.80	14.19	20.29	45.64	0.30	0.12	0.47
15		10.94	8.67	17.98	22.58	38.79	0.43	0.25	0.36
Days									
5	MA	1.07	6.37	1.89	3.06	4.75	82.54	0.20	0.13
10		0.91	5.88	3.18	4.38	5.39	78.92	1.21	0.14
15		1.68	4.17	6.02	6.76	6.18	73.00	2.09	0.09
Days									
5	IND	4.76	2.00	2.50	1.94	4.47	0.25	83.35	0.73
10		8.31	4.28	5.16	2.17	5.70	0.84	70.98	2.55
15		9.80	4.98	7.64	3.40	5.73	1.53	64.38	2.55
Days									
5	THA	10.87	6.13	8.58	4.78	4.69	1.89	1.12	61.94
10		14.11	6.68	9.88	5.89	3.16	2.62	0.62	57.03
15		15.14	5.47	14.39	6.24	2.19	3.08	0.74	52.76

Note: Each entry in the tables denotes the percentage of forecast error variance of markets on the left-hand side explained by the markets at the top.
The VDC estimated based on VECM

Table 3.12 Decomposition of Variance for Recovery Model

		Percentage of Forecast Variance Explained by Innovations in							
		PHI	JP	KR	HK	SG	MA	IND	THA
Days	Variables Explained								
5	PHI	94.91	0.66	0.33	1.36	1.04	0.10	0.54	1.06
10		91.52	1.70	0.53	1.17	1.77	0.40	0.65	2.25
15		88.04	3.14	0.62	1.24	2.87	0.34	0.62	3.13
Days									
5	JP	9.27	89.30	0.29	0.22	0.26	0.47	0.04	0.16
10		8.34	89.02	0.22	0.12	0.14	1.43	0.06	0.66
15		5.83	90.64	0.28	0.37	0.34	1.40	0.22	0.92
Days									
5	KR	8.40	27.75	62.79	0.12	0.08	0.02	0.05	0.78
10		8.26	28.96	60.42	0.39	0.27	0.17	0.13	1.38
15		6.28	30.33	59.34	0.57	0.68	0.73	0.18	1.89
Days									
5	HK	5.77	16.90	9.89	66.70	0.26	0.10	0.04	0.34
10		4.80	16.88	8.43	67.67	0.64	0.10	0.09	1.39
15		3.50	15.67	7.53	60.36	10.66	0.56	0.20	1.52
Days									
5	SG	13.18	18.23	5.93	13.75	48.59	0.01	0.17	0.15
10		14.02	20.38	3.92	13.77	46.71	0.34	0.49	0.36
15		10.79	21.76	3.42	17.66	44.80	0.65	0.48	0.45
Days									
5	MA	5.67	9.09	1.63	5.27	9.00	69.13	0.04	0.19
10		4.21	13.46	1.11	5.22	8.86	66.45	0.39	0.30
15		3.07	15.58	0.88	8.48	9.18	62.05	0.38	0.39
Days									
5	IND	9.00	10.11	7.87	6.16	3.73	0.62	62.01	0.51
10		7.70	13.73	8.63	5.34	3.75	0.33	59.31	1.21
15		5.84	14.50	8.11	4.71	4.20	0.61	60.00	2.03
Days									
5	THA	4.90	5.25	4.80	1.76	1.78	1.26	0.83	79.42
10		4.85	9.11	4.02	1.02	1.35	1.01	0.69	77.95
15		3.96	11.04	3.28	0.86	1.07	0.69	0.49	78.60

Note: Each entry in the tables denotes the percentage of forecast error variance of markets on the left-hand side explained by the markets at the top.
The VDC estimated based on VECM

The variance decomposition results are presented in Tables 3.9 to 3.12 for the pre-crisis, crisis, post-crisis and recovery models respectively. Results for four alternative days are reported although results are discussed only for the 15-day horizon, on the assumption that the intermediate horizons represent the continuing dynamic adjustment of the stock market in each country to a particular shock.

The main diagonal shows the 'degree of exogeneity', representing how much of a market's own variance is explained by its own shock over the forecast horizon. If a variable explains most of its own shocks, then the variances of other variables do not contribute to the explanation and it is therefore said to be relatively exogenous. 'Degrees of exogeneity' from the above tables are summarized for all sub-periods in Table 3.13.

Table 3.13 Comparison of 'degree of exogeneity'

	Degree of exogeneity (%)			
	Pre-crisis	Crisis	Post-crisis	Recovery
Philippine	83.67	87.43	85.84	88.04
Japan	92.45	89.52	93.00	90.64
Korea	96.52	87.36	66.83	59.34
Hong Kong	84.66	61.20	62.59	60.36
Singapore	51.22	37.78	38.79	44.80
Malaysia	32.86	72.92	73.00	62.05
Indonesia	49.03	61.97	64.38	60.00
Thailand	73.35	56.49	52.76	78.60

Since no variance is completely accounted for by its own shocks, it is clear that none of the Asian stock markets is completely isolated from the others. The first column of Table 3.13 reveals that market integration before the financial crisis was limited and markets were relatively segmented. For example, in relatively exogenous Philippine, Japanese Hong Kong and Korean stock markets almost 80%-90% of the forecast error variance is explained by their own shocks. Other market that appears relatively exogenous is Thailand, where 70% of its variance is explained by its own innovations. By far the most endogenous markets are Singapore, Indonesia and Malaysia, where approximately half of the variance is explained by innovations in other markets. In order to understand how much any one market is dependent on others, it is necessary to examine further the variance decomposition results shown in Table 3.9. These suggest that Hong Kong and Singapore have the largest effect on Malaysia, together explaining almost 50% of the forecast error variance in Malaysia (Hong Kong accounts for 26%, Singapore for 24%). This could be explained by the strong economic ties and close geographic proximity between these three countries. Moreover, the Hong Kong stock market appears to exert relatively great influence on other markets generally. Innovations in Hong Kong explain 28% of the forecast error variance in Singapore, 25% in Malaysia, 20% in Indonesia and 8% in Thailand. The dominant role of Hong Kong during the pre-crisis period is in agreement with the earlier results provided by the within-sample multivariate Granger-causality tests.

Variance decomposition (VDC) results also support these findings and show the importance of the 1997 financial crash. In general, the crash brought about significant changes to the interactive dependency of markets. This can be seen from differences in the decomposition results before and during the period of the crisis. Table 3.13 clearly shows that, the 'degree of exogeneity' for most of countries were reduced during the crisis period, implying that markets became more endogenous (more dependent on other markets). This is consistent with the Granger causality test results showing that stock market interdependencies were strengthened during the crisis. Furthermore, it is interesting to observe that the 'degree of exogeneity' in Japan was reduced by less (only reduced around 5%) than in other stock markets. This indicates that Japan responded only weakly to innovations in other countries during the crisis period. The 'degree of exogeneity' increased in Malaysia during the crisis period (from 32.86% to 72.92%), indicating that Malaysia was slightly alienated from the region during the crisis period. More detailed insights into the findings of the variance decomposition analysis can be found by examining the results for the crisis period shown in Table 3.10. Here the VDC results for the crash period show that the impact of Hong Kong and Singapore market on the Malaysian market fell significantly from the pre-crash period, from 50% to only about 9% of the forecast error variance. This result could indicate that the propagation mechanism among the three markets was significantly altered by the financial crash.

In the post-crisis model, examining the 'degree of exogeneity' in Table 3.13 reveals that for the majority of markets, the percentage of forecast error variance that can be explained by other markets is not significantly changed compared to the crisis period. Some other interesting results can be observed in Table 3.11, including the increased influence of the Japanese market on fluctuations in other markets. During the post-crisis period, Japan explains 18% of the variance of Korea, 13% for Hong Kong and 9% for Singapore. In addition, Japan also explains around 10%-15% of variance for Indonesia and Thailand. In contrast, no market can explain more than 3% of the variance of Japan. This result is in agreement with the Granger causality tests, reported earlier, that show the increasing influence of Japan after the financial crisis.

With respect to the recovery period, Table 3.13 shows that Singapore becomes more exogenous than before. Table 3.12 further reveals that innovations in the Singapore market account for a much greater proportion of the error variance in other Asian stock markets than is the case in reverse. For instance, the Singapore market explains 10% of the forecast error variance in Hong Kong, 10% in Malaysia and, and around 5% in Indonesia. This implies that the Singapore has become one of the leading stock markets in Asia in more recent years. Before 2003, Singapore is an 'endogenous' market with almost 50 percent of its forecast error variance explained by the other markets in the system. This shows the early openness of the Singaporean stock market and its vulnerability to shocks occurring in leading stock markets. In the past, due to geographical and economical proximity, Singapore and Hong Kong had strong linkages. However, while Hong Kong exerted considerable influence of about 28% on Singapore, Singapore had hardly any impact on Hong Kong. Singapore accounted for no more than 1% of the forecast error variances of Hong Kong. Therefore, Singapore was quite easily influenced by shocks from Hong Kong before 2003. In contrast, the interaction mechanism between Singapore and Hong Kong substantially changed during the recovery period, with Singapore accounting for approximately 10% of the forecast error variance in Hong Kong, and Hong Kong explaining only 17% of the forecast error variance of Singapore. Furthermore, during the recovery period, the 'degree of exogeneity' of the majority of markets is lower than in the post-crisis period. For example, in the markets of Korea and Hong Kong Malaysia and Indonesia, up to 40% of the shocks are explained by innovations in other markets. This result strongly suggests that Asian stock markets have become more open and more interdependent in recent years. Finally, innovations in Japan lead to large fluctuations in Korea, Hong Kong and Singapore. In addition, the Japanese market also explains part of the error variances of Malaysia, Indonesia and Thailand. This supports the findings reported in the previous sections and leads to the conclusion that the influence of the Japanese stock market has become stronger in the Asian region after the financial turmoil.

Monetary policies during the crisis

It is possible that some of the differences between the crisis period results and those of other sub-periods may be caused by different monetary policies and it is therefore interesting to explore these further.

Monetary policy is normally implemented by manipulating interest rates (such manipulation also has implication for exchange rates). The following paragraphs examine interest rate and exchange rate movements in the crisis-hit countries[14].

Following Fukuda (2002), all Asian countries appear to have used *de facto* pegs to the U.S. dollar. During the crisis, they allowed their currencies to be devalued against the dollar. They reverted to a peg against the dollar as the crisis ended.

The Asian financial crisis started in Thailand in mid-1997, with the Thai baht under significant pressure due to speculative attacks. The initial response from the Thai government was intervention in the foreign exchange market. Following a significant worsening of the foreign reserve position, the baht was floated in early July 1997. Since these actions failed to stop the sharp decline in the value of the baht, the Thai government sought assistance from the IMF in early August 1997. After an agreement was reached with the IMF, interest rates in Thailand were raised sharply and kept relatively high for the remainder of 1997 and early 1998. Toward mid-1998 interest rates were gradually reduced, following a gradual return of stability in the currency market.

[14] Excess returns will not be looked at since the risk-free rate is benchmarked to treasury bills that are not issued daily.

Following the speculative attacks on the baht, other currencies also came under significant downward pressure.

Malaysia experienced a serious devaluation of the ringgit and the initial response of the government was a sharp increase in the official interest rate. On September 1998, the Malaysian government shifted its exchange rate from a managed float to a fixed exchange rate. Malaysia did not seek assistance from the IMF and interest rates in that country remained relatively stable thereafter.

The Philippine peso also experienced serious devaluation of its currency from August 1997. Domestic interest rates rose in the second half of 1997. For example, in early October 1997, the overnight interbank call rate increased from around 12% to 102% within a few days. In early 1998, the peso stopped falling against the dollar and movements in domestic interest rates stabilized.

In Indonesia, with fears of a banking system collapse, the authorities chose to float the rupiah against the $US on 14 August and to increase interest rates, with overnight rates rising to near 100%. Between late October and early December 1997 the Indonesian rupiah came under increasing pressure. At the end of October, Indonesia announced a $23 billion external assistance package led by the IMF. Monetary policy was to be geared to defend the exchange rate and to avoid a spread of panic.

In Korea, the authorities allowed the currency to depreciate against the dollar between July and September 1997. However, between late October and early December 1997, a crisis of external debt financing emerged. In response, domestic interest rates were raised significantly. The Korean government also sought assistance from the IMF in early December 1997. In the first few months of 1998, the Korean exchange rate and overnight call rate fluctuated sharply. A solution emerged after an agreement reached with foreign banks to roll over most of Korea's short-term debts, with stability gradually returning to the foreign exchange market.

In October 1997, the Hong Kong dollar, which had been pegged at 7.8 to the U.S. since 1983, came under speculative pressure. The Hong Kong Monetary Authority imposed controls on capital outflows and raised interest rates to defend the local currency. Finally, the Monetary Authority (effectively the city's central bank) spent more than US$1 billion but managed to maintain the peg.

Since the early 1990s Japan had maintained a loose monetary policy (zero interest rate policy) in order to boost bank lending and growth in the real economy. This monetary policy did not significantly change during the crisis.

It can be seen that virtually all countries at the centre of the Asian financial crisis adopted a high interest rate policy in an attempt to defend their currencies. This action is consistent with the traditional view that tight monetary policy is necessary for supporting a currency (higher interest rates increase the return on investment and hence reduce capital outflows, discouraging speculative attacks on the currency). However, an alternative view is that a tightening of monetary policy may be counter-productive when balance of payment crises occur simultaneously with financial crises, as is the case of the Asian financial crisis. This is because sharply higher interest rates will adversely affect economic activity and financial market confidence, leading to further depreciation of the currency (Caporale, Cipollini and Demetriades, 2000).

To summarize, the appropriateness of using a high interest rate policy to defend the exchange rate for Asian countries in the financial crisis has been the subject of significant debate among researchers. This issue is a natural extension of the work and undoubtedly a subject for future research.

3.7 Summary, conclusions and policy implications

This chapter investigates long-term and short-term relationships in Asian equity markets during the period from 1992 to 2007. Special attention is given to the impact of the 1997-1998 Asian financial crisis on the index returns of eight Asian economies. The Johansen multivariate cointegration technique is first implemented to determine whether long-term relationships exist (or existed) between Asian stock markets. Thereafter, Granger causality tests are performed for the total period and pre-crisis, crisis, post-crisis and recovery sub-periods, to capture the impact of the crisis on time-varying lead-lag relationships between the markets. Finally, short-term causal relationships before, during and after the financial crisis are examined by variance decomposition. As a precondition for the test of cointegration, each return series is also tested for stationarity (the results indicate that all market return series are stationary after first differencing).

The cointegration analysis suggests that a single cointegrating relationship among the return series for the total period as well as for the pre-crisis, post-crisis and recovery sub-periods under investigation. The findings strongly point toward a long-run equilibrium relationship between the sampled Asian markets. The Granger causality and variance decomposition analyses are also employed to capture the short-run dynamics among the series. The results reveal significant and substantial short-run relationships between these markets. The high integration of Asian equity markets may be attributable, at least in part, to the long-standing trends in trade and investment interactions, the more recent convergence in monetary policies and the almost universal process of economic reform.

The cointegrating vectors are further investigated using zero-loading restriction tests. The results show that the sampled markets were relatively segmented prior to the 1997-1998 Asian financial crisis. However, the level of long-run integration appears to be stronger in the post-crisis and recovery periods than was the case in the pre-crisis period. Increased cross-country market integration after the crisis implies that these Asian stock markets now simultaneously adjust to new information, thereby eliminating opportunities for any abnormal profits that may have been associated with lagged information processing. The Granger causality and variance decomposition analyses show quite similar results. A number of additional results were obtained and a summary of them follows.

First, market reforms and the increasing globalization of financial markets in the early 1990s has brought the equity markets of Asian countries closer together. Prior to the financial crisis, Hong Kong apparently played a dominant role in Asia, exhibiting strong influence on almost all other markets in the sample. Although Hong Kong played a key role during the 1990s, its influence was significantly diminished during the recovery period and it was replaced as the leading market by Singapore. This finding is supported by variance decomposition analysis, where Singapore is seen to exert substantial influence on Hong Kong in the recovery period, while the reverse is not the case.

Second, Granger causality test results indicate that significant two-way causality relationships between the returns of Asian stock markets existed during the crisis. The increase in feedback causality during the month of the market crash suggests that the crash started more or less simultaneously in all countries sampled.

Third, unlike previous studies, which found either a leading role for Japan (Ghosh, Saidi and Johnson, 1999; Masih and Masih, 2001) or no leading role (Yang, Kolari and Min, 2003), the results here show that the Japanese stock market started exerting its leading role <u>after</u> the financial crisis and that this has intensified in more recent years. The impact of Japan after the crisis may be because information from the Japanese stock market, with its economic dominance in the Asian region, is of special importance to investors. Before the financial crisis, due to segmentation of markets in the Asian region, investors may have focused mostly on information generated within their own markets. After experiencing the financial crisis, investors may have realized that the Japanese stock market could behave as a safe harbour for portfolio diversification since it did not show many causal links to other stock markets during the crisis. Therefore, after the financial crisis international investors may have tended to overreact to news from the Japanese market, placing less weight on information from other markets.

Fourth, close relationships are found between the returns of Indonesia, the

Philippines, Malaysia and Thailand. This is probably due to their similar financial and regulatory structure.

Fifth, the findings also highlight some disparities in the extent of market integration among the Asian equity markets. Granger-causal relationships show that the developed markets with larger market capitalization (Japan, Korea, Singapore and Hong Kong) normally Granger-cause the returns of some of the emerging markets with smaller capitalization (Malaysia, Philippines, Indonesia). However, it is hard to detect causal influence by emerging markets on developed markets. This finding is further reinforced by the variance decomposition analysis, where developed markets have extremely low proportions of variance explained by emerging markets, while developed markets are considerably more important in explaining the behaviour of emerging markets.

Sixth, Malaysia, which imposed restrictions on cross-country investment after the financial crisis, became less responsive to innovations in foreign markets. Around 50% of the error variance in the Malaysian stock market could be explained by the collective shocks to the other markets before the crisis but less 20% of error variance can be so explained in the post-crisis period.

Seventh, the Korean stock market is the only market to exhibit a causal influence on both Hong Kong and Japan during the pre-crisis period. However, this relationship is absent during the crisis and its aftermath.

Several policy and economic implications can be derived from these findings. First, the results show an enhanced integration of stock markets in Asia, resulting in a reduction of portfolio diversification benefits over time. Second, financial integration in the Asian region can bring positive payoffs. For instance, it is well known that when a financial market is integrated with other markets it has increased ability to attract productivity-enhancing investment from abroad, injecting liquidity into the domestic market. The rapid growth of the emerging Asian markets in the early 1990s, gaining benefits from large capital inflows, is a good example. On the other hand, financial integration also brings systemic risks, as illustrated by the Asian financial crisis, including the danger of rapid capital flow reversals.

Specifically, the empirical results obtained here show that Asian economies are not immune from external shocks within the region. These findings suggest that Asian countries need to strengthen their financial system and regulatory framework before opening their capital markets. Third, the strong causality results emanating from Hong Kong and Singapore indicate the immense role these markets play in Asian financial market integration. Fourth, policy makers should be concerned about economic and financial developments not only in their domestic markets, but also in other financial markets in the region when designing policy. Finally, despite the relatively high number of interdependencies and overall degree of integration, the degree of financial integration of Asian stock markets is still lower than in the European Union. This can be illustrated by the variance decomposition results. For example, for the majority of Asian stock markets, more than 70% of their forecast error variance is explained by their own innovations (in some cases more than 80%). In other words, only 30% of the variance is explained by other markets. This phenomenon appears even in the most active market, Hong Kong, where about 50% of forecast error variance is explained by its own innovations. As a point of comparison, recent work by Worthington, Katsuura, Masaki and Higgs (2003a) found that non-domestic markets explained 50% of the variance for the French stock market, 65.9% for Germany, 60.1 for the Netherlands and 65% for Spain. This indicates that, compared with the European Union, financial integration in the Asian region has a considerable way to go.

Appendix 3.1 The Chronological table of the big events in Asia

Date	Country	Description of what happened
May 14-15,1997	Thailand	Thailand's baht currency is hit by massive sell-off
July 2, 1997	Thailand	After four months of defending the weakening baht, the Bank of Thailand announced free float of baht. Baht loses 10% of its pre-float value.
July 20	Philippines	IMF grants US $ 1000 million as emergency grant after Peso falls outside a widened band to defend the basket peg
July 24	Malaysia	Malaysia Ringgit comes under speculative attack.
August 11	Thailand	IMF led by Japan's pressure pledges US $ 16 billion to Thailand as rescue package
	Indonesia	Indonesia's Rupiah under attack. Bank Indonesia's attempt to solve the troubles proved unsuccessful.
September 4	Philippines	Philippine Peso falls to the lowest level before central bank intervenes to maintain basket peg
	Malaysia	Malaysia spends US $ 20 billion to prop the share market
October 8	Indonesia	Indonesia considers asking IMF for an emergency bailout
October 20-23	Hong Kong	Hong Kong stock market declined by nearly 25% in value in 4 days
November 3	Japan	Japan's Sanyo Securities files for bankruptcy
	South Korea	South Korea Won loses 7%, biggest one-day loss
	South Korea	South Korea begins talk with IMF for tens of billions in emergency aid
November 8	Japan	Japan's third financial house to apply for closure: the seventh largest Yamaichi Securities
November 12	Japan	Nikkei-225 stock index fell to its historical lowest level
November 14	Japan	Major sell-off in Japan as a result of rising concerns about the health of the financial system. Nikkei-225 fell 2.33%
November 20	South Korea	Korean Stock Market plunges with a loss of 7.2%
November 24	Japan	Tokyo City Bank, a regional bank closes
November 25	South Korea	Korea agrees to IMF conditions for restructuring $55 billion
December 3	Malaysia	Malaysia imposes tough reforms
December 22	South Korea	Korean won plunges further
December 25		IMF and lender nations finance US $ 10 billion to Korea
January 12, 1998	Hong Kong	Peregrine of Hong Kong files for liquidation from stock market loss
May 21	Indonesia	Indonesia's President Suharto resigns after a wave of bloody riots
September 1	Malaysia	Malaysia announces going back to fixed. All free market currency transactions is abolished
December 1998	Asia	Most currencies that had overshot (Baht; Rupiah; Peso; Won) recovered about half way from their worst declines.

Source: Internet publications of Asian Reports, 1997-1998.

Appendix 3.2 Asian Capital Access Index

Capital Access Index (CAI)

	2007		2006		2005	
Country	CAI	Rank in the world	CAI	Rank in the world	CAI	Rank in the world
Hong Kong	8.27	1	8.07	1	7.84	2
Singapore	7.88	4	8.00	2	7.77	3
Malaysia	7.14	13	7.12	12	6.88	16
Japan	7.07	15	6.88	16	6.76	19
Korea	6.87	19	6.58	20	6.37	23
Thailand	6.36	26	6.61	19	5.71	30
Philippines	4.50	62	4.67	56	4.44	58
Indonesia	4.40	64	4.34	63	4.48	57

Notes: Data is only available for these three years

Source: 2007 Capital Access Index, Capital Studies, Milken Institute, January 2008

Chapter 4 Modelling Stock Volatility and Examining the Day of the Week Effect on Stock Return and Volatility

4.1 Introduction

In Chapter 3, we highlight the time series behaviour of stock returns. In this chapter we investigate the presence of volatility effects in stock prices attributable to uncertainties in the price fluctuations themselves (variations in the volatility of stock returns).

Volatility is important to finance. This is mainly because volatility is synonymous with risks. For a rational financial decision maker, returns constitute only one part of the decision-making process. Another part that must be taken into account is the risk or volatility of returns. Engle (1991) argues that risk-averse investors should reduce their investments in assets with higher return volatilities. Therefore, the investigation of volatility patterns is a useful exercise. Meanwhile, as discussed in the previous chapters, the 1997-98 Asian financial turmoil rocked Asian equity markets severely. During that period, stock market volatilities in Asian stock exchanges increased substantially and investors' confidence was badly shaken. Thus, after the financial crisis the high volatility in the stock market received a great deal of attention from market participants, including investors, dealers, brokers and regulators. Market participants care more about stock market volatility, not just because it is perceived as a measure of risk, but also because they worry about the excessive volatility in which observed fluctuations in stock prices are not accompanied by important news about market fundamentals. In addition, greater volatility may also increase the cost of waiting by investors, thereby delaying investment and economic growth. Given these concerns, the main objective of this chapter is to characterize the dynamic behaviour of stock returns and volatility in Asian stock markets. In particular, we will pay attention to two important aspects. First, because volatility is a key input to pricing financial products and asset allocation decisions, we look at this parameter for Asian stock markets. In addition, particular attention is given to the empirical relationship between stock returns and volatility by employing a Threshold Autoregressive GARCH (1,1)-in-mean specification. Moreover, since some previous studies have shown that stock market volatility surged dramatically during the financial crisis (Daly, 2003), it is interesting to examine whether volatilities in Asian stock markets calm down after the crisis and whether the volatilities go back to pre-crisis levels.

Secondly, day-of-the-week effects patterns in returns and volatility also play an important role for investors wishing to take advantage of relatively regular shifts in the market by designing trading strategies that exploit such predictability. If investors can identify patterns in both returns and volatility, then it is easier to make investment decisions and design profitable strategies. For example, if investors know whether there are variations in volatility that arise from day-of-the-week effects (whether a high (low) return is associated with a corresponding high (low) return for a given day) then they may adjust their portfolios accordingly. Moreover, evidence of day-of-the-week effects appears to conflict with the efficient market hypothesis since these imply that investors could develop trading strategies to benefit from these seasonal regularities. Having considered whether day-of-the-week effects are empirically important, we extend the analysis by both examining the behaviour of these effects over time and attempting to explain any observed instabilities.

This chapter is structured as follows. Section 4.2 provides a brief review of the literature. Section 4.3 contains a description of the models of expected stock returns, volatility and day-of-the-week effects used in this chapter. Section 4.4 contains a discussion of the empirical evidence. Section 4.5 concludes the chapter.

4.2 Literature Review

4.2.1 Volatility Modelling

To capture the volatility in financial time-series, several models of conditional volatility have been proposed. In particular, the Autoregressive Conditional Heteroskedasticity (ARCH) process proposed by Engle (1982) and many of its generalizations (such as the GARCH model developed by Bollerslev, 1986) have been successfully applied to asset pricing, problems of optimal portfolio choice, strategies of dynamic hedging and pricing of derivative securities[15]. In these models, one very common finding is that shocks to volatility are often persistent.

In stock markets, besides the high persistence in volatility of stock returns, the consequences of financial liberalization for stock markets in emerging markets have been under close observation from many researchers. This is mainly because such liberalization may bring more foreign investors and cause changes in volatility. The findings are, however, by no means consistent. Richards (1996b) use an autoregressive conditional heteroskedasticity (ARCH) approach to examine volatilities of nine emerging markets (Argentina, Chile, India, Korea, Brazil, Greece, Mexico, Thailand and Zimbabwe), covering the period from December 1975 to September 1995. He finds no evidence to support the assertion that the volatility of stock returns in emerging markets increased following financial liberalization. He suggests that emerging market returns, although always volatile, may actually become less volatile following increased foreign participation. The rationale is that domestic capital could easily move abroad in the pre-liberalization period, making large changes in asset prices more likely. However, the opening of markets allows more investors to share a given amount of risk, therefore reducing the volatility of returns. Another study carried out by Kassimatis (2002) supports the findings of Richards (1996b). He investigates whether stock market volatility increased following financial liberalization in six developing countries (Argentina, India, Philippines, South Korea, Pakistan and Taiwan). An EGARCH

[15] See Schwert (1989, 1990) and Bollerslev, Chou and Kroner (1992) for a survey of some of these studies.

(Engle and Ng, 1993) model is employed in his analysis. His empirical results show that volatility fell after the sample countries opened up their stock markets to foreign investors, except for the Philippines. However, Gooptu (1993) investigates portfolio flows to emerging markets and reveals that stock market volatility increases after market liberalization. He concludes that the increased volatility may result from herding behaviour and rapid switching of portfolios between markets. In more recent years, emphasis has shifted towards the differential impact of liberalization across countries. For instance, Huang and Yang (2000) examine ten emerging markets, using a GARCH model with generalized error distribution (GED), for the period 1988-98. Their results show that the volatility of the stock markets increased after liberalization in three of the countries analyzed (Mexico, South Korea and Turkey), but decreased in Argentina, Chile, Malaysia and the Philippines. Jayasuriya (2002) adopts an asymmetric GARCH methodology for fifteen emerging markets for a long sample period from December 1984 to March 2000, finding that volatility may decrease, increase or remain unchanged after liberalization. In addition, he concludes that countries that experience higher post-liberalization volatility are generally characterized by lower market transparency, lower investor protection and higher market exit restrictions. Dhir (2007) analyzes twelve developing markets from February 1976 to December 2006. His univariate and multivariate GARCH methodology shows the differential impact of liberalization on volatility. On average, conditional volatility fell during the post-liberalization period in Argentina, Chile, Philippines and Mexico; conditional volatility increased during the post-liberalization period in India, Thailand and Zimbabwe; volatility did not significantly change for Korea, Malaysia, Jordan and Brazil. Further, he finds that the impact of stock market liberalization is conditioned by the degree of market integration prior to liberalization and high integration will lead to lower volatility.

Despite the wide interest in stock market volatility, only a few studies examine whether stock markets have become more volatile after the financial crises. Schwert (1998) investigates the October 1987 crisis and finds that stock volatility peaked during the crisis but returned to pre-crisis levels immediately after the financial turbulence. Law

(2006) investigates the impact of the 1997-98 East Asian financial turmoil on Malaysian equity markets, using the EGARCH model. His empirical results demonstrate that the volatility due to the financial crisis was both high and persistent. Although by the end of his sample period, March 2003, the stock volatility had decreased, it had still not returned to pre-crisis levels.

Two theories address the influence of financial liberalization on financial volatility. The first, 'financial liberalization theory', argues that the liberalization process will increase savings and investment in emerging markets, therefore leading to more stable and high economic growth rates. In the view of liberalization theorists, even if volatility increases, it will not harm the real economy. They consider that the resulting increased information flow could make markets more efficient. On the other hand, in the second theory, 'the Keynesian view', the opening of the financial market will introduce more volatility because of the increased volume and pace of transactions, and that liberalization will both produce an excessive boom-bust pattern in financial markets and destabilize economic development. It seems that evidence from the Asian crisis favours the Keynesian view, but we still need to examine the dynamic pattern of volatility in Asia for significant changes in volatility before and after the crisis. This would allow a more accurate evaluation of the Keynesian view.

4.2.2 Relationships between stock returns and volatility

Another broad application of univariate GARCH models is to examine the relationship between stock returns and volatility (as a proxy for risk). Fortunately, a framework for studying risk and return is provided by the Generalised Autoregressive Conditional Heteroskedasticity-In-Mean (GARCH-M) model of Engle, Lilien and Robins (1987). The advantage of the GARCH-M model is that it handles time series data that fail to satisfy the basic assumptions of the classical linear regression model. It is specified by the equation

$$R_{it} = \alpha + \alpha_1 R_{it-1} + ...\alpha_n R_{it-n} + \beta_i h_t^{1/2} + \varepsilon_{it} \qquad \text{(mean equation)}$$

$$h_t = \omega + \theta\varepsilon_{t-1}^2 + \lambda h_{t-1} \qquad \text{(variance equation)}$$

where h_t is the conditional variance. The inclusion of the conditional variance in the mean equation of GARCH-M is similar to the CAPM in that it describes the presence of a risk component in stock returns. The β_i coefficient is explained as a risk aversion parameter, which assumes a positive linear relationship between the conditional variance and returns. The stability condition for the GARCH (1,1) variance equation is $\theta + \lambda < 1$. In this chapter, GARCH models are estimated on a country by country basis.

Given concerns about the effectiveness of portfolio diversification within the Asian region, understanding the nature of risk and return is very useful. GARCH-M therefore provides a platform for examining the risk-return relationship. Many attempts have been made to explore the relationship between risk and return by using various formulations of the GARCH-M model. The somewhat disappointing result, however, is that most empirical studies have led to controversial findings. Using the GARCH-M model, Baillie and DeGennaro (1990) find little evidence to support a significant relationship between stock returns and volatility in the United States. Shin (2005) also fails to find a significant relationship in his study of fourteen emerging international stock markets.

Black (1976) and Christie (1982), however, point out that stock returns tend to be negatively correlated with changes in volatility. They state that a reduction in the equity value of a firm would raise its debt-to-equity ratio, hence raising the risk of the firm as manifested by an increase in volatility. As a result, volatility will be negatively related to the current return on that stock. Li, Yang, Hsiao and Chang (2005) investigate the twelve largest international stock markets from January 1980 to December 2001. They find evidence of a significant negative relationship between stock returns and volatility in six out the twelve markets. Lee, Lee and Rui (2001) also found significant negative relationships in their study of two Chinese stock exchanges. They argue that the negative relationship is due to the use of *ex post* data as well as the different time frame used in their study.

There are also empirical findings which support the existence of positive and statistically significant relations between risk and return in stock markets. For example, Dean and Faff (2001) apply the EGARCH-M model and find evidence of a positive relationship between the market risk premium and its variance in the Australian stock market. Guo and Neely (2006) examine eighteen international stock markets and report evidence of a significant positive risk-return trade-off. With respect to emerging markets, Salman (2002) finds a positive and significant association between risk and return in the Turkish market. Yakob and Delpachitra (2006) also find a positive linear relationship in China and Malaysia which indicates that investors are compensated for assuming high risk. In general, these positive findings imply that the CAPM may still have value in explaining risk-return relationships.

Lundblatt (2007) concludes that although previous studies typically find a statistically insignificant relation between the market risk premium and its expected volatility and that several previous studies even find a negative risk return trade-off, these findings are due to small samples. He states that small-sample inference is plagued by the fact that conditional volatility has no explanatory power for realized returns. Furthermore, when nearly two centuries of U.S. equity market returns are used (stock price index returns from 1802 to 1987), he finds a positive and statistically significant risk-return trade-off.

In general, although the existing literature about the relationship between stock returns and volatility is quite mixed, most of the studies mentioned above still report the existence of significant conditional heteroskedasticity in stock price behaviour, hence suggesting the use of the GARCH class of models. Further, the mixed results also encourage us to uncover the risk-return relationship in Asian region. Given the different backgrounds of each stock market, we expect that the risk-return relationship could vary from one country to another. Meanwhile, we suspect that the 1997-98 financial crises might also affect the relationship between stock market returns and volatility.

4.2.3 Day-of-the-week effects in stock returns and volatility

In more recent years, economists and investors have cared more about daily variation, particularly in the form of day-of-the-week effects, in both security market returns and volatility. An understanding of day-of-the-week effects in both returns and volatility is important to financial managers, financial analysts and investors, since it can help them develop appropriate buying and selling strategies. For example, investors can take long positions on days of high return and low volatility. In this way, investors can effectively reduce portfolio risk and increase return.

Day-of-the-week effects in stock market returns have been extensively documented in early studies. These effects indicate that the average daily returns are not the same for all days of the week. Empirical studies conducted in the US and UK stock markets find that the average return on Friday is abnormally high while the average return on Monday is abnormally low. This phenomenon has been documented by many previous studies, such as Cross (1973), French (1980) and Keim and Stambaugh (1984). In other stock markets such as Japan, Singapore, Australia and France, significant negative returns appear on Tuesdays (Agrawal and Tandon, 1994; Jaffe and Westerfield, 1985). Following these findings, several studies have attempted to explain day-of-the-week effects, especially the Monday effect. Two important theories arise from these studies. First, the calendar time hypothesis states that the returns-generating process is a continuous activity and that Monday's mean return should be different from returns on other days. The rationale is that this mean return is estimated over three days from the closing price on Friday until the closing price on Monday, implying that the mean return should be three times higher than on other weekdays (French, 1980). Second, the trading time hypothesis states that stock returns are generated as a result of transactions, implying that average returns will be the same for all weekdays because each day's return represents one day's investment (French, 1980).

In fact, the empirical findings for day-of-the-week effects are inconsistent with both hypotheses, the most striking empirical regularity being the negative return on Monday. The most satisfactory explanation that has been given for the negative return on Monday is that the most unfavourable news usually appears during the weekend. Such news influences the majority of the investors negatively, causing them to sell on the following Monday. The most satisfactory explanation of negative returns on Tuesdays is that the bad news of the weekend affects US markets first, with a negative influence on other markets lagged by one day. Other explanations of day-of-the-week effects invoke settlement procedures (Lakonishok and Levi, 1982) and intense institutional trading activity (Sias and Starks, 1995) etc[16].

As stated earlier, in recent years, some attention has been turned towards day-of-the-week effects in stock volatilities. However, only a few studies focus on this topic and their results are inconsistent. Kiymaz and Berumnet (2003) investigate five developed economies (Canada, Germany, Japan, UK and USA). They find the highest volatility of stock returns on Monday for Germany and Japan, on Friday for Canada and United States, and on Thursday for the United Kingdom. In addition, for most countries the lowest volatility is found on Tuesdays. Apolinario, Santana, Sales and Caro (2006) find no day-of-the-week effects in stock volatility that are common to thirteen European markets. They find Monday effects in Portugal and United Kingdom, Tuesday effects in Germany and Belgium, Monday and Thursday effects in Spain, Holland, Italy and Switzerland, and Tuesday and Friday effects in Austria. Bhattacharya, Sarkar and Mukhopadhyay (2003) study the stability of day-of-the-week effects in volatility in the Indian equity market using a GARCH framework. Their sample covers January 1991 to September 2000. They split the entire sample into two sub-periods, 1991-1995 and 1995-2000. The results show that day-of-the-week effects in volatility are different in the two sub-periods. That is, no day-of-the-week effects are found in period 1991-1995, while significant positive day effects are present on Monday, Wednesday and Friday in period 1995-2000. They conclude that inter-exchange arbitrage opportunities due to the existence of account period settlement cycles could lead to such seasonality.

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[16] Lakonishok and Levi (1982) argue that investors pay a higher price for stock on Friday as this give them more calendar days for payment. Sias and Starks (1995) report a strong positive link between institutional trading and day of week effects.

Although day-of-the week effects are widely found in a large number of previous studies, and reasonable explanations have been given, the evidence may have data-mining biases[17]. Sullivan, Timmermann and White (2001) investigate nearly 9500 different calendar effects and find that, although many different calendar rules produce abnormal returns that are highly statistically significant when considered in isolation, once evaluated in the context of the full universe from which such rules were drawn, calendar effects no longer remain significant. The day-of-the week effects here must therefore be interpreted with caution and with the realisation that it may not be possible to draw strong conclusions.

Having examined the previous literature, we plan to make contributions to the existing research in the following respects. First, previous statements about volatility are often based on estimates of the variance of stock returns over relatively long periods of time and therefore are of little use to investors who want to make periodic decisions on portfolio allocation. In our study, we examine the behaviour of stock volatility not only for the full sample period but also for the four sub-sample periods.

Second, most previous findings are obtained by estimation procedures that have not accounted for asymmetric market behaviour. Hence, we extend the previous studies by incorporating such behaviour.

Third, most previous studies model stock volatility by assuming the normal density function, although this is not sufficient to account for leptokurtosis in the data. The Generalized Error Distribution (GED) is used here to overcome this problem.

[17] Sullivan *etal.* (2001) argue that economics is primarily a non-experimental science. Typically, it cannot generate new data sets on which to test hypotheses independently of the data that may have led to a particular theory. Hence errors arise from relying too heavily on data-mining practices. In other words, while some patterns discovered by data mining are potentially useful, many others might just be coincidental and are not likely to be repeated in the future.

Fourth, most earlier studies of day-of-the-week effects investigate patterns only in stock returns. This study contributes to the literature by documenting day-of-the-week patterns in both returns and volatility.

Fifth, there is lack of research about the impact of the financial crisis on the dynamic behaviour of stock market volatility. In this study, we examine the impact of both financial liberalization and financial crisis on the dynamic behaviour of volatility.
Finally, most existing studies focus on developed European markets and there is a general lack of such research in Asian stock markets,. Thus, it is worth scrutinizing stock volatility in Asia.

4.3 Empirical Methodology

Index return series tend to exhibit time varying volatility (ARCH effects). However, traditional ARCH models cannot handle certain important facts. Poon and Granger (2003) point out that the basic ARCH model cannot capture kurtosis in a satisfying way. The standardized residuals in ARCH estimations tend to include large kurtosis. Further, when large shocks are controlled for, ARCH effects tend to be reduced or completely disappear.

Many empirical studies of financial time series have successfully used the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process of Bollerslev (1986) to model the behaviour of the conditional variance over time. The GARCH model has the advantage of incorporating heteroskedasticity into the estimation procedure. It also has the ability to accommodate the tendency towards volatility clustering in financial data, especially high frequency data[18].

In the following subsections, we present brief reviews of the empirical methodology and testing procedures used in this study, including the modelling of conditional

[18] Volatility clustering in stock returns implies that large (small) price changes follow large (small) price changes of either signs.

volatility; risk-return and day-of-the-week effects. A common feature of all models is the use of GARCH processes for the conditional variance.

4.3.1 The Basic Model: AR (1)-GARCH (1, 1)

Let R_t denote the return on a market index at time t. The first model that we consider assumes a simple AR (1) process for R_t, with a conditional normal distribution,

$$R_t = a + bR_{t-1} + \varepsilon_t, \tag{4.1}$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t) \tag{4.2}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{4.3}$$

The bR_{t-1} component is included in the mean equation to account for autocorrelation induced by nonsynchronous trading in the assets that make up a market index. The reason why infrequent trading in some securities can induce autocorrelation in the market index is easily explained with an example. Consider two securities A and B, where B trades less frequently than A. When market news become available the price of security A reacts faster than that of security B. The lagged reaction of the price of B generates a serial correlation between the returns on two securities. If both securities are included in the same index, the serial cross-correlation will generate autocorrelation in the index. The parameterization that we use to account for the effect of nonsynchronous trading follows the approach of Lo and Mackinley (1989) and Nelson (1991). An alternative approach, proposed by Scholes and Williams (1977), models index returns using an MA (1) process. As pointed out by Nelson (1991), there is little difference between the two approaches.

The GARCH (1,1) parameterization for the conditional variance implies that current volatility depends on past squared innovations and an autoregressive component. Although this specification is not as general as the GARCH (p, q) model proposed by Bollerslev (1986), most empirical applications find that a parsimonious parameterization is sufficient to model the conditional variance. Since equation (4.3) defines a variance, a non-negativity restriction has to be imposed on both α and β. Bollerslev (1986) shows that sum of $(\alpha+\beta)$ has to be smaller than 1.0 for the volatility process to be stationary.

The suggested parameterization of the model is extremely simple. In particular, the mean equation to explain market index returns contains only an autoregressive component. However, since the focus of the study is mainly on volatility, it can be argued that a possible misspecification of the mean equation is not of great concern. For example, according to Nelson (1992), the conditional variance estimates obtained from a GARCH model are robust to an incorrect specification of the conditional mean.

4.3.2 Non-normal Conditional Distribution

Estimating the GARCH model requires the adoption of some density function for innovation vector ε_t. The most commonly used density function is the normal distribution. However, starting from the work of Mandelbrot (1963) and Fama (1965), empirical research has found evidence that changes in stock prices exhibit fatter tails than in a normal distribution. In other words, early studies find the unconditional distributions of stock price changes to be leptokurtic. In addition, a large number of very high and very low returns observed in Asian stock markets (shown in Chapter 3) also suggest that leptokurtosis might be relevant here. Hence the normal distribution may be not appropriate here since it fails to capture the 'fat tails' in the data. In many studies, the Student-*t* distribution is considered as an alternative to the normal. However, when the empirical distribution of asset returns has very fat tails, the fourth moment of the *t*-distribution may fail to exist. De Santis and Imrohoroglu (1997) show that the GED distribution can improve the fit of the univariate GARCH model, in particular where using high frequency financial data. For this reason, we use the

Generalized Error Distribution (GED) to overcome this problem[19] (but a Student-*t* distribution could also be used) :

$$f(\varepsilon_t) = \frac{v \exp\left[-(1/2)\left|\varepsilon_t h_t^{-1/2} / \lambda\right|^v\right]}{\lambda 2^{[(v+1)/v]}\Gamma(1/v)} h_t^{-1/2}$$

Here $\Gamma(\cdot)$ is the gamma function, v is a measure of the thickness of the tails of the distribution and λ is a constant.

$$\lambda = \left[\frac{2^{(-2/v)}\Gamma(1/v)}{\Gamma(3/v)}\right]^{1/2}$$

For $v = 2$ the GED distribution coincides with the normal, for $v < 2$ it has thicker tails than the normal and for $v > 2$, it has thinner tails than the normal. The kurtosis for the GED distribution is equal to

$$k = \frac{\Gamma\left[\frac{5}{2}(1+\beta)\right]\Gamma\left[\frac{1}{2}(1+\beta)\right]}{\{\Gamma\left[\frac{3}{2}(1+\beta)\right]\}^2}$$

where $\beta = (2 - v)/v$.

4.3.3 Asymmetry effect test

To test for the presence of an asymmetric response of variance to past shocks, Engle and Ng (1993) asymmetric tests of sign, size bias and joint tests have been widely applied.

[19] See Box and Tiao (1973) for a theoretical discussion of the Generalized Error Distribution and Nelson (1991) for an application to financial data.

The sign bias test is constructed to test the different impact on volatility of positive and negative innovations. The negative size bias test examines the impact on volatility of large and small negative innovations, while the positive size bias test examines the impact on volatility of large and small positive innovations.

If the sign bias test is employed, the squared residual is a direct function of the residual itself.

$$\varepsilon_t^2 = \lambda_0 + \lambda_1 S_{t-1}^- + v_t \tag{4.4}$$

S_{t-1}^- is a dummy variable which takes the value 1 when $\varepsilon_t < 0$ and 0 otherwise. In this test it is possible to analyze the conditional variance, since the squared residual is used and the variance depends on the sign of the lagged residuals. The coefficient λ_1 indicates whether the sign of the residuals matters. Once the coefficient is statistically significant, it does matter for the conditional variance. The negative size bias test can be written as

$$\varepsilon_t^2 = \lambda_0 + \lambda_1 S_{t-1}^- \varepsilon_{t-1} + v_t \tag{4.5}$$

As an extension, the negative size bias test examines the impact of both the sign and the size of a negative shock on conditional variance.

The positive size bias test is similar to the negative size bias test, but the term $S_{t-1}^- \varepsilon_{t-1}$ is replaced by the term $S_{t-1}^+ \varepsilon_{t-1}$ where $S_{t-1}^+ = 1 - S_{t-1}^-$. This gives

$$\varepsilon_t^2 = \lambda_0 + \lambda_1 S_{t-1}^+ \varepsilon_{t-1} + v_t \tag{4.6}$$

The three tests (sign bias test, negative size bias test and positive size bias test) can also be carried out jointly within one model:

$$\varepsilon_t^2 = \lambda_0 + \lambda_1 S_{t-1}^- + \lambda_2 S_{t-1}^- \varepsilon_{t-1} + \lambda_3 S_{t-1}^+ \varepsilon_{t-1} + v_t \tag{4.7}$$

4.3.4 Asymmetric property, risk-return relationship, Threshold Autoregressive GARCH (1,1)-in-mean Model

The GARCH (1,1) model appears to be sufficient to describe the volatility evolution of typical stock return series. However, it only considers the symmetric behaviour of volatility. Recent empirical evidence indicates that the impact of news may be 'asymmetric'. Specifically, negative shocks to returns (bad news) will generate more volatility than positive shocks (good news) of equal magnitude. This asymmetric effect on conditional variance has been investigated extensively in studies using the Threshold Autoregressive GARCH (TAR-GARCH) model (Glosten, Jagannathan and Runkle, 1993) and the EGARCH model (Nelson, 1991). The EGARCH model considers the log of the conditional variance while the TAR-GARCH does not. Therefore, the leverage effect is exponential in the EGARCH model while it is quadratic in TAR-GARCH. The EGARCH model essentially smooths the response to shocks. Some behavioural finance literature (Xin, 2007; Tuinstra et al., 2006) argues that there is evidence that markets respond differently to negative and positive shocks, and this calls for a discrete jump when the sign changes irrespective of size. This may imply that the TAR-GARCH specification is more attractive than EGARCH. Moreover, Engle and Ng (1993) find that the TAR-GARCH model performs better than other asymmetry models in their own Monte Carlo experiments.

Recent studies have typically used GARCH-in-Mean models (Engle, Lilien and Robins, 1987) to model the risk-return relationship. To incorporate asymmetry in the investigation of the relationship between stock returns and conditional volatility for Asian stock markets, the model is estimated using the TAR-GARCH (1,1)-in-mean specification[20], as follows:

$$R_t = a + bR_{t-1} + ch_t^{1/2} + \varepsilon_t \tag{4.8}$$

[20] The dummy variable used here distinguishes only between positive and negative shocks and does not constrain the response itself.

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t) \tag{4.9}$$

$$h_t = \omega + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2 \tag{4.10}$$

The influence of volatility on stock returns is captured by the estimated coefficient c. A significant and positive value of c implies that investors will be compensated by higher returns for bearing a higher level of risk, while a significant negative coefficient implies that investors will be penalized for bearing risk.

The difference between equation (4.10) and the traditional GARCH (1, 1) (equation 4.3) is that positive and negative shocks are differentiated by using an indicator variable, I_{t-1}. This takes a value of unity when the previous shock is negative and zero otherwise. This specification allows us to examine asymmetry in volatility with respect to ε_{t-1}. A positive value of η implies that a negative innovation increases conditional volatility. Thus, an asymmetric effect is captured by the hypothesis that $\eta > 0$. The system described by equation (4.10) can be viewed as a more general model since the standard GARCH(1,1)-in-mean specification can be achieved by the restriction that $\eta = 0$.

4.3.5 Modelling the Day-of-the-week effects on Stock Return and Volatility

In order to investigate the presence of day-of-the-week effects in both return and volatility, day-of-the-week dummy variables are introduced into the specifications of the TAR-GARCH (1,1) model, which is written as:

$$R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t \tag{4.11}$$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2 \tag{4.12}$$

Here D_1, D_2, D_4, D_5 are zero-one dummy variables for Monday, Tuesday, Thursday and Friday. Following Kiymaz and Berument (2003), we exclude Wednesday to avoid the dummy variable trap.

Parameters were estimated using the QML technique of Bollerslev and Wooldridge (1992). The optimization algorithm used is the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton method.

4.4 Empirical Results

4.4.1 Asymmetry effect test results

Table 4.1 reports the results of sign bias, negative size bias, positive size bias and joint tests for the symmetry GARCH (1,1) model. These tests are useful in deciding whether there is asymmetry in responses to volatility shocks. For the overall sample period, the results of the sign bias test are significant for Japan, Singapore and Thailand. The negative sign bias test results are significant for Hong Kong, Japan, Singapore, Malaysia, Philippines and Thailand, indicating negative asymmetry in these markets. However, for Korea and Indonesia, the hypothesis of negative asymmetry can not be accepted. On the other hand, the results of the positive sign bias test are significant only for Hong Kong and Japan, suggesting positive asymmetry for these two markets only.

The test results for the sub-periods do not reveal as much asymmetry as in the overall period but asymmetry effects still can be found in a number of markets. During the pre-crisis period, the results of the sign bias, the positive sign bias and joint tests are significant for Singapore. The negative sign bias test results are significant for Hong Kong, Japan and Thailand. During the crisis period, the results of the sign bias test are significant in Malaysia. The results of the negative sign bias test are significant in Hong Kong, Singapore and Malaysia. The joint test results are significant for Hong Kong and Malaysia. During the post-crisis period, the sign bias results are significant for Hong Kong and Philippines, the negative sign bias results are significant for Malaysia and

Philippines while significant positive sign bias results are found for Hong Kong and Japan. Finally, during the recovery period, the sign bias results are significant for Japan and the negative sign bias results are significant for Thailand (suggesting negative asymmetry in Thailand).

To summarize, these tests suggest that asymmetric patterns of volatility are present in some Asian stock markets, but the evidence is not quite conclusive. Therefore, further investigation is needed and a model of asymmetric volatility is required.

Table 4.1 Sign and Size Bias Tests

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Whole sample period								
Sign bias test	1.38 [0.16]	2.04 [0.03]**	2.09 [0.03]**	1.30 [0.19]	0.75 [0.44]	0.86 [0.38]	0.91 [0.35]	1.76 [0.07]*
Negative sign bias test	2.26 [0.02]**	1.97 [0.04]**	1.73 [0.08]*	0.19 [0.84]	1.90 [0.06]*	1.71 [0.08]*	0.93 [0.35]	1.92 [0.06]*
Positive sign bias test	2.46 [0.01]**	1.80 [0.07]*	0.99 [0.31]	0.38 [0.70]	1.51 [0.13]	0.79 [0.43]	1.12 [0.26]	0.58 [0.56]
Joint test	12.83 [0.00]***	14.71 [0.00]***	5.14 [0.16]	5.00 [0.17]	6.37 [0.09]*	5.22[0.14]	3.28 [0.35]	6.77 [0.07]*
Panel B: Pre-crisis period								
Sign bias test	0.33 [0.74]	1.14 [0.25]	1.82 [0.07]*	1.44 [0.15]	1.41 [0.15]	0.47 [0.64]	0.83 [0.40]	0.09 [0.92]
Negative sign bias test	1.69 [0.09]*	1.74 [0.08]*	0.69 [0.48]	1.43 [0.15]	1.51 [0.12]	0.79 [0.43]	1.22 [0.22]	1.83 [0.07]*
Positive sign bias test	1.06 [0.28]	1.42 [0.15]	2.03 [0.04]**	0.73 [0.46]	0.43 [0.66]	0.43 [0.66]	0.71 [0.48]	1.26 [0.21]
Joint test	1.42 [0.69]	4.06 [0.25]	8.95 [0.03]**	5.18 [0.16]	3.85 [0.27]	0.74 [0.86]	2.03 [0.56]	5.10 [0.16]
Panel C: crisis period								
Sign bias test	0.22 [0.82]	0.57 [0.56]	1.03 [0.30]	0.40 [0.69]	1.95 [0.05]*	0.61 [0.54]	0.66 [0.50]	1.31 [0.19]
Negative sign bias test	1.93 [0.06]*	0.75 [0.45]	1.69 [0.09]*	0.01 [0.99]	1.73 [0.08]*	0.29 [0.77]	0.14 [0.88]	0.08 [0.93]
Positive sign bias test	1.01 [0.31]	0.44 [0.65]	1.53 [0.12]	0.04 [0.96]	0.70 [0.47]	0.19 [0.84]	0.34 [0.73]	0.16 [0.87]
Joint test	8.65 [0.03]**	1.08 [0.78]	2.54 [0.47]	0.38 [0.94]	6.80 [0.07]*	1.70 [0.63]	1.44 [0.69]	3.21 [0.36]
Panel D: post-crisis period								
Sign bias test	1.92 [0.05]*	1.24 [0.22]	0.96 [0.33]	0.49 [0.61]	0.93 [0.35]	1.75 [0.07]*	0.84 [0.39]	0.14 [0.89]
Negative sign bias test	0.06 [0.95]	0.75 [0.45]	0.13 [0.89]	0.21 [0.83]	1.67 [0.09]*	1.92 [0.06]*	1.21 [0.22]	0.47 [0.64]
Positive sign bias test	2.25 [0.02]**	2.13 [0.03]**	0.18 [0.86]	0.39 [0.70]	0.07 [0.93]	0.86 [0.39]	0.70 [0.48]	0.32 [0.74]
Joint test	6.01 [0.09]*	5.33 [0.14]	2.16 [0.54]	1.64 [0.65]	0.31 [0.95]	5.24 [0.17]	2.01 [0.57]	0.48 [0.97]
Panel E: recovery period								
Sign bias test	0.01[0.99]	1.97 [0.05]*	0.70 [0.48]	0.28 [0.77]	1.17 [0.23]	0.08 [0.93]	0.31 [0.75]	1.03 [0.30]
Negative sign bias test	0.54 [0.59]	0.44 [0.65]	0.13 [0.89]	0.25 [0.79]	-1.34 [0.17]	-0.01 [0.98]	-0.23 [0.81]	1.76 [0.07]*
Positive sign bias test	1.51 [0.13]	0.31 [0.75]	0.47 [0.63]	1.29 [0.19]	0.44 [0.65]	0.69 [0.48]	1.31 [0.18]	0.27 [0.78]
Joint test	3.15 [0.37]	8.61 [0.03]**	1.81 [0.61]	3.12 [0.37]	2.15 [0.54]	0.86 [0.83]	2.42 [0.48]	3.19 [0.36]

Notes: The above table shows a t-statistics of sign bias, negative sign bias, positive sign bias and Joint bias test give by Engle and Ng (1993). *p*-values are in parentheses.

4.4.2 Conditional mean and volatility

Since asymmetric effects are present in some Asian stock markets (a TAR-GARCH model can capture this effect) and the risk-return relationship is also of research interest (a GARCH-M model can capture this effect), it is useful to combine these models to obtain a 'hybrid' TAR-GARCH-M model. Tables 4.2 to 4.6 present the results of fitting GARCH (1,1) and Threshold Autoregressive GARCH (1,1)-in-mean (TAR-GARCH-M) models for the whole period (08/01/1992 to 08/03/ 2007), the pre-crash period (08/01/1992 to 01/07/1997), the crisis period (02/07/1997 to 31/12/1998), the post-crash period (01/01/1999 to 03/2003) and the recovery period (07/03/2003 to 08/03/2007) respectively. The sub-period analysis allows comprehensive investigation of the impact on stock volatility of the 1997-98 financial crisis and of the relationship between stock returns and volatility in the sampled stock markets. In summarizing the estimated results, we first consider the mean equation.

The evidence from the daily return series for the whole sample period indicates that, with the exception of Japan, all Asian stock returns display significant positive serial correlation. This is also the case for the pre-crisis and crisis sub-periods. However, the results from the post-crash period are different from those of the first two sub-periods and show very few significant of AR components. In post-crash period, only the stock returns of Malaysia and Philippines have significant AR coefficients. In addition, for the recovery sample period, serial correlation in returns is present only for Malaysia, Philippines, Indonesia and Thailand. No serial correlation can be observed in returns for Hong Kong, Japan, Singapore and Korea. These findings show that serial correlation is more characteristic of emerging markets. Returns in the more developed markets show pre-crisis serial correlation that disappears after the crash. The existence of serial correlation in stock markets indicates the violation of the random-walk hypothesis for stock prices. Our findings indicate that the Asian stock markets became more efficient after the financial crisis, and that developed Asian stock markets have become more efficient than emerging markets in recent years.

Table 4.2 Parameter Estimates of fitting GARCH (1,1), TAR-GARCH (1,1)-M for the whole sample period

Model	GARCH(1,1)	TAR-GARCH(1,1)-M	Model	GARCH(1,1)	TAR-GARCH(1,1)-M
Parameter	**Hong Kong**		Parameter	**Malaysia**	
	A. Return equations			A. Return equations	
a	0.070 (3.39)***	0.068 (0.84)	a	0.036 (2.40)**	0.092 (3.36)***
b	0.041 (1.98)**	0.047 (2.55)***	b	0.107 (8.03)***	0.107 (3.19)***
c	-	-0.009 (-0.15)	c	-	0.051 (1.42)
	B. Variance equations			B. Variance equations	
ω	0.021 (2.58)***	0.032 (2.85)***	ω	0.011 (2.27)**	0.013 (2.59)***
α	0.062 (5.96)***	0.036 (4.68)***	α	0.091 (5.52)***	0.056 (4.77)***
β	0.930 (87.91)***	0.919 (71.55)***	β	0.901 (57.50)***	0.906 (59.72)***
η	-	0.068 (3.22)***	η	-	0.075 (3.41)***
wald statistics (χ^2)	6.33**		wald statistics (χ^2)	6.21**	
υ	1.237 (25.13)***	1.261 (25.36)***	υ	1.147 (28.49)***	1.155 (27.44)***
AIC/SIC	3.59/3.61	3.58/3.60	AIC/SIC	3.08/3.09	3.07/3.08
Log Likelihood	-5396.24	-5384.75	Log Likelihood	-4621.11	-4609.01
Parameter	**Japan**		Parameter	**Philippine**	
	A. Return equations			A. Return equations	
a	0.019 (0.84)	0.043 (0.63)	a	-0.005 (-0.52)	-0.079 (-0.46)
b	-0.028 (-1.58)	-0.025 (-1.39)	b	0.135 (5.38)***	0.137 (2.38)**
c	-	-0.031 (-0.53)	c	-	0.043 (0.49)
	B. Variance equations			B. Variance equations	
ω	0.044 (2.68)***	0.049 (3.21)***	ω	0.145 (3.23)***	0.146 (2.47)**
α	0.070 (5.56)***	0.023 (2.81)***	α	0.134 (3.71)***	0.072 (3.10)***
β	0.910 (57.79)***	0.908 (65.62)***	β	0.822 (15.74)***	0.829 (17.50)***
η	-	0.100 (4.61)***	η	-	0.119 (3.47)***
wald statistics (χ^2)	22.90***		wald statistics (χ^2)	45.51***	
υ	1.307 (23.86)***	1.336 (22.48)***	υ	1.115 (22.40)***	1.125 (25.62)***
AIC/SIC	3.56/3.57	3.55/3.56	AIC/SIC	3.55/3.57	3.54/3.56
Log Likelihood	-5345.96	-5325.71	Log Likelihood	-5327.54	-5316.31
Parameter	**Singapore**		Parameter	**Indonesia**	
	A. Return equations			A. Return equations	
a	0.045 (2.39)**	0.097 (1.38)	a	0.077 (0.61)	0.111 (8.79)***
b	0.064 (2.64)***	0.062 (2.83)***	b	0.181 (3.80)***	0.181 (5.66)***
c	-	-0.065 (-1.01)	c	-	-0.014 (-0.41)
	B. Variance equations			B. Variance equations	
ω	0.044 (2.11)**	0.041 (2.01)**	ω	0.024 (1.83)*	0.025 (1.81)*
α	0.108 (3.50)***	0.057 (3.21)***	α	0.100 (2.74)***	0.084 (2.87)***
β	0.869 (22.21)***	0.872 (23.22)***	β	0.890 (28.63)***	0.893 (28.17)***
η	-	0.094 (2.89)***	η	-	0.041 (1.89)*
wald statistics (χ^2)	26.80***		wald statistics (χ^2)	6.81***	
υ	1.233 (23.66)***	1.242 (23.97)***	υ	1.101 (24.04)***	1.098 (25.84)***
AIC/SIC	3.14/3.15	3.13/3.14	AIC/SIC	3.41/3.42	3.41/3.42
Log Likelihood	-4710.79	-4697.22	Log Likelihood	-5119.24	-5116.69
Parameter	**Korea**		Parameter	**Thailand**	
	A. Return equations			A. Return equations	
a	0.052 (1.69)*	-0.008 (-0.08)	a	-0.021 (-0.61)	0.124 (5.42)***
b	0.041 (2.20)**	0.044 (2.93)***	b	0.086 (3.06)***	0.083 (16.62)***
c	-	0.029 (0.51)	c	-	-0.119 (-2.24)**
	B. Variance equations			B. Variance equations	
ω	0.028 (1.91)*	0.033 (2.11)**	ω	0.136 (2.53)**	0.136 (3.71)***
α	0.060 (3.47)***	0.035 (3.04)***	α	0.114 (5.53)***	0.078 (5.79)***
β	0.931 (48.24)***	0.928 (46.31)***	β	0.849 (28.28)***	0.845 (44.42)***
η	-	0.058 (2.92)***	η	-	0.092 (3.84)***
wald statistics (χ^2)	6.36**		wald statistics (χ^2)	37.22***	
υ	1.322 (24.91)***	1.338 (24.78)***	υ	1.171 (17.21)***	1.168 (17.46)***
AIC/SIC	4.01/4.02	4.00/4.01	AIC/SIC	3.83/3.84	3.82/3.83
Log Likelihood	-6016.31	-6005.68	Log Likelihood	-5743.85	-5734.77

Note: The t-values are indicated in the parentheses. Wald statistic has an asymptotic χ^2 (1) distribution for testing the hypothesis $\alpha + \beta = 1$. The critical values at 10% significance level are 2.71, 5% level are 3.84, 1% level are 6.64.

GARCH: $R_t = a + bR_{t-1} + \varepsilon_t$ $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$ TAR-GARCH: $R_t = a + bR_{t-1} + ch_t^{1/2} + \varepsilon_t$ $h_t = \omega + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$

Table 4.3 Parameter Estimates of fitting GARCH (1,1), TAR-GARCH (1,1)-M for pre-crisis period

Model	GARCH(1,1)	TAR-GARCH(1,1)-M	Model	GARCH(1,1)	TAR-GARCH(1,1)-M
Parameter	Hong Kong		Parameter	Malaysia	
	A. Return equations			A. Return equations	
a	0.086 (7.14)***	-0.088 (-2.59)***	a	0.052 (1.42)	0.186 (1.35)
b	0.052 (1.81)*	0.060 (3.61)***	b	0.106 (2.28)**	0.112 (2.55)**
c	-	0.125 (10.05)***	c	-	0.144 (1.05)
	B. Variance equations			B. Variance equations	
ω	0.064 (2.24)**	0.106 (2.21)**	ω	0.018 (2.06)**	0.017 (1.92)*
α	0.075 (3.89)***	0.050 (2.96)***	α	0.056 (5.18)***	0.045 (3.31)***
β	0.898 (34.69)***	0.861 (21.97)***	β	0.930 (72.26)***	0.931 (72.47)***
η	-	0.092 (2.52)**	η	-	0.023(1.12)
wald statistics (χ^2)	10.28***		wald statistics (χ^2)	10.31***	
υ	1.203 (14.83)***	1.221 (15.72)***	υ	1.227 (16.71)***	1.214 (16.78)***
AIC/SIC	3.51/3.54	3.51/3.54	AIC/SIC	3.00/3.03	3.00/3.03
Log Likelihood	-1895.42	-1891.54	Log Likelihood	-1618.12	-1616.77
Parameter	Japan		Parameter	Philippine	
	A. Return equations			A. Return equations	
a	0.008 (0.19)	-0.134 (-0.96)	a	0.024 (0.57)	-0.227 (-1.08)
b	-0.042 (-1.32)	-0.041 (-1.15)	b	0.210 (6.65)***	0.207 (4.95)***
c	-	0.097 (0.83)	c	-	0.191 (1.21)
	B. Variance equations			B. Variance equations	
ω	0.037 (2.18)**	0.033 (1.93)*	ω	0.074 (1.71)*	0.085 (1.44)
α	0.063 (4.41)***	0.015 (1.77)*	α	0.107 (2.73)***	0.071 (2.51)**
β	0.915 (52.31)***	0.922 (49.92)***	β	0.867 (16.88)***	0.848 (13.09)***
η		0.093 (3.48)***	η		0.099 (1.81)*
wald statistics (χ^2)	20.99***		wald statistics (χ^2)	8.04***	
υ	1.261 (14.79)***	1.303 (13.74)***	υ	1.232 (16.07)***	1.241 (16.15)***
AIC/SIC	3.44/3.48	3.42/3.45	AIC/SIC	3.39/3.42	3.38/3.42
Log Likelihood	-1858.21	-1845.63	Log Likelihood	-1830.72	-1825.41
Parameter	Singapore		Parameter	Indonesia	
	A. Return equations			A. Return equations	
a	0.012 (0.33)	-0.105 (-0.29)	a	0.065 (11.57)***	-0.183 (-30.51)***
b	0.152 (5.33)***	0.152 (3.79)***	b	0.291 (36.32)***	0.296 (27.71)***
c	-	0.113 (0.29)	c	-	0.127 (1.33)
	B. Variance equations			B. Variance equations	
ω	0.141 (2.94)***	0.138 (2.95)***	ω	0.292 (2.24)**	0.228 (7.86)***
α	0.108 (3.81)***	0.061 (2.19)**	α	0.286 (2.75)***	0.232 (3.57)***
β	0.741 (11.56)***	0.748 (11.81)***	β	0.474 (4.54)***	0.501 (19.26)***
η		0.118 (2.33)**	η		0.035 (0.48)
wald statistics (χ^2)	25.89***		wald statistics (χ^2)	59.22***	
υ	1.277(15.09)***	1.285 (14.52)***	υ	1.020 (14.58)***	1.018 (16.41)***
AIC/SIC	2.74/2.77	3.42/3.45	AIC/SIC	2.49/2.52	2.48/2.52
Log Likelihood	-1482.25	-1478.75	Log Likelihood	-1345.06	-1339.48
Parameter	Korea		Parameter	Thailand	
	A. Return equations			A. Return equations	
a	-0.017 (-0.38)	-0.028 (-1.34)	a	-0.044 (-0.99)	-0.024 (-0.11)
b	0.064 (2.01)**	0.070 (2.15)**	b	0.136 (5.26)***	0.147 (3.72)***
c	-	0.191 (1.22)	c	-	-0.032 (-0.18)
	B. Variance equations			B. Variance equations	
ω	0.205 (3.36)***	0.179 (3.31)***	ω	0.133 (1.80)*	0.181 (1.45)
α	0.117 (4.47)***	0.091 (3.24)***	α	0.106 (3.97)***	0.044 (2.35)***
β	0.787 (18.77)***	0.776 (17.78)***	β	0.846 (17.74)***	0.814 (10.18)***
η	-	0.079 (1.72)*	η	-	0.169 (2.17)**
wald statistics (χ^2)	15.64***		wald statistics (χ^2)	18.60***	
υ	1.517 (16.76)***	1.502 (16.31)***	υ	1.242 (15.63)***	1.255 (14.91)***
AIC/SIC	3.50/3.52	3.49/3.53	AIC/SIC	3.65/3.67	3.63/3.67
Log Likelihood	-1888.76	-1884.85	Log Likelihood	-1970.51	-1961.52

Note: : The t-values are indicated in the parentheses. Wald statistic has an asymptotic $\chi^2(1)$ distribution for testing the hypothesis $\alpha+\beta=1$. The critical values at 10% significance level are 2.71, 5% level are 3.84, 1% level are 6.64.

GARCH: $R_t=a+bR_{t-1}+\varepsilon_t$, $h_t=\omega+\alpha\varepsilon_{t-1}^2+\beta h_{t-1}$ TAR-GARCH: $R_t=a+bR_{t-1}+ch_t^{1/2}+\varepsilon_t$ $h_t=\omega+\beta h_{t-1}+(\alpha+\eta I_{t-1})\varepsilon_{t-1}^2$

Table 4.4 Parameter Estimates of fitting GARCH (1,1), TAR-GARCH (1,1)-M for crisis period

Model	GARCH(1,1)	TAR-GARCH(1,1)-M	Model	GARCH(1,1)	TAR-GARCH(1,1)-M
Parameter	**Hong Kong**		Parameter	**Malaysia**	
	A. Return equations			A. Return equations	
a	-0.039 (-0.30)	-0.013 (0.11)	a	-0.256 (-2.97)***	-0.274 (-2.39)**
b	0.042 (1.65)*	0.056 (1.61)	b	0.147 (2.36)***	0.125 (3.84)***
c	-	-0.014(-0.06)	c	-	-0.098 (-0.76)
	B. Variance equations			B. Variance equations	
ω	0.784 (1.14)	0.404 (0.71)	ω	0.684 (1.84)*	0.368 (1.76)*
α	0.191 (3.08)***	0.166 (3.01)***	α	0.180 (2.40)**	0.112 (2.28)**
β	0.725 (15.78)***	0.816 (21.82)***	β	0.698 (6.09)***	0.716 (13.89)***
η	-	0.253 (2.14)***	η	-	0.213 (2.11)**
wald statistics (χ^2)	8.99***		wald statistics (χ^2)	28.23***	
υ	1.359 (9.83)***	1.443 (8.84)***	υ	1.029 (13.72)***	1.066 (15.18)***
AIC/SIC	4.83/4.91	4.81/4.90	AIC/SIC	5.14/5.25	5.14/5.24
Log Likelihood	-733.81	-727.55	Log Likelihood	-780.91	-779.31
Parameter	**Japan**		Parameter	**Philippine**	
	A. Return equations			A. Return equations	
a	-0.151(-2.06)**	-0.638 (-1.78)*	a	-0.292 (-8.31)***	-0.256 (-4.51)***
b	-0.073(-1.51)	-0.075 (-1.58)	b	0.162 (6.03)***	0.177 (2.82)***
c	-	0.266 (1.31)	c	-	0.221(1.63)
	B. Variance equations			B. Variance equations	
ω	0.316 (2.09)**	0.165 (2.01)**	ω	0.299 (0.79)	0.125 (2.45)**
α	0.122 (3.01)***	0.016 (0.52)	α	0.133 (1.68)*	0.079 (1.71)*
β	0.798 (13.46)***	0.868 (22.75)***	β	0.833 (6.90)***	0.825 (15.91)***
η	-	0.161 (2.36)**	η	-	0.143 (1.98)*
wald statistics (χ^2)	9.89***		wald statistics (χ^2)	4.85**	
υ	1.246 (8.79)***	1.301 (7.28)***	υ	1.146 (8.74)***	1.182 (10.21)***
AIC/SIC	4.05/4.12	4.04/4.14	AIC/SIC	4.65/4.73	4.61/4.71
Log Likelihood	-613.89	-611.04	Log Likelihood	-706.51	-698.15
Parameter	**Singapore**		Parameter	**Indonesia**	
	A. Return equations			A. Return equations	
a	-0.246 (-2.20)**	-0.709 (-1.99)*	a	-0.201 (-1.23)	-0.294 (-0.81)
b	0.151 (2.00)**	0.148 (1.94)*	b	0.118 (4.15)***	0.146 (3.88)***
c	-	0.323 (1.21)	c	-	-0.009(-0.12)
	B. Variance equations			B. Variance equations	
ω	0.715 (2.53)**	0.599 (2.43)**	ω	0.751 (1.54)	0.486 (1.12)
α	0.339 (3.42)***	0.111 (2.45)**	α	0.231 (2.36)**	0.034 (1.99)*
β	0.571 (6.40)***	0.652 (9.03)***	β	0.746 (15.47)***	0.880 (26.65)***
η	-	0.225 (2.13)***	η	-	0.162 (2.12)**
wald statistics (χ^2)	9.01***		wald statistics (χ^2)	3.09*	
υ	1.301 (9.16)***	1.353 (8.98)***	υ	1.011 (11.08)***	1.021 (10.36)***
AIC/SIC	4.36/4.44	4.34/4.44	AIC/SIC	5.01/5.10	5.01/5.10
Log Likelihood	-660.88	-657.13	Log Likelihood	-760.55	-758.41
Parameter	**Korea**		Parameter	**Thailand**	
	A. Return equations			A. Return equations	
a	-0.165 (-0.91)	-0.558 (-1.46)	a	-0.560 (-13.29)***	-0.667 (-27.83)***
b	0.109 (1.79)	0.111 (1.96)*	b	0.098 (4.63)***	0.071 (1.25)
c	-	0.145 (1.13)	c	-	-0.375 (-2.03)**
	B. Variance equations			B. Variance equations	
ω	0.116 (1.07)	0.097 (0.99)	ω	0.593 (1.85)*	0.327 (4.03)***
α	0.169 (3.29)***	0.124 (2.23)**	α	0.104 (2.65)***	0.068 (2.92)***
β	0.816 (19.18)***	0.853 (23.61)***	β	0.824 (14.94)***	0.884 (16.86)***
η	-	0.088 (1.28)	η	-	0.012 (0.35)
wald statistics (χ^2)	2.72*		wald statistics (χ^2)	7.24***	
υ	1.293 (7.65)***	1.283 (7.58)***	υ	1.246 (9.03)***	1.221 (8.96)***
AIC/SIC	5.18/5.26	5.18/5.27	AIC/SIC	4.86/4.94	4.85/4.94
Log Likelihood	-785.91	-784.55	Log Likelihood	-738.17	-734.04

Note: : The t-values are indicated in the parentheses. Wald statistic has an asymptotic $\chi^2(1)$ distribution for testing the hypothesis $\alpha+\beta=1$. The critical values at 10% significance level are 2.71, 5% level are 3.84, 1% level are 6.64.

GARCH: $R_t = a + bR_{t-1} + \varepsilon_t \quad h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$ TAR-GARCH: $R_t = a + bR_{t-1} + ch_t^{1/2} + \varepsilon_t \quad h_t = \omega + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$

Table 4.5 Parameter Estimates of fitting GARCH (1,1), TAR-GARCH (1,1)-M for post-crisis period

Model	GARCH(1,1)	TAR-GARCH(1,1)-M	Model	GARCH(1,1)	TAR-GARCH(1,1)-M
Parameter	**Hong Kong**		Parameter	**Malaysia**	
	A. Return equations			A. Return equations	
a	-0.023 (-0.42)	-0.868 (-1.72)*	a	-0.089 (-3.77)***	-0.311 (-18.01)***
b	0.028 (1.16)	0.026 (0.76)	b	0.083 (3.95)***	0.099 (39.38)***
c	-	-0.299 (-1.64)	c	-	0.133 (1.26)
	B. Variance equations			B. Variance equations	
ω	0.074 (1.57)	0.071 (1.91)*	ω	0.204 (0.96)	0.168 (3.93)***
α	0.048 (2.78)***	0.026 (2.01)**	α	0.193 (2.51)**	0.106 (3.03)***
β	0.929 (37.89)***	0.932 (44.33)***	β	0.731 (12.11)***	0.757 (17.04)***
η	-	0.034 (2.88)***	η	-	0.174 (6.59)***
wald statistics (χ^2)	4.81**		wald statistics (χ^2)	11.64***	
υ	1.361 (12.00)***	1.381 (12.67)***	υ	1.054 (12.07)***	1.084 (13.87)***
AIC/SIC	3.96/4.00	3.95/4.00	AIC/SIC	3.40/3.43	3.38/3.43
Log Likelihood	-1628.91	-1623.24	Log Likelihood	-1396.09	-1389.82
Parameter	**Japan**		Parameter	**Philippine**	
	A. Return equations			A. Return equations	
a	-0.062 (-1.25)	-0.124 (-0.41)	a	-0.111 (-17.90)***	-0.152 (-17.52)***
b	-0.024 (-0.81)	-0.022 (-0.76)	b	0.101 (51.49)***	0.101 (13.55)***
c	-	0.031 (0.16)	c	-	0.029 (0.90)
	B. Variance equations			B. Variance equations	
ω	0.163 (2.61)***	0.158 (2.62)***	ω	0.385 (2.87)***	0.339 (2.65)***
α	0.071 (3.41)***	0.029 (2.38)**	α	0.164 (2.99)***	0.076 (2.54)**
β	0.874 (31.90)***	0.878 (32.77)***	β	0.682 (11.19)***	0.721 (9.26)***
η	-	0.082 (2.28)**	η	-	0.135 (2.53)**
wald statistics (χ^2)	7.48***		wald statistics (χ^2)	33.39***	
υ	1.402 (11.71)***	1.411 (11.03)***	υ	1.002 (11.29)***	1.006 (31.47)***
AIC/SIC	3.85/3.89	3.84/3.89	AIC/SIC	3.48/3.52	3.48/3.52
Log Likelihood	-1581.34	-1578.61	Log Likelihood	-1429.86	-1428.21
Parameter	**Singapore**		Parameter	**Indonesia**	
	A. Return equations			A. Return equations	
a	-0.058 (-0.95)	-0.468 (-1.13)	a	0.020 (3.25)***	0.189 (0.47)
b	0.036 (0.74)	0.029 (1.23)	b	0.041 (6.85)***	0.041 (0.63)
c	-	0.281 (0.97)	c	-	-0.096 (-0.53)
	B. Variance equations			B. Variance equations	
ω	0.243 (2.58)**	0.233 (2.81)***	ω	0.289 (1.45)	0.297 (1.09)
α	0.112 (3.13)***	0.068 (2.31)**	α	0.174 (4.29)***	0.119 (3.05)***
β	0.788 (14.34)***	0.787 (15.28)***	β	0.711 (12.65)***	0.721 (13.19)***
η	-	0.112 (1.78)*	η	-	0.101 (1.82)*
wald statistics (χ^2)	20.13***		wald statistics (χ^2)	24.53***	
υ	1.242 (13.03)***	1.242 (13.78)***	υ	1.116 (14.10)***	1.111 (11.06)***
AIC/SIC	3.61/3.65	3.60/3.65	AIC/SIC	3.93/3.97	3.93/3.97
Log Likelihood	-1484.67	-1480.36	Log Likelihood	-1614.71	-1614.43
Parameter	**Korea**		Parameter	**Thailand**	
	A. Return equations			A. Return equations	
a	0.063 (0.70)	-0.008 (-0.29)	a	-0.041 (-0.55)	-0.570 (-2.73)
b	0.037 (1.06)	0.036 (1.35)	b	0.021 (0.41)	0.022 (0.47)
c	-	0.025 (0.83)	c	-	-0.207 (-1.61)
	B. Variance equations			B. Variance equations	
ω	0.046 (1.06)	0.635 (0.29)	ω	0.710 (1.51)	0.807 (2.14)**
α	0.016 (2.41)**	0.011 (1.32)	α	0.151 (2.90)***	0.144 (2.16)***
β	0.973 (58.50)***	0.970 (46.25)***	β	0.662 (4.15)***	0.623 (4.94)***
η	-	0.013 (0.55)	η	-	0.050 (0.69)
wald statistics (χ^2)	3.80*		wald statistics (χ^2)	6.83***	
υ	1.221 (12.11)***	1.224 (12.20)***	υ	1.218 (14.13)***	1.206 (14.51)***
AIC/SIC	4.75/4.79	4.75/4.79	AIC/SIC	4.05/4.10	4.05/4.10
Log Likelihood	-1952.19	-1951.89	Log Likelihood	-1666.41	-1665.05

Note: The t-values are indicated in the parentheses. Wald statistic has an asymptotic $\chi^2(1)$ distribution for testing the hypothesis $\alpha + \beta = 1$. The critical values at 10% significance level are 2.71, 5% level are 3.84, 1% level are 6.64.

GARCH: $R_t = a + bR_{t-1} + \varepsilon_t \quad h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$ TAR-GARCH: $R_t = a + bR_{t-1} + ch_t^{1/2} + \varepsilon_t \quad h_t = \omega + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon^2_{t-1}$

Table 4.6 Parameter Estimates of fitting GARCH (1,1), TAR-GARCH (1,1)-M for the recovery period

Model	GARCH(1,1)	TAR-GARCH(1,1)-M	Model	GARCH(1,1)	TAR-GARCH(1,1)-M
Parameter	**Hong Kong**		**Parameter**	**Malaysia**	
	A. Return equations			A. Return equations	
a	0.096 (2.50)**	0.153 (4.64)***	a	0.062 (3.21)***	-0.037 (-0.71)
b	0.037 (1.01)	0.041 (1.58)	b	0.111 (2.19)**	0.108 (3.75)***
c	-	0.057 (0.53)	c	-	0.166 (2.04)**
	B. Variance equations			B. Variance equations	
ω	0.015 (1.40)	0.018 (1.05)	ω	0.007 (1.36)	0.006 (1.15)
α	0.035 (3.04)***	0.031 (2.08)**	α	0.079 (3.82)***	0.079 (3.84)***
β	0.952 (63.54)***	0.948 (43.10)***	β	0.912 (37.29)***	0.915 (34.46)***
η	-	0.011 (0.33)	η	-	0.018 (0.69)
wald statistics (χ^2)	4.52**		wald statistics (χ^2)	3.17*	
υ	1.211 (13.39)***	1.209 (13.47)***	υ	1.237 (14.75)***	1.222 (14.99)***
AIC/SIC	2.85/2.89	2.85/2.89	AIC/SIC	2.01/2.04	2.01/2.05
Log Likelihood	-1118.15	-1118.01	Log Likelihood	-787.43	-786.71
Parameter	**Japan**		**Parameter**	**Philippine**	
	A. Return equations			A. Return equations	
a	0.113 (3.20)***	0.072 (0.42)	a	0.092 (1.65)*	0.042 (0.35)
b	-0.016 (-1.02)	-0.015 (-0.49)	b	0.056 (1.12)	0.115 (3.78)***
c	-	0.064 (0.57)	c	-	0.011 (0.06)
	B. Variance equations			B. Variance equations	
ω	0.036 (1.48)	0.023 (1.11)	ω	0.148 (1.31)	0.096 (0.71)
α	0.059 (2.64)***	0.036 (1.71)*	α	0.064 (1.71)*	0.061 (1.67)*
β	0.919 (32.47)***	0.918 (41.02)***	β	0.861 (10.66)***	0.903 (7.82)***
η		0.054 (2.16)**	η	-	-0.027 (-0.43)
wald statistics (χ^2)	6.71***		wald statistics (χ^2)	13.46***	
υ	1.311 (11.33)***	1.344 (12.18)***	υ	1.148 (10.85)***	1.148 (10.78)***
AIC/SIC	3.23/3.27	3.22/3.27	AIC/SIC	3.38/3.43	3.38/3.43
Log Likelihood	-1269.88	-1266.43	Log Likelihood	-1331.05	-1330.65
Parameter	**Singapore**		**Parameter**	**Indonesia**	
	A. Return equations			A. Return equations	
a	0.125 (5.25)***	0.084 (0.43)	a	0.193 (3.78)***	0.239 (0.56)
b	-0.055 (-1.34)	-0.055 (-1.54)	b	0.117 (3.06)***	0.117 (2.31)**
c	-	0.044 (0.21)	c	-	0.154 (1.01)
	B. Variance equations			B. Variance equations	
ω	0.022 (1.99)*	0.022 (1.81)*	ω	0.164 (2.83)***	0.272 (1.04)
α	0.065 (3.17)***	0.058 (2.66)***	α	0.088 (4.04)***	0.047 (1.17)
β	0.912 (35.76)***	0.911 (32.93)***	β	0.826 (20.82)***	0.761 (4.51)***
η	-	0.011 (0.34)	η	-	0.097 (2.74)***
wald statistics (χ^2)	6.94***		wald statistics (χ^2)	15.58***	
υ	1.177 (14.28)***	1.176 (14.14)***	υ	1.264 (11.90)***	1.263 (11.25)***
AIC/SIC	2.62/2.66	2.62/2.67	AIC/SIC	3.39/3.42	3.39/3.44
Log Likelihood	-1028.68	-1028.57	Log Likelihood	-1333.65	-1332.39
Parameter	**Korea**		**Parameter**	**Thailand**	
	A. Return equations			A. Return equations	
a	0.180 (3.70)***	0.126 (0.58)	a	0.064 (3.47)***	-0.125 (-1.86)*
b	-0.038 (-1.21)	-0.026 (-0.69)	b	0.046 (5.02)***	0.055 (1.66)*
c	-	0.022 (0.13)	c	-	0.143 (4.67)***
	B. Variance equations			B. Variance equations	
ω	0.092 (3.07)***	0.111 (3.01)***	ω	0.266 (2.38)**	0.335 (2.57)**
α	0.076 (3.83)***	0.031 (2.48)**	α	0.103 (4.08)***	0.054 (1.82)*
β	0.876 (37.74)***	0.853 (30.65)***	β	0.764 (14.59)***	0.714 (11.43)***
η	-	0.172 (2.61)***	η	-	0.134 (1.79)*
wald statistics (χ^2)	8.94***		wald statistics (χ^2)	21.16***	
υ	1.304 (12.63)***	1.377 (12.49)***	υ	1.120 (7.65)***	1.131 (7.48)***
AIC/SIC	3.43/3.47	3.42/3.46	AIC/SIC	3.38/3.42	3.38/3.42
Log Likelihood	-1350.74	-1342.81	Log Likelihood	-1330.01	-1327.63

Note: The t-values are indicated in the parentheses. Wald statistic has an asymptotic $\chi^2(1)$ distribution for testing the hypothesis $\alpha + \beta = 1$. The critical values at 10% significance level are 2.71, 5% level are 3.84, 1% level are 6.64.

GARCH: $R_t = a + bR_{t-1} + \varepsilon_t$ $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$ TAR-GARCH: $R_t = a + bR_{t-1} + ch_t^{1/2} + \varepsilon_t$ $h_t = \omega + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$

With respect to the estimated variance equation, it can be observed that the parameters (α, β) are all positive and significant. This satisfies the restriction that α and β must be non-negative, with correctly signed parameters. The α and β estimates are highly significant in both GARCH and TAR-GARCH (1,1)-M specifications, confirming the presence of ARCH in all series. The estimated β coefficients in the conditional variance equation are considerably larger than the α coefficients, implying that volatility is predicted mainly by the AR component. In addition, the high value of β indicates that time varying volatility has long memory for Asian stock markets. As for the stationarity of the variance process, across the whole sample $\alpha + \beta$ is 0.992 for Hong Kong, 0.992 for Malaysia, 0.980 for Japan, 0.956 for the Philippines, 0.977 for Singapore, 0.990 for Indonesia, 0.991 for Korea and 0.963 for Thailand. Since this persistence measure ($\alpha + \beta$) is very close to one, the Wald test is performed to examine the null hypothesis $\alpha + \beta = 1$ (the test results are shown in Table 4.2-4.6 named as the 'Wald statistics'). The null hypothesis of IGARCH is rejected, hence the restrictions required for stationarity, that the sum of the parameters α and β should be less than unity ($\alpha + \beta < 1$), seem to hold for the estimated models. This indicates that the conditional volatility process is stationary. In other words, a current shock to volatility does not persist indefinitely in conditioning the future variances, so that shocks decay slowly with time. However, the sum was rather close to one, indicating long persistence of volatility shocks in Asian stock markets.

Another striking result from the variance equation is that good news and bad news have differential effects on the conditional variance[21]. The TAR-GARCH (1,1)-M model shows that the η coefficient is positive and significant for almost all Asian stock markets and for nearly all sub-periods. This indicates the presence of leverage effects and an asymmetric impact of news. Good news has influence α, while bad news has marginal influence $(\alpha + \eta)$. Taking results for the whole sample period as an example, the conditional variance impact of good news in the Hong Kong stock market is 0.036 while the bad news impact is 0.104. As for Malaysia, the good news impact is 0.056

[21] 'news' here refer to news about volatility

while the bad news impact is 0.131. In Japan good news has an impact of 0.023 while bad news has an impact of 0.123. For the Philippines, good news has an impact of 0.072 while the bad news impact is 0.191. The leverage term (η) is also highly significant for Singapore (0.094), Indonesia (0.041), Korea (0.058) and Thailand (0.092).

4.4.3 Evidence for non-normal conditional distributions

Table 4.2-4.6 also reports the estimates of the tail-thickness parameter v. The results reject the null hypothesis that the tail-thickness parameter v is equal to 2.0 (benchmark value for normality). In all cases the parameter is significantly smaller than 2.0, which implies a conditional distribution with fatter tails than the normal.

4.4.4 Relationship between stock returns and volatility

The evidence raises the question of whether investors in Asian equity markets are compensated for undertaking a high level of risk. We address this by using the TAR-GARCH (1,1)-M model, in which the coefficient c measures the relationship between market return and risk.

In general, the results for the whole sample period show no evidence of a positive and significant reward-to-risk relationship. The estimates of the c coefficient are mostly small in magnitude and vary in sign across countries. Table 4.2 shows that the c coefficient is negative for all markets except Malaysia, Philippines and Korea, where the coefficient is positive. However, with the exception of Thailand, none of the c estimates is statistically significant. These findings suggest that there is no significant contemporaneous relationship between stock returns and volatility in Asian stock markets.

It has been argued that the stock market crash may have had a substantial impact on stock market behaviour. In particular, Choudhry (1996) and Shin (2005) provide evidence of changes in the relationship between the risk premium and volatility before and after the 1997-98 financial crash. To investigate the impact of Asian financial crisis, we need to further analyze the risk-return relationships for the sub-periods. The results of sub-sample periods are reported in Tables 4.3 to 4.6. In Table 4.3, it is interesting to note that the estimates of c are positive in seven out of eight markets in the pre-crash period, although only one of them is statistically significant. Only Hong Kong has a significant result during this period. In contrast, during the crisis and post-crisis period the c coefficients are negative for Hong Kong, Malaysia, Indonesia and Thailand but are still non-significant. In the recovery period, however, all the estimated coefficients of c in the conditional mean equations are positive and two (Malaysia and Thailand) are significant.

In summary, in contradiction to predictions of the CAPM, there is no evidence of a significant positive relationship between risk and return in Asian stock markets, and it is interesting to find that in fact there are more negative risk-premium coefficients (albeit non-significant) in the crisis and post-crisis periods than in other periods. Negative risk-premium requires only that the return to risky assets is less than the risk free rate which is almost certainly true when stock prices are falling, so that $R_m - R_f < 0$. In the empirical analysis here no risk-free assets were used, but the coefficient can be interpreted as ($R_m - R_f$). More generally, according to Glosten *et al.* (1993), an inverse relationship between risk and return is theoretically possible. Glosten *et al.* (1993) argues that a larger risk premium may not be required because investors may want to save relatively more when future seems more risky. If transferring income to the future is risky and risk-free assets are not available, then the price of the risky asset may be bid up considerably, thereby reducing the risk premium. However, his argument depends on rising stock prices as risky assets are bid up in an attempt to increase savings. In the results here stock prices fall during the crisis period. Since the fall in price is accompanied by an increase in volatility. There is a measured fall in the *average* risk premium for the crisis period. This empirical finding suggests that the 1997-98 financial crash could be responsible for the change from a positive to a negative risk-return relationship.

4.4.5 The conditional volatility movement analysis

Figure 4.1 below shows conditional volatility levels in different Asian countries over the period January 1992 to March 2000. This provides a revealing image of the time-varying nature of volatility.

Conditional volatility levels appear to follow a similar time path in most Asian countries. Most noticeably, all Asian countries experience a volatility spike around the onset of the 1997 Asian crisis with volatility falling rapidly in most markets following the crisis. This indicates that Asian stock markets shows instant reaction to undesirable market event by the sudden change in the volatility. With the passage of time, normally after a few days, markets begins to revive from the shock of the event and starts to fluctuate within the normal range. However, the volatility spike due to the Asian financial crisis had a more prolonged effect in Japan and Thailand relative to other Asian markets.

Interestingly, the empirical results also show that the financial liberalization that started in 1993-1994 in Asia did not have a significant impact on volatility in any of the sampled countries. Volatility is seen to be stable and at a low level until the onset of the crisis. This is rather surprising since many previous studies show that stock markets exhibit either increasing or decreasing volatility following liberalization (for example Dhir 2007 and Law 2006). On the other hand, this result might imply that the financial structure of Asian stock markets is different from that of other emerging markets in the world.

It is noticeable that the Mexican Peso crisis in 1994 did not cause a large volatility spike for most Asian countries, in contrast to the impacts of the 1997-1998 shocks. Internal shocks (local news) apparently have greater impact than external shocks in Asian stock markets.

Figure 4.1 also shows that the financial crisis is not the only high volatility episode in some Asian stock markets. It is evident that volatility is also generally high during 2001, particularly in Japan, Korea and the Philippines. This spike appears to coincide with the bursting of the dot com bubble and may imply that these three markets are more integrated with the rest of the world.

Finally, stock market volatility appears to fall after 2001, returning to pre-crisis levels. Overall, this would suggest that the 1997-98 Asian financial crisis was a particularly important major event affecting the time path of volatility in most Asian markets during the sampled period.

4.4.6 Specification tests

Next we evaluate the robustness of the results using a series of specification tests. Panel A of Tables 4.7 to 4.11 reports the Ljung-Box test statistics of the series of standardized and squared standardized residuals, denoted by Q(12) and $Q^2(12)$. With a few exceptions, none of these are statistically significant for the overall sample period, indicating an absence of serial correlation in the residuals.

In order to test whether the GARCH (1,1) and TAR-GARCH (1,1)-M models have adequately captured the persistence in volatility, with no ARCH effects left in the residuals from these models, an ARCH-LM test was conducted. The results (see Panel B) indicate that the standardized residuals do not exhibit any ARCH effects and therefore that the models are not mis-specified.

Figure 4.1 Time series plots of Conditional Variance

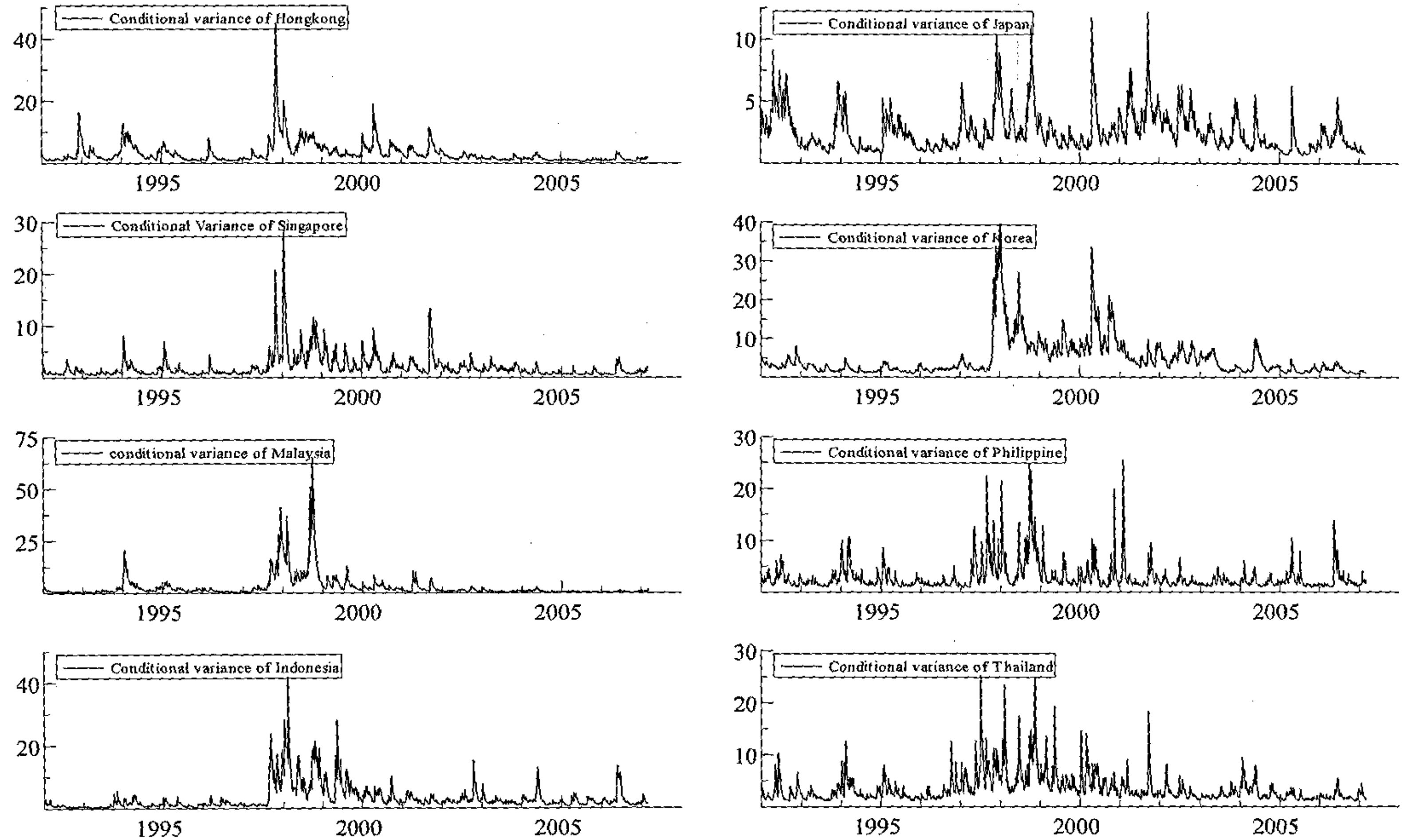


Table 4.7 Specification test for the whole sample

	HK	JP	SG	KR	MA	PHI	IND	THA
				Specification tests: GARCH				
Panel A: Autocorrelation Q statistics								
Q(12)	27.34[0.01]***	10.64[0.47]	19.51[0.06]*	14.53[0.20]	15.97[0.14]	13.71[0.24]	14.50 [0.20]	30.77[0.00]***
$Q^2(12)$	6.52[0.76]	4.59[0.91]	4.92[0.89]	7.94[0.63]	12.20[0.27]	3.27[0.97]	6.13 [0.80]	1.84[0.99]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.33[0.91]	0.40[0.87]	0.37[0.89]	0.98[0.43]	1.12[0.34]	0.25[0.95]	0.34 [0.93]	0.15[0.98]
ARCH-LM (12)	0.55[0.88]	0.37[0.97]	0.41[0.95]	0.65[0.79]	0.99[0.44]	0.28[0.99]	0.38 [0.97]	0.15[0.99]
				Specification tests: TAR-GARCH-M				
Panel A: Autocorrelation Q statistics								
Q(12)	26.32[0.01]***	8.66[0.46]	14.72[0.17]	12.91[0.29]	13.28[0.18]	14.12[0.22]	13.19 [0.28]	29.32[0.01]***
$Q^2(12)$	6.26[0.79]	7.59[0.66]	4.13[0.94]	8.14[0.61]	10.98[0.35]	2.73[0.98]	7.62[0.66]	1.63[0.99]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.31[0.93]	0.77[0.58]	0.38[0.88]	1.02[0.40]	1.03[0.40]	0.21[0.97]	0.26 [0.94]	0.13[0.99]
ARCH-LM (12)	0.53[0.89]	0.61[0.83]	0.40[0.96]	0.67[0.77]	0.91[0.54]	0.23[0.99]	0.54 [0.88]	0.13[0.99]

Table 4.8 Specification test for the pre-crisis sample

	HK	JP	SG	KR	MA	PHI	IND	THA
				Specification tests: GARCH				
Panel A: Autocorrelation Q statistics								
Q(12)	19.39[0.05]**	17.17[0.11]	10.58[0.48]	17.11[0.11]	12.48[0.32]	13.01[0.29]	20.80[0.03]**	11.27[0.42]
$Q^2(12)$	8.02[0.62]	2.52[0.99]	4.38[0.92]	13.56[0.19]	7.38[0.68]	9.56[0.47]	3.25[0.97]	5.08[0.88]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.51[0.79]	0.09[0.99]	0.15[0.98]	1.42[0.20]	0.56[0.75]	0.03[0.99]	0.23[0.96]	0.30[0.93]
ARCH-LM (12)	0.66[0.78]	0.20[0.99]	0.34[0.97]	1.18[0.28]	0.64[0.80]	0.78[0.66]	0.26[0.99]	0.44[0.94]
				Specification tests: TAR-GARCH-M				
Panel A: Autocorrelation Q statistics								
Q(12)	16.99[0.11]	16.46[0.12]	11.26[0.42]	19.36[0.05]*	12.51[0.32]	15.25[0.17]	21.14[0.03]**	12.17[0.35]
$Q^2(12)$	8.99[0.53]	5.01[0.88]	5.39[0.86]	14.44[0.15]	8.58[0.57]	8.43[0.58]	3.24[0.97]	5.69[0.83]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.41[0.87]	0.39[0.88]	0.27[0.94]	1.50[0.17]	0.79[0.57]	0.31[0.93]	0.15[0.98]	0.38[0.88]
ARCH-LM (12)	0.74[0.70]	0.40[0.96]	0.43[0.95]	1.31[0.20]	0.76[0.68]	0.68[0.76]	0.25[0.99]	0.52[0.89]

Table 4.9 Specification test for the crisis sample

	HK	JP	SG	KR	MA	PHI	IND	THA
				Specification tests: GARCH				
Panel A: Autocorrelation Q statistics								
Q(12)	18.46[0.07]*	14.52[0.20]	7.80[0.73]	12.41[0.33]	7.64[0.74]	3.75[0.97]	8.95[0.62]	6.78[0.81]
$Q^2(12)$	6.16[0.80]	11.28[0.33]	5.70[0.83]	3.11[0.97]	7.99[0.62]	3.64[0.96]	5.07[0.88]	15.73[0.11]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.42[0.86]	0.30[0.93]	0.48[0.81]	0.20[0.97]	0.36[0.90]	0.20[0.97]	0.49[0.81]	0.76[0.59]
ARCH-LM (12)	0.55[0.87]	0.82[0.62]	0.45[0.93]	0.28[0.99]	0.61[0.83]	0.28[0.99]	0.50[0.91]	1.17[0.30]
				Specification tests: TAR-GARCH-M				
Panel A: Autocorrelation Q statistics								
Q(12)	18.97[0.06]**	13.17[0.28]	8.99[0.62]	11.43[0.40]	6.90[0.80]	4.37[0.95]	8.08[0.70]	6.94[0.80]
$Q^2(12)$	7.27[0.69]	9.22[0.51]	6.41[0.77]	2.68[0.98]	6.11[0.80]	5.82[0.82]	5.56[0.85]	12.39[0.25]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.82[0.55]	0.18[0.98]	0.56[0.76]	0.18[0.98]	0.53[0.78]	0.42[0.86]	0.53[0.77]	0.48[0.82]
ARCH-LM (12)	0.68[0.76]	0.67[0.77]	0.50[0.91]	0.24[0.99]	0.47[0.92]	0.41[0.96]	0.49[0.91]	0.94[0.50]

Table 4.10 Specification test for the post-crisis sample

	HK	JP	SG	KR	MA	PHI	IND	THA
			Specification tests: GARCH					
Panel A: Autocorrelation Q statistics								
Q(12)	10.91[0.45]	6.91[0.80]	9.54[0.57]	8.74[0.64]	13.56[0.25]	15.65[0.15]	10.57[0.47]	19.78[0.04]**
$Q^2(12)$	6.11[0.80]	9.61[0.47]	4.18[0.93]	6.10[0.80]	3.41[0.97]	2.03[0.99]	5.69[0.87]	7.71[0.65]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.33[0.92]	0.97[0.44]	0.48[0.82]	0.40[0.87]	0.18[0.98]	0.11[[0.99]	0.42[0.86]	0.14[0.99]
ARCH-LM (12)	0.51[0.90]	0.73[0.72]	0.38[0.96]	0.49[0.91]	0.28[0.99]	0.16[0.99]	0.78[0.72]	0.71[0.73]
			Specification tests: TAR-GARCH-M					
Panel A: Autocorrelation Q statistics								
Q(12)	12.63[0.31]	6.89[0.80]	11.07[0.43]	8.56[0.66]	16.06[0.13]	15.17[0.17]	13.15 [0.28]	19.76[0.04]**
$Q^2(12)$	6.83[0.74]	8.44[0.58]	5.98[0.81]	5.01[0.89]	4.98[0.89]	1.89[0.99]	7.29[0.69]	8.59[0.57]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.38[0.88]	1.01[0.41]	0.81[0.55]	0.30[0.93]	0.29[0.94]	0.10[0.99]	0.43[0.85]	0.13[0.99]
ARCH-LM (12)	0.58[0.85]	0.63[0.80]	0.55[0.88]	0.42[0.95]	0.41[0.95]	0.15[0.99]	0.77[0.67]	0.77[0.67]

Table 4.11 Specification test for the recovery sample

	HK	JP	SG	KR	MA	PHI	IND	THA
				Specification tests: GARCH				
Panel A: Autocorrelation Q statistics								
Q(12)	8.63[0.65]	4.91[0.93]	12.08[0.35]	6.53[0.83]	11.12[0.43]	9.70[0.55]	5.11[0.92]	8.81[0.63]
$Q^2(12)$	11.07[0.35]	5.23[0.87]	10.38[0.40]	6.71[0.75]	14.89[0.13]	1.57[0.99]	9.81[0.45]	0.44[0.99]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.9[0.48]	0.32[0.92]	1.55[0.15]	0.60[0.72]	0.66[0.67]	0.17[0.98]	0.37[0.89]	0.05[0.99]
ARCH-LM (12)	1.01[0.44]	0.41[0.95]	0.94[0.49]	0.48[0.92]	1.27[0.22]	0.13[0.99]	0.78[0.66]	0.04[0.99]
				Specification tests: TAR-GARCH-M				
Panel A: Autocorrelation Q statistics								
Q(12)	8.65[0.65]	4.95[0.93]	12.23[0.34]	6.63[0.82]	11.69[0.38]	7.97[0.71]	5.94[0.87]	11.12[0.43]
$Q^2(12)$	11.32[0.33]	9.21[0.51]	10.79[0.37]	8.11[0.61]	16.28[0.11]	0.93[0.99]	9.03[0.52]	0.33[0.99]
Panel B: ARCH LM tests								
ARCH-LM (6)	0.97[0.43]	0.78[0.58]	1.58[0.14]	0.92[0.47]	0.71[0.63]	0.12[0.99]	0.32[0.92]	0.03[0.99]
ARCH-LM (12)	1.02[0.42]	0.68[0.76]	0.99[0.45]	0.63[0.81]	1.38[0.16]	0.08[0.99]	0.71[0.73]	0.02[1.00]

4.4.7 Day-of-the-week effects in stock returns and volatility

$$R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t \tag{4.11}$$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2 \tag{4.12}$$

Day-of-the-week effects in return and variance are captured through TAR-GARCH (1,1) using dummy variables. Table 4.12 reports the estimated parameters for the mean and variance specifications using Equations (4.11) and (4.12) for the full sample period. Volatility is not included in the return equation using GARCH-in-means because this effect is not robust across sub-periods. Note that Wednesday is excluded from the equation to avoid the dummy variable trap. Positive (negative) returns or volatility means higher (lower) returns than on Wednesdays.

Before interpreting the results, one should be aware that, although day-of-the week effects may be found in this section, the evidence may be subject to data-mining biases as suggested by Sullivan et al. (2001). The day-of-the week effects must therefore be interpreted with caution and with the realisation that it may not be possible to draw strong conclusions.

Table 4.12 reports the estimates for the full sample. It is found that Monday returns are significantly higher in Singapore. On the other hand, volatility in Singapore market is also higher on Monday. This may mean that investors want to be compensated for taking higher risks by receiving higher returns, as financial theory suggests. Hong Kong does not show day-of-the-week effects in returns but volatilities are lower on Tuesday and Thursday than on Wednesday. The Philippines market shows asymmetry in that the coefficient for the Monday dummy is significantly positive in the volatility equation but negative in the returns equation. Indonesia also shows asymmetry, with the coefficient on the Tuesday dummy being significantly positive in the volatility equation but negative in the returns equation. Additionally, Monday, Tuesday and Thursday returns are significantly lower than Wednesday for Thailand, but volatility is higher on Monday. These results indicate that investors should not trade on Mondays in the Philippines or Thailand (due to lower return but high volatility on Mondays) or on Tuesdays in Indonesia (since high risk is associated with low returns on these days).

It is also interesting to note that lower returns and higher volatility on Monday are observed. There seem to be two possible explanations for this interesting phenomenon. The first is based on Miller (1988), who attributes the negative returns on Monday to a shift in the broker-investor balance in decisions to buy and sell. Miller (1988) argues that during the workday, individual investor, who are too busy to do their own research, tend to follow the recommendations of their brokers, recommendations that are skewed to the buy side. During the weekend, however, individual investors have time to do their own portfolio research and tend to make decisions to sell on Monday. Institutional investors avoid Monday trading and use it for making planning for the entire week. This leads to an excess of sell orders on Monday. Miller's hypothesis is supported by evidence showing that odd-lot sales, attributed to individual investors, are highest on Mondays while institutional volume is particularly low.

The second explanation is related to the informed trader hypothesis. French and Roll (1986) argue that informed investors trading on private information may cause the higher variance after the holidays. Foster and Viswanathan (1990) use a similar argument. Due to inadequate regulation and weak enforcement of rules, insider trading is likely to occur in Asian stock markets and hence Asian insiders accumulate information during weekends. This could partly explain why excessive fluctuations are observed in Asian stock markets on Monday.

For the overall period, there is no evidence of day-of-the-week effects in either returns or volatility for Japan and Korea, and only weak evidence for other countries. It is noteworthy that Brook and Persand (2001) also reported no day-of-the-week effects in Korea. This finding might be explained by Kohers, Kohers, Pandey and Kohers (2004), who demonstrate that day-of-the-week effects tend to disappear in some developed countries after the 1990s, arguing that this was the result of improvements in market efficiency over time.

Table 4.12 Day-of-the-week effects in return and volatility for full sample period

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Estimates of return equation and volatility equations								
Return equation								
Constant	0.069	0.020	0.069*	0.033	0.051***	-0.058	0.125***	0.088***
	[0.202]	[0.732]	[0.083]	[0.549]	[0.000]	[0.173]	[0.000]	[0.001]
Monday	0.016	-0.107	0.041***	-0.029	-0.125***	-0.059	-0.168***	-0.463***
	[0.825]	[0.238]	[0.001]	[0.774]	[0.000]	[0.368]	[0.001]	[0.000]
Tuesday	-0.031	0.019	-0.104*	-0.078	-0.040	-0.122*	-0.124**	-0.243***
	[0.661]	[0.798]	[0.076]	[0.343]	[0.165]	[0.067]	[0.015]	[0.000]
Thursday	-0.041	0.010	-0.007	0.099	-0.021	0.148**	-0.035	-0.092*
	[0.448]	[0.894]	[0.842]	[0.204]	[0.385]	[0.013]	[0.492]	[0.059]
Friday	0.001	-0.041	0.009	0.016	0.026	0.156***	0.111	0.058
	[0.992]	[0.592]	[0.860]	[0.843]	[0.600]	[0.008]	[0.838]	[0.320]
Return_{t-1}	0.046***	-0.025	0.067***	0.043**	0.110***	0.142***	0.183***	0.093***
	[0.001]	[0.152]	[0.001]	[0.018]	[0.000]	[0.000]	[0.000]	[0.001]
Volatility equation								
ω	0.179**	0.031	0.010**	0.070	0.068	0.142	0.029	0.148
	[0.017]	[0.770]	[0.012]	[0.526]	[0.120]	[0.308]	[0.652]	[0.222]
α	0.035***	0.025***	0.062***	0.037***	0.056***	0.081***	0.095***	0.081***
	[0.000]	[0.003]	[0.001]	[0.003]	[0.000]	[0.001]	[0.000]	[0.000]
β	0.918***	0.903***	0.859***	0.924***	0.906***	0.801***	0.881***	0.831***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
η	0.070***	0.095***	0.105***	0.061***	0.071***	0.137***	0.045**	0.101***
	[0.001]	[0.000]	[0.003]	[0.004]	[0.001]	[0.000]	[0.027]	[0.001]
Monday	-0.017	0.168	0.181*	0.006	-0.010	0.332**	0.074	0.328
	[0.875]	[0.235]	[0.097]	[0.967]	[0.854]	[0.024]	[0.380]	[0.110]
Tuesday	-0.215**	-0.086	0.127	-0.151	-0.079	0.102	0.182*	0.284
	[0.048]	[0.616]	[0.200]	[0.370]	[0.166]	[0.574]	[0.080]	[0.220]
Thursday	-0.335***	-0.109	-0.014	-0.076	-0.100	-0.059	0.121	-0.344*
	[0.008]	[0.503]	[0.907]	[0.684]	[0.170]	[0.727]	[0.277]	[0.062]
Friday	-0.137	0.198	-0.005	0.057	-0.067	-0.081	-0.069	-0.187
	[0.267]	[0.197]	[0.949]	[0.716]	[0.378]	[0.648]	[0.512]	[0.318]
Log likelihood	-5378.49	-5318.24	-4687.18	-6002.149	-4603.215	-5298.33	-5104.21	-5697.695
Panel B: Autocorrelation Q statistics								
Q(6)	10.111	4.535	9.648	9.510	9.246	10.025	8.343	31.460***
	[0.109]	[0.605]	[0.138]	[0.147]	[0.187]	[0.128]	[0.215]	[0.000]
Q(12)	16.434	9.848	17.126	12.693	11.804	18.491	13.411	38.955***
	[0.159]	[0.629]	[0.145]	[0.392]	[0.427]	[0.131]	[0.340]	[0.000]
Panel C: ARCH-LM tests								
ARCH-LM(6)	0.268	0.979	0.515	0.892	0.528	0.305	0.427	0.140
	[0.951]	[0.437]	[0.796]	[0.499]	[0.781]	[0.934]	[0.863]	[0.990]
ARCH-LM(12)	0.488	0.800	0.483	0.606	0.372	0.303	0.685	0.160
	[0.922]	[0.650]	[0.925]	[0.838]	[0.956]	[0.989]	[0.762]	[0.999]

Note: *P*-values are reported in parentheses under the corresponding coefficient. (*), (**) and (***) correspond to significance at 10%, 5% and 1% levels.

Models : $R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$$

Table 4.13 Day-of-the-week effects in return and volatility for pre-crisis period

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Estimates of return equation and volatility equations								
Return equation								
Constant	0.177	0.004	0.073	0.005	0.117**	0.048	0.128***	0.189**
	[0.149]	[0.965]	[0.221]	[0.942]	[0.027]	[0.511]	[0.001]	[0.048]
Monday	-0.174	-0.299**	-0.195**	-0.060	-0.268**	-0.155	-0.159***	-0.644***
	[0.361]	[0.027]	[0.049]	[0.669]	[0.029]	[0.139]	[0.004]	[0.000]
Tuesday	-0.062	0.086	-0.103	-0.085	-0.144	-0.243**	-0.156***	-0.426***
	[0.701]	[0.510]	[0.248]	[0.452]	[0.113]	[0.016]	[0.008]	[0.000]
Thursday	-0.175	0.072	-0.038	0.014	-0.019	0.031	-0.042	-0.163
	[0.255]	[0.613]	[0.655]	[0.902]	[0.865]	[0.761]	[0.469]	[0.125]
Friday	-0.106	-0.036	-0.060	-0.066	-0.006	0.098	-0.026	-0.052
	[0.468]	[0.779]	[0.498]	[0.541]	[0.927]	[0.335]	[0.629]	[0.640]
$Return_{t-1}$	0.058	-0.037	0.147***	0.070**	0.107**	0.216***	0.336***	0.178***
	[0.206]	[0.240]	[0.000]	[0.016]	[0.035]	[0.000]	[0.000]	[0.000]
Volatility equation								
ω	0.167	0.013***	0.001***	0.171	0.045	0.244	0.195	0.468***
	[0.329]	[0.009]	[0.004]	[0.284]	[0.613]	[0.121]	[0.369]	[0.008]
α	0.051***	0.014	0.066**	0.092***	0.047***	0.066**	0.156	0.041**
	[0.002]	[0.104]	[0.015]	[0.003]	[0.001]	[0.019]	[0.157]	[0.036]
β	0.872***	0.924***	0.738***	0.757***	0.923***	0.852***	0.575**	0.756***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.037]	[0.000]
η	0.088	0.101***	0.123**	0.100*	0.026	0.109	0.115	0.240***
	[0.127]	[0.002]	[0.020]	[0.057]	[0.247]	[0.131]	[0.186]	[0.000]
Monday	0.062	0.030	0.279*	0.285	-0.054	-0.087	-0.109	0.154
	[0.814]	[0.913]	[0.097]	[0.396]	[0.669]	[0.744]	[0.356]	[0.599]
Tuesday	-0.142	-0.043	0.282*	-0.157	-0.167	-0.152	0.203	0.001
	[0.597]	[0.874]	[0.071]	[0.555]	[0.225]	[0.531]	[0.162]	[0.998]
Thursday	-0.283	-0.006	0.082	-0.040	0.019	-0.250	0.090	-0.625***
	[0.270]	[0.979]	[0.594]	[0.868]	[0.894]	[0.244]	[0.465]	[0.004]
Friday	-0.025	0.175	0.090	0.223	0.092	-0.332	-0.122	-0.561**
	[0.934]	[0.503]	[0.513]	[0.441]	[0.466]	[0.168]	[0.392]	[0.027]
Log likelihood	-1889.18	-1838.21	-1472.45	-1883.37	-1607.70	-1817.46	-1335.12	-1934.84
Panel B: Autocorrelation Q statistics								
Q(6)	8.351	5.012	4.496	6.987	12.182**	4.519	6.589	8.567
	[0.214]	[0.542]	[0.610]	[0.322]	[0.058]	[0.607]	[0.361]	[0.199]
Q(12)	15.322	14.868	10.848	12.232	13.835	17.448	16.186	12.623
	[0.224]	[0.549]	[0.542]	[0.411]	[0.311]	[0.134]	[0.106]	[0.397]
Panel C: ARCH-LM tests								
ARCH-LM(6)	0.883	0.483	0.419	1.399	0.782	0.358	0.358	0.736
	[0.506]	[0.821]	[0.866]	[0.211]	[0.583]	[0.905]	[0.905]	[0.620]
ARCH-LM(12)	2.014**	0.472	0.437	1.378	0.801	0.692	0.367	0.854
	[0.020]	[0.931]	[0.948]	[0.169]	[0.649]	[0.760]	[0.974]	[0.593]

Note: P-values are reported in parentheses under the corresponding coefficient. (*), (**) and (***) correspond to significance at 10%, 5% and 1% levels.

Models : $R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t$

$$\varepsilon_t \middle| I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$$

Table 4.14 Day-of-the-week effects in return and volatility for crisis period

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Estimates of return equation and volatility equations								
Return equation								
Constant	0.137	0.187	0.035	0.317	-0.385	-0.100	-0.394	-0.157
	[0.640]	[0.365]	[0.917]	[0.252]	[0.182]	[0.724]	[0.237]	[0.647]
Monday	-0.478	-0.538*	-0.956***	-0.839*	-0.710*	-0.513	0.098	-0.742
	[0.216]	[0.099]	[0.005]	[0.065]	[0.052]	[0.140]	[0.807]	[0.105]
Tuesday	-0.202	-0.265	-0.173	-1.006**	0.116	-0.325	-0.130	-0.356
	[0.573]	[0.274]	[0.554]	[0.017]	[0.791]	[0.324]	[0.751]	[0.422]
Thursday	-0.466	-0.416	-0.258	-0.442	-0.599	-0.171	-0.167	-0.373
	[0.267]	[0.130]	[0.451]	[0.139]	[0.134]	[0.683]	[0.729]	[0.429]
Friday	-0.222	-0.716**	0.093	-0.294	0.177	-0.234	0.303	-0.032
	[0.602]	[0.013]	[0.826]	[0.430]	[0.610]	[0.449]	[0.472]	[0.938]
Return_{t-1}	0.070	-0.087*	0.189***	0.139**	0.111**	0.113**	0.124**	0.107*
	[0.264]	[0.065]	[0.006]	[0.012]	[0.040]	[0.021]	[0.023]	[0.052]
Volatility equation								
ω	1.173	1.047*	0.178*	-1.331	4.046***	2.224**	8.116***	9.061***
	[0.236]	[0.095]	[0.054]	[0.114]	[0.001]	[0.018]	[0.000]	[0.001]
α	0.011	0.019	0.136*	0.101	0.331**	0.017	0.175	0.370*
	[0.734]	[0.405]	[0.062]	[0.104]	[0.028]	[0.336]	[0.212]	[0.085]
β	0.869***	0.863***	0.686***	0.891***	0.386**	0.934***	0.406**	0.021
	[0.000]	[0.000]	[0.000]	[0.000]	[0.014]	[0.000]	[0.013]	[0.919]
η	0.208***	0.240**	0.292**	0.012	0.233**	0.196***	0.326	-0.332
	[0.002]	[0.010]	[0.021]	[0.861]	[0.041]	[0.000]	[0.261]	[0.144]
Monday	-1.563	-0.121	0.131	3.688**	-1.385	-1.669	-6.898***	-2.686
	[0.224]	[0.868]	[0.908]	[0.031]	[0.539]	[0.121]	[0.000]	[0.371]
Tuesday	-1.675	-2.561**	-1.399	1.131	4.046	-3.006***	-6.313***	-3.672
	[0.374]	[0.011]	[0.100]	[0.436]	[0.200]	[0.005]	[0.002]	[0.173]
Thursday	-0.109	-1.429	-0.671	0.933	-1.384	-0.948	-0.520	-2.045
	[0.946]	[0.118]	[0.363]	[0.475]	[0.618]	[0.484]	[0.860]	[0.493]
Friday	-1.478	0.013	-2.190**	2.096**	-4.006***	-5.482***	-8.255**	-5.095*
	[0.309]	[0.986]	[0.035]	[0.050]	[0.006]	[0.001]	[0.012]	[0.056]
Log likelihood	-718.28	-601.76	-645.05	-778.105	-770.71	-684.71	-740.980	-735.4
Panel B: Autocorrelation Q statistics								
Q(6)	14.793**	6.137	2.800	7.456	4.149	1.840	4.528	1.210
	[0.022]	[0.408]	[0.833]	[0.281]	[0.656]	[0.934]	[0.606]	[0.976]
Q(12)	18.894*	13.630	11.373	12.559	6.648	3.979	11.011	5.810
	[0.091]	[0.325]	[0.497]	[0.402]	[0.880]	[0.984]	[0.528]	[0.925]
Panel C: ARCH-LM tests								
ARCH-LM(6)	0.880	0.081	0.554	0.226	1.056	1.178	0.511	1.397
	[0.509]	[0.997]	[0.766]	[0.968]	[0.388]	[0.317]	[0.799]	[0.215]
ARCH-LM(12)	0.711	0.708	0.764	0.320	0.843	0.544	0.476	1.526
	[0.740]	[0.742]	[0.686]	[0.985]	[0.605]	[0.884]	[0.927]	[0.113]

Note: *P*-values are reported in parentheses under the corresponding coefficient. (*), (**) and (***) correspond to significance at 10%, 5% and 1% levels.

Models : $R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$$

Table 4.15 Day-of-the-week effects in return and volatility for post-crisis period

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Estimates of return equation and volatility equations								
Return equation								
Constant	-0.160	-0.196	-0.257***	-0.190	-0.082***	-0.259***	0.012	-0.070
	[0.173]	[0.120]	[0.000]	[0.499]	[0.000]	[0.000]	[0.895]	[0.610]
Monday	0.156	0.246	0.123	0.205	-0.135	0.171	-0.172	-0.391***
	[0.373]	[0.262]	[0.385]	[0.680]	[0.221]	[0.139]	[0.272]	[0.001]
Tuesday	0.229	0.036	0.230***	0.324	0.084	0.019	0.068	0.123
	[0.177]	[0.833]	[0.000]	[0.269]	[0.401]	[0.856]	[0.629]	[0.489]
Thursday	0.173	0.221	0.203	0.312	-0.019	0.292***	-0.002	0.046
	[0.353]	[0.223]	[0.178]	[0.339]	[0.843]	[0.004]	[0.989]	[0.785]
Friday	0.066	0.151	0.309***	0.365	0.034	0.258**	0.045	0.295
	[0.717]	[0.330]	[0.001]	[0.247]	[0.728]	[0.013]	[0.753]	[0.248]
$Return_{t-1}$	0.028	-0.020	0.022	0.038	0.092***	0.097***	0.044	0.019
	[0.421]	[0.458]	[0.242]	[0.407]	[0.000]	[0.000]	[0.208]	[0.707]
Volatility equation								
ω	0.197	0.417	0.274	0.955	0.157	0.110	0.831*	0.387
	[0.560]	[0.198]	[0.328]	[0.494]	[0.461]	[0.728]	[0.095]	[0.631]
α	0.022*	0.032	0.067**	0.020*	0.093**	0.080	0.298***	0.134**
	[0.089]	[0.140]	[0.013]	[0.097]	[0.016]	[0.335]	[0.000]	[0.050]
β	0.930***	0.880***	0.786***	0.720***	0.760***	0.703***	0.483***	0.645***
	[0.000]	[0.000]	[0.000]	[0.009]	[0.000]	[0.000]	[0.000]	[0.001]
η	0.056*	0.090**	0.130**	0.130*	0.203*	0.147*	0.005	0.050
	[0.065]	[0.012]	[0.028]	[0.085]	[0.065]	[0.091]	[0.954]	[0.472]
Monday	-0.222	0.681	-0.361	0.896	0.434	0.540	0.725	0.411
	[0.608]	[0.197]	[0.338]	[0.377]	[0.128]	[0.351]	[0.317]	[0.547]
Tuesday	-0.229	-0.647	0.042	0.215	0.345	0.391	0.079	0.896
	[0.696]	[0.181]	[0.913]	[0.867]	[0.289]	[0.422]	[0.885]	[0.270]
Thursday	-0.187	0.028	0.327	-0.755	0.446	0.054	0.354	-0.251
	[0.687]	[0.953]	[0.430]	[0.376]	[0.143]	[0.881]	[0.590]	[0.718]
Friday	-0.037	-0.431	-0.190	0.608	0.401	0.294	0.240	0.701
	[0.925]	[0.375]	[0.628]	[0.409]	[0.177]	[0.514]	[0.697]	[0.209]
Log likelihood	-1624.51	-1573.63	-1476.967	-1948.15	-1387.86	-1421.87	-1613.01	-1656.13
Panel B: Autocorrelation Q statistics								
Q(6)	0.695	1.131	4.380	3.453	10.383	9.245	10.330	16.764**
	[0.995]	[0.980]	[0.625]	[0.750]	[0.109]	[0.160]	[0.121]	[0.010]
Q(12)	12.338	7.410	9.065	7.244	15.670	17.056	15.196	23.186**
	[0.419]	[0.829]	[0.697]	[0.841]	[0.207]	[0.148]	[0.289]	[0.026]
Panel C: ARCH-LM tests								
ARCH-LM(6)	1.555	4.387***	0.957	0.417	0.171	0.255	0.607	0.317
	[0.557]	[0.001]	[0.453]	[0.867]	[0.984]	[0.957]	[0.724]	[0.928]
ARCH-LM(12)	1.532	3.305***	0.649	0.672	0.303	0.340	0.841	0.717
	[0.107]	[0.001]	[0.800]	[0.797]	[0.988]	[0.981]	[0.632]	[0.735]

Note: *P*-values are reported in parentheses under the corresponding coefficient. (*), (**) and (***) correspond to significance at 10%, 5% and 1% levels.

Models : $R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$$

Table 4.16 Day-of-the-week effects in return and volatility for recovery period

	HK	JP	SG	KR	MA	PHI	IND	THA
Panel A: Estimates of return equation and volatility equations								
Return equation								
Constant	0.086	0.143	0.131*	0.117	0.058	0.118***	0.301***	0.169*
	[0.386]	[0.161]	[0.054]	[0.303]	[0.119]	[0.000]	[0.001]	[0.057]
Monday	0.141	0.048	0.008	0.040	-0.007	-0.225	-0.346**	-0.338**
	[0.291]	[0.761]	[0.944]	[0.758]	[0.895]	[0.227]	[0.019]	[0.016]
Tuesday	-0.109	-0.065	-0.086	-0.076	-0.014	-0.117	-0.192	-0.107
	[0.291]	[0.607]	[0.215]	[0.633]	[0.763]	[0.334]	[0.164]	[0.130]
Thursday	0.007	-0.081	-0.007	0.125	-0.008	0.101*	-0.134	-0.115
	[0.957]	[0.450]	[0.948]	[0.332]	[0.901]	[0.055]	[0.314]	[0.220]
Friday	0.062	-0.037	0.042	0.082	0.034	0.003	0.007	0.045
	[0.603]	[0.791]	[0.701]	[0.566]	[0.531]	[0.940]	[0.941]	[0.673]
$Return_{t-1}$	0.040	-0.002	-0.056***	-0.027	0.116***	0.050***	0.134***	0.065***
	[0.296]	[0.945]	[0.000]	[0.328]	[0.002]	[0.000]	[0.003]	[0.000]
Volatility equation								
ω	0.153	0.044	0.109	0.104	0.095**	0.099	0.424	0.257
	[0.147]	[0.844]	[0.351]	[0.519]	[0.025]	[0.735]	[0.140]	[0.215]
α	0.016	0.024	0.052**	0.016	0.069***	0.054	0.039	0.038
	[0.721]	[0.601]	[0.039]	[0.783]	[0.000]	[0.636]	[0.204]	[0.127]
β	0.920***	0.865***	0.903***	0.847***	0.923***	0.879**	0.652***	0.728***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.012]	[0.000]	[0.000]
η	0.045	0.103	0.022	0.174**	0.001	0.005	0.181	0.141**
	[0.593]	[0.353]	[0.532]	[0.011]	[0.995]	[0.941]	[0.122]	[0.033]
Monday	0.141	0.134	0.030	0.074	-0.061	0.411	0.421	0.547
	[0.413]	[0.544]	[0.829]	[0.755]	[0.309]	[0.728]	[0.309]	[0.111]
Tuesday	-0.119	0.041	-0.070	-0.151	-0.094	0.175	0.171	0.379
	[0.526]	[0.879]	[0.645]	[0.497]	[0.489]	[0.864]	[0.553]	[0.294]
Thursday	-0.343	-0.184	-0.229	-0.021	-0.152	-0.348	-0.363	-0.218
	[0.102]	[0.519]	[0.309]	[0.941]	[0.237]	[0.761]	[0.301]	[0.493]
Friday	-0.036	0.295	-0.107	0.206	-0.133	0.019	-0.181	-0.316
	[0.827]	[0.243]	[0.423]	[0.358]	[0.348]	[0.947]	[0.581]	[0.226]
Log likelihood	-1112.51	-1263.14	-1024.33	-1339.98	-783.35	-1320.97	-1323.59	-1314.52
Panel B: Autocorrelation Q statistics								
Q(6)	3.431	1.551	7.809	4.104	8.251	6.681	4.553	2.073
	[0.753]	[0.956]	[0.252]	[0.663]	[0.220]	[0.351]	[0.602]	[0.913]
Q(12)	9.792	5.483	13.362	7.324	13.967	8.874	7.061	10.531
	[0.634]	[0.940]	[0.343]	[0.835]	[0.303]	[0.414]	[0.853]	[0.569]
Panel C: ARCH-LM tests								
ARCH-LM(6)	1.491	0.802	1.522	0.866	0.552	0.151	0.526	0.048
	[0.178]	[0.568]	[0.167]	[0.518]	[0.768]	[0.988]	[0.788]	[0.995]
ARCH-LM(12)	1.493	0.768	0.958	0.523	0.933	0.158	1.114	0.042
	[0.120]	[0.683]	[0.486]	[0.901]	[0.512]	[0.999]	[0.344]	[0.999]

Note: *P*-values are reported in parentheses under the corresponding coefficient. (*), (**) and (***) correspond to significance at 10%, 5% and 1% levels.

Models : $R_t = \alpha_0 + a_1 D_{1t} + a_2 D_{2t} + a_4 D_{4t} + a_5 D_{5t} + bR_{t-1} + \varepsilon_t$

$$\varepsilon_t | I_{t-1} \sim GED(0, h_t)$$

$$h_t = \omega + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_4 D_4 + \lambda_5 D_5 + \beta h_{t-1} + (\alpha + \eta I_{t-1})\varepsilon_{t-1}^2$$

Tables 4.13 to 4.16 report sub-period analysis for the pre- and post-crisis periods. The purpose of sub-period analysis is to determine whether day-of-the-week effects are persistent over time. Clearly, during the sampled period, there may be significant changes in the microstructure and efficiency of markets. The first sub-sample is the period from 08/01/1992 to 01/07/1997, prior to the financial crisis of 1997-1998. During this period, returns are significantly lower for Singapore on Monday while volatility is higher on Monday and Tuesday. This suggests that trading on Mondays in Singapore during the pre-crisis period was not properly risk compensated. For Thailand, returns are significantly lower on both Monday and Tuesday while volatility is significantly lower on Thursday and Friday. For some other stock markets (Japan, Malaysia, Philippines and Indonesia) day-of-the-week effects are found in returns but not in volatilities, although Monday returns are generally the lowest of any day of the week in these markets. There is no evidence for the day-of-the-week effects for either Hong Kong or Korea.

The second sub-period covers the 1997-98 Asian financial crisis, from 02/07/1997 to 31/12/1998. Returns are significantly lower on Monday in Singapore, Korea and Malaysia. There are no day-of-the-week effects in stock returns for Hong Kong, Japan, Philippines, Indonesia and Thailand during this period. This finding is consistent with Hui (2005), who also found little evidence of day-of-the-week effects in returns for most Asian countries during the Asian crisis period. It seems likely that the unusual volatility induced by the stock market crash removed the day-of-the-week patterns in stock *returns*. However, there is clear evidence of day-of-the-week patterns in *volatility*, particularly Friday effect.

The post-crisis sample covers the period from 01/01/1999 to 06/03/2003. Day-of-the-week effects in stock returns are observed in only three countries during this period. Monday returns are significantly lower in Thailand while returns are significantly higher on Thursday and Friday in the Philippines. Tuesday and Friday returns are significantly higher in Singapore. For the remaining markets none of the estimated day-of-the-week coefficients is statistically significant for returns. The most striking result during the post-crisis period is that no day-of-the-week effects exist for volatility. This is possibly because non-informational factors such as insider trading exerted less influence on stock market activity and therefore did not induce abnormal volatility patterns.

Finally, the last sub-sample covers a relatively stable economic period, from 07/03/2003 to 08/03/2007. Day-of-the-week effects in stock returns are only present in two countries. Returns are significantly higher on Thursday in the Philippines but are significant lower on Monday in Indonesia and Thailand. Moreover, consistent with the findings of post-crisis period, there is still no evidence of day-of-the-week effects in volatility.

Overall, the findings of the sub-period analysis provide several important conclusions and implications. First, in Asia, day-of-the-week effects occur mainly in the less developed markets. In the relatively mature markets such as Hong Kong, Japan and Korea, there is little evidence of day-of-the-week effects. Second, these effects do not persist over time since the number of effects is significantly reduced after the Asian financial crisis. In particular, day-of-the-week effects in volatility fall away after the crash. This may perhaps be attributed to post-crisis changes in microstructure and improvements in market efficiency. While Wong, Hui and Chan (1992) argues that this is due to improvements in the settlement system, other reasons are possible. For example, more restrictive regulatory enforcement of rules may have made insider trading much more difficult and therefore improved market efficiency. This removes the reason for Monday effects and hence reduces the validity of Miller (1988) and Roll (1986) hypothesis.

4.5 Conclusion

Non-linearities in the structure of returns are investigated in Asian stock markets using a time series modelling approach (GARCH and TAR-GARCH-M models). Specifically, volatility clustering, asymmetry properties, risk-return relationships and day-of-the-week effects in return and risk are examined.

We find strong evidence of time-varying volatility. Volatility clustering appears to characterize Asian stock markets. As a consequence, GARCH processes can be successfully used to model second order conditional moments in these markets. In most cases a high level of persistence in volatility is found. Asymmetry effects are also found in Asian stock markets. That is, bad news will generate more volatility than good news. A volatility spike is found in Asian stock markets around the onset of the 1997 Asian crisis, although similar effects are not found for financial liberalization, the Mexican Peso crisis and other major events. This is inconsistent with Dhir (2007) and Law (2006), who argue that there are significant changes in volatility trends in response to financial liberalization and external shocks. The results here may indicate that Asian stock markets could have regional characteristics that make them are subject to regional factors than to external shocks.

Given the high level of volatility that characterizes most Asian stock markets, we examine whether investors are rewarded with higher average returns for taking on market risk, using a TAR-GARCH (1,1)-M model. Surprisingly, the result fails to produce convincing evidence to support a significant positive linear relationship between risk and return. On the contrary, a observed negative(albeit non-significant) risk-return trade-off is found during the crisis and post-crisis periods. This finding is inconsistent with most asset-pricing models and it seems likely that the financial crisis is responsible.

In the last part of the analysis, day-of-the-week effects in stock returns and volatility are explored. Overall, there is scattered weak evidence of day-of-the-week effects in stock returns. In volatility, there is little evidence of day of week effects except perhaps for the crisis period. Returns are lower and volatility higher on Mondays, but mostly for a few emerging markets of the sample. This phenomenon could be explained by the Miller (1988) hypothesis and the informed trader hypothesis. The existence of day-of-the-week effects raises question about the efficiency of Asian emerging markets. On the other hand, the sub-period analysis shows little evidence of day-of-the-week effects in both returns and volatility after the financial crisis. This might be due to stricter regulation and improved financial structure. In other words, this suggests improved post-crash market efficiency in Asian emerging markets.

Chapter 5 Multivariate GARCH Analysis of Volatility Transmission and Spillover Effects in Asian Stock Markets

5.1 Introduction

Chapter 3 described an investigation of long term interdependencies and information transmission across Asian markets, generally relying upon Granger-causality testing of market indices. However, this method focused on spillovers between markets of the mean returns (conditional first moments of the returns) and failed to capture the persistence of volatility (time variation in the conditional variance of stock returns). It has been argued that information transmission across markets might occur not only through mean returns but also through volatility. That is, cross-market flows of information might not be visible when in form of returns. However, there could be strong effect through volatility. Kyle (1985) argues that more information may be revealed in the volatility of a price than in the price itself, while Singh, Kumar and Pandey (2009) suggests that if two markets are integrated then any external shock in one market will affect both the mean and the variance of return in other markets. Moreover, volatility is a measure of risk, so that understanding volatility transmission across markets helps in portfolio diversification and asset allocation. Since stock volatilities in individual Asian stock markets were modelled in Chapter 4, the main objective of this chapter is to examine the cross-market transmission of volatility.

Close examination of the nature of volatility transmission is important in aiding the effectiveness of monetary policy and in addressing financial stability issues. This is mainly because the complexity of volatility interrelationships represents a potential source of systemic financial instability – stock price volatility propagation could lead a large shock in one market to destabilize another. To this extent, an understanding of the market return volatility linkages could help policymakers to implement effective monetary policy to maintain financial stability.

Understanding volatility spillover across markets is also beneficial to investors and stock traders. It is well established that stock traders in a given market incorporate into their 'buy' and 'sell' decisions not only information generated domestically but also relevant information produced by other stock markets. Therefore, understanding the ways in which stock markets interact permits investors to carry out hedging and trading strategies more successfully.

The earliest research about the source of volatility spillover is offered by modern portfolio theory (Markowitz, 1952), which established the importance of risk and return in the determination of investor demand for financial assets. In the basic portfolio model, an investor finds an optimal balance between risk and return by maximising the expected portfolio return for a given level of risk, thereby choosing from the efficient frontier. Within this framework, the portfolio return reflects the weighted average of the returns from the various assets included in the portfolio, while the variance of the portfolio return (total risk) is determined by the variance of the return to each asset and covariation between all assets in the portfolio. Since a portfolio may be internationally diversified, this formulation provides the earliest theoretical explanation for volatility spillover effects.

Fleming, Kirby and Ostdiek (1998) also provide a theoretical explanation for the volatility spillover effects based on mean-variance portfolio optimization and speculative trading. They derive a theoretical relationship between the demand for financial assets and market return volatilities such that an information event altering the expectation of volatilities in one market will influence demand and trading in another. This is considered to be a general explanation for cross-market volatility spillovers.

Methodologically, much recent work uses autoregressive conditional heteroskedastisity (ARCH) and univariate generalised autoregressive conditional heteroskedasticity (univariate GARCH) models to study conditional volatility and volatility spillover across markets. Since multivariate GARCH models have had little use, such procedures are applied in this chapter to model the volatility spillover process. In addition, a more flexible BEKK specification (Baba, Engle, Kraft, and Kroner, 1990) allows the estimation to avoid the assumption, used in much of the previous literature, of constant correlation between returns.

The remainder of this chapter will be organized in the following manner. Section 5.2 provides a brief literature review on volatility spillovers, Section 5.3 outlines the specification of the multivariate BEKK model, Section 5.4 presents and discusses the estimation results and Section 5.5 presents conclusions and policy recommendations.

5.2 Review of Literature on Volatility Spillovers

Interdependence among international stock markets has been studied in two broad contexts: interdependence in stock returns and interdependence in stock volatility. Research on interdependence in stock returns was reviewed in chapter 3 (Defusco *et al.*, 1996; Climent and Meneu, 2003; Manning, 2002; Chancharat and Valadkhani, 2007) while research on interdependence in stock volatility is reviewed below.

Methodologically, the existing literature on cross-market volatility spillover includes two main groups of studies. The first group is represented by univariate GARCH models. This approach normally adopts the two-step GARCH estimation procedure. The first step uses univariate GARCH to model the volatility of each market individually. In the second step the volatility of one market estimated in step one is added to the conditional volatility equation of another market. In one application, Hamao, Masulis and Ng (1990) use a GARCH-M model to document volatility spillovers pre- and post-October 1987 in the three major stock markets (New York, Tokyo and London). They find limited volatility spillovers before the crash, but spillovers in multiple directions after the crash. In a more recent application of univariate GARCH models, Curci, Grieb and Reyes (2002) study price and volatility spillovers between five Latin American markets, as well as transmissions to Latin America from Japan, the UK and the US. They find evidence of bi-directional price relationships between Argentina, Brazil, Chile, Mexico, and Peru, and some evidence of volatility spillovers between these markets. They find that volatility is transmitted from the U.S. to Argentina, Brazil and Mexico, from the UK to Brazil and Peru. Evidence of stock market volatility spillovers has also been found by Kaltenhaeuser (2003), for markets in the Euro area, the US, and Japan. In summary, these studies all use two-step univariate GARCH estimation and indicate the widespread occurrence of financial market volatility spillovers. Unfortunately univariate GARCH models have major weaknesses. That is, the information contained in the variance-covariance matrix of residuals derived from the univariate GARCH framework cannot be effectively utilized in estimating the effects of volatility spillovers. The multivariate approach explicitly deals with these shortcomings.

The second group of studies involve a number of multivariate GARCH models which have been proposed in the recent literature. Tse and Tsui (2002) assert that the MGARCH models are potentially more useful than univariate GARCH models with respect to the parameterization of conditional cross-movements. One of the earliest attempts in this category was the VECH model of Bollerslev, Engle and Wooldridge (1988). This approach extended the basic model of Engle and Bollerslev (1986) by using the simultaneous equation form of the original model. However, the VECH model requires large number of coefficients to be estimated, leaving relatively few degrees of freedom in the estimation process. To overcome this problem, Bollerslev (1990) introduced the Constant Conditional Correlation (CCC) model, which simplified the estimation of the multivariate GARCH coefficients by imposing restrictions on the variance-covariance matrix derived from the system of simultaneous equations. This methodology has been used in a number of recent empirical studies. For example, Karolyi (1995) used a multivariate CCC-GARCH model to find the short-run interdependence of volatility in the Toronto and New York stock markets. Koutmos and Booth (1995) applied the model to the daily returns of the New York, Tokyo and London stock exchanges. Their results reveal the importance of US market in transmitting both return and volatility to other markets. Booth *et al.* (1997) examined Scandinavian stock markets using a multivariate CCC-EGARCH model, finding a small number of significant volatility spillovers. Abraham and Seyyed (2006) used a bivariate EGARCH model to investigate the emerging Gulf markets of Saudi Arabia and Bahrain, finding volatility spillover from the smaller though more liberal and accessible Bahrain market to the larger and less accessible Saudi market. For Asian markets, Miyakoshi (2003) examined volatility spillovers between Japan, the US and seven Asian markets, using a bivariate EGARCH model. While they found regional integration between Asian countries they failed to find volatility co-movement between the US and Asian markets other than Japan.

Although the CCC model is a useful improvement over the VECH model of time-varying volatilities in financial time series, this model also has drawbacks. Firstly, the major assumption of constant correlations between the different variables in the system of equations is thought to be unrealistic. Login and Solnik (1995) demonstrate that equity returns cannot be properly modelled under such an assumption. Furthermore, the model does not guarantee a positive definite estimated variance-covariance matrix (a necessary condition to guarantee a solution to the system of equations – Hurditt, 2004).

In more recent years, researchers have used various other methods to examine volatility spillover effects. For example, Chuang, Lu and Tswei (2007) investigate the interdependence of volatility in six East Asian stock markets. They first model the returns in a VAR-BEKK framework to obtain six conditional market variances and then apply a vector autoregressive model (VAR) to the variances. They show that interdependence between equity market conditional variances is high. In addition, they find that the Japanese market is the most influential in transmitting volatility to other East Asian markets. Yu and Hassan (2008) use an MGARCH-BEKK model to examine the transmission of stock volatility between Middle East, North African (MENA) and world stock markets. Their results reveal large and predominantly positive volatility spillovers between MENA and world stock markets. Singh et al. (2009) investigate price and volatility spillovers between North American, European and Asian stock markets by a multivariate GARCH-BEKK model. They observe that significant volatility spillover takes place from Korea, Singapore, Malaysia, Taiwan and Hong Kong to the US and that London is mostly affected by Japan, Singapore and Hong Kong.

The BEKK-GARCH model has gained recent popularity for examining volatility transmission because the BEKK specification is both more general and more flexible than other variations of the multivariate GARCH model – there is no restriction imposed on the coefficients and the equations contain all ARCH and GARCH items (Qiao, Liew and Wong, 2007). A further advantage of this model is that it uses a quadratic form of the parameterization of the original system of equations, thereby ensuring the positive definiteness of the variance-covariance matrix without significantly changing the information content of the system of equations. Finally, it avoids both the unrealistic assumption of constant correlation between variables (the CCC model) and the generated regressor problem associated with the two-step estimation procedures of many earlier studies (Pagan, 1984). The advantages of the BEKK parameterization of the multivariate GARCH make it suitable for the analysis of volatility linkages and it is therefore used in this chapter to investigate volatility linkages between Asian stock markets.

5.3 Empirical Methodology

5.3.1 The Model

In this chapter, a bivariate representation of BEKK model is used to examine the pair-wise volatility linkages between the Asian stock markets. The important feature of this specification is that it allows the conditional variances and covariances of the two series to influence each other, so the formulation allows volatility spilllover effects in one or even both directions to be examined. Furthermore, a bivariate representation does not require the estimation of many parameters, as observed by Caporale, Pittis and Spagnolo (2006), Arago and Fernandez (2007). Including many variables and lags creates a difficult optimization problem (Singh *et al.*, 2009) but according to Caporale *et al.* (2006), a bivariate system can be used with no loss of generality, justifying the use of a bivariate BEKK model here. In addition, this model is designed in such a way that the estimated covariance matrix (H_t) will be positive definite, which is a requirement needed to guarantee non-negative estimated variances. These conditions are guaranteed during the estimation. Specifically, a VAR (1)-bivariate BEKK GARCH (1,1) model in the following form:

$$R_t = \alpha + \beta' R_{t-1} + \varepsilon_t \tag{5.1}$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \tag{5.2}$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B \tag{5.3}$$

Here R_t is a 2×1 vector of market index returns at time t. The α reflects long-term mean return. The market information available at time t-1 is represented by the information set I_{t-1}. The matrix C is a lower triangular matrix that is used to derive the constants for the variance equation.

$$C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$$

The ε_t represents the innovation for each market at time t with its corresponding 2×2 conditional variance-covariance matrix, H_t.

$$H_t = \begin{bmatrix} h_{11,t} & h_{12t} \\ h_{12t} & h_{22,t} \end{bmatrix}$$

The mean equation is modelled as a vector autoregression of order one because of the autocorrelation found in the return series and because the influence that one market has on another often lasts no more than one day (Isakov and Perignon, 2000).

The bivariate case of BEKK parameterisation for multivariate GARCH (1,1) model in equation (5.3) can be written as:

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = C'C + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{2,t-1}\varepsilon_{1,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} +$$

$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{5.4}$$

5.3.2 The Volatility Transfers

In order to identify volatility spillover transfers between markets in the framework of a BEKK-GARCH (1,1) model, the conditional variance equation, ignoring the constant terms C, is expanded into following:

$$h_{11,t} = c_{11}^{2} + c_{12}c_{21} + a_{11}^{2}\varepsilon_{1,t-1}^{2} + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^{2}\varepsilon_{2,t-1}^{2} + b_{11}^{2}h_{11,t-1}^{2} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^{2}h_{22,t-1}^{2} \quad (5.6)$$

$$h_{22,t} = c_{22}^{2} + a_{12}^{2}\varepsilon_{1,t-1}^{2} + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^{2}\varepsilon_{2,t-1}^{2} + b_{12}^{2}h_{11,t-1}^{2} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^{2}h_{22,t-1} \quad (5.7)$$

$$h_{12} = c_{12}c_{11} + c_{22}c_{12} + a_{11}a_{12}\varepsilon_{1,t-1}^{2} + (a_{11}a_{22} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^{2} + b_{11}b_{12}h_{11,t-1} + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1}$$
$$+ b_{21}b_{22}h_{22,t-1} \quad (5.8)$$

The term $h_{11,t}$ describes the conditional variance (volatility) for the first market at time t and $h_{12,t}$ shows the conditional covariance between the first and second markets. The error term, ε_{t-1}, in each model, represents the effect of 'news' (unexpected volatility shocks) in each model on different countries (Hassan and Malik, 2007). In observing volatility spillovers, it is necessary to measure the impact of the lagged squared residuals, $\varepsilon_{1,t-1}^{2}$ and $\varepsilon_{2,t-1}^{2}$, and the lagged variances, $h_{11,t-1}$ and $h_{22,t-1}$, on the variances of the stock returns $h_{11,t}, h_{22,t}$. ε_{t-1}^{2} is the variance shock arising from innovations in the returns equation lagged one period. This is in one sense short-term since it only enters the variance equation at one date, but is long-term in the sense that it continues to enter the variance equation through the lagged variance itself, h^2. Therefore, the parameter a_{ij} of the 2×2 matrix A measures the transmission of innovations from the market i to j. The parameter b_{ij} of the 2×2 matrix B measures the persistence in the conditional volatility between the market i to market j. There are several studies (Zahnd, 2002; Yu and Hassan, 2008; Singh *et al.*, 2009), that only explain parameter a_{ij} as the volatility spillover from market i to market j. This is because the effect of lagged variances on the present variance is delayed. Zahnd (2002) notes that shocks in asset variances should first take effect through the squared residuals and that the impact of lagged variance on the present variance is a second round effect. Thus, only a_{ij} is interpreted as a volatility spillover effect. Here, however, a_{ij} and b_{ij} can both be interpreted as volatility spillovers, but of different types. As stated earlier, Hassan and Malik (2007) explain that the error term, ε, represents 'news' or some unanticipated event (unexpected shocks) in a particular market. Thus, a_{ij} is explained as conditional variance of market j is affected by volatility news generated from market i. Since h measures persistence in the conditional volatility, b_{ij} is explained as conditional variance of market j affected by volatility persistence generated in market i. Moreover, according to Agren (2006), the coefficients of the BEKK specification do not represent any direct impact since the parameters are squared or cross-multiplied, implying that interpretation of the individual parameter coefficients is not straightforward. Nevertheless, Agren (2006) asserts that a_{ij} and b_{ij} are important indicators measuring volatility transmission from market i to market j whose statistical significance can be established.

Overall, the statistical significance level of a_{ij} and b_{ij} is of interest and tells about the volatility spillover. Significant a_{ij} term represents transmission of more recent shocks (innovations) from market i to market j. This interprets as 'news' since it reflects more recent information (news shocks). On the other hand, Significant b_{ij} represents transmission of persistence in conditional volatility (conditional variance) from market i to market j. This interprets as persistent volatility transmission relationship since conditional variance includes all past information. The significance of a_{ij} and b_{ij} terms will be analyzed separately and both of them reflects direct volatility transmission relationships.

Table 5.1 Parameter estimates of BEKK model for full sample period from 8th January 1992 to 8th March 2007

Parameters	HK-JP		HK-SG		HK-MA		HK-PHI		HK-KOR		HK-IND		HK-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.215***	14.33	0.149***	9.93	0.225***	14.51	0.217***	16.01	0.274***	16.13	0.252***	24.53	0.223***	12.25
a_{12}	0.039	1.32	0.200***	16.24	-0.012	-1.04	0.034	1.60	-0.009	-0.40	0.028	1.63	-0.116***	-4.74
a_{21}	-0.026*	1.73	0.289***	15.70	0.021	1.50	-0.045**	-2.20	0.017	1.08	0.021	1.61	0.001	0.03
a_{22}	0.222***	11.48	0.147***	9.13	0.276***	22.04	0.339***	13.07	0.233***	15.53	0.245***	17.92	0.353***	16.94
b_{11}	0.968***	214.56	0.621***	22.17	0.917***	97.37	0.970***	211.35	0.945***	52.5	0.907***	114.03	0.976***	197.49
b_{12}	0.010	1.50	-0.447***	-12.17	-0.193***	5.01	0.010	1.29	0.045*	1.70	-0.164***	-8.21	-0.042***	-4.94
b_{21}	0.005	0.72	-0.386***	10.62	0.101	1.62	0.019**	2.03	-0.028	-1.52	-0.033	-1.37	0.012	1.64
b_{22}	0.958***	158.25	0.776***	21.55	0.913***	95.00	0.907***	69.67	0.958***	50.42	0.905***	124.82	0.901***	87.69

Parameters	JP-MA		JP-SG		JP-PHI		JP-KOR		JP-IND		JP-THA		MA-SG	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.271***	14.78	0.174***	11.40	0.219***	14.35	0.233***	14.43	0.208***	13.40	0.337***	10.77	0.242***	15.83
a_{12}	0.042***	3.86	0.130***	8.24	0.006	0.34	0.051***	2.90	-0.003	-0.03	0.036	1.47	-0.002	-0.11
a_{21}	0.015	1.24	-0.166**	-10.20	-0.017	-1.07	0.041***	3.56	0.022	1.57	0.038	1.62	0.016	1.28
a_{22}	0.264***	18.32	0.278***	36.97	0.352***	16.55	0.241***	15.54	0.344***	20.22	0.206***	15.07	0.328***	10.95
b_{11}	0.946***	136.16	0.919***	124.99	0.891***	134.15	0.963***	214.46	0.948***	107.46	0.918***	114.75	0.972***	108.27
b_{12}	0.018***	5.00	-0.273***	-32.23	0.239***	11.04	0.021***	4.03	0.028	1.16	-0.021	-1.53	-0.024	-1.24
b_{21}	0.002	0.66	0.382***	28.72	0.282***	15.31	0.012***	3.42	0.029	1.61	-0.023	-1.63	0.041***	8.20
b_{22}	0.965***	274.01	0.792***	87.71	0.828***	127.13	0.969***	258.45	0.950***	33.43	0.931***	112.05	0.964***	74.15

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for HK-JP, a_{12} represents transmission of innovations from HK to JP, while a_{21} represents transmission of innovations from JP to HK.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for HK-JP, b_{12} represents persistence in conditional volatility transmission from HK to JP, while b_{21} represents persistence in conditional volatility transmission from JP to HK.

Table 5.1 Parameter estimates of BEKK model for full sample period from 8th January 1992 to 8th March 2007 (cont'd)

Parameters	MA-PHI		MA-KOR		MA-IND		MA-THA		SG-PHI		SG-KOR		SG-IND	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.280***	12.34	0.276***	15.40	0.264***	20.53	0.285***	15.70	0.174***	10.50	0.162***	7.30	0.305***	12.70
a_{12}	-0.042	1.47	-0.006	-0.45	-0.047***	-3.10	-0.035	-1.40	-0.002	-0.08	0.124***	2.84	0.064***	3.17
a_{21}	0.023	1.38	0.021**	1.98	0.022**	2.52	0.012	0.92	0.096***	7.99	0.147***	14.38	-0.030	1.55
a_{22}	0.110***	3.40	0.203***	11.79	0.311***	13.43	0.229***	13.83	0.303***	12.11	0.125***	5.06	0.191***	9.56
b_{11}	0.872***	57.69	0.962***	205.74	0.977***	139.06	0.935***	65.35	0.982***	237.77	0.830***	45.56	0.937***	52.16
b_{12}	-0.053	-1.63	0.007	1.55	0.278***	6.46	-0.251***	-11.95	-0.006	-1.01	0.123***	6.72	-0.146***	-4.71
b_{21}	0.031	1.59	0.015***	3.75	-0.126***	-4.21	0.168**	15.27	0.031***	7.78	0.221**	19.18	0.050	1.62
b_{22}	0.674***	27.23	0.977***	250.08	0.964***	122.35	0.694***	46.26	0.930***	97.54	0.929***	37.10	0.923***	87.54
Parameters	SG-THA		PHI-KOR		PHI-IND		PHI-THA		KOR-IND		KOR-THA		IND-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.310***	12.71	0.186***	14.76	0.209***	11.18	0.126***	5.24	0.169***	13.85	0.191***	11.23	0.237***	18.80
a_{12}	0.020	0.58	0.157***	15.52	0.098***	3.67	0.045	1.45	-0.062***	-3.87	-0.087**	5.43	0.025	1.38
a_{21}	-0.005	-0.48	-0.028*	-1.77	0.030	1.60	0.089***	5.23	-0.036*	-1.66	0.038	1.28	0.017	1.18
a_{22}	0.305***	13.61	0.318***	19.02	0.294***	16.33	0.297***	11.58	0.215***	11.94	0.207***	18.99	0.116***	9.60
b_{11}	0.819***	23.88	0.918***	306.81	0.946***	82.88	0.860***	45.26	0.873***	98.08	0.673***	41.64	0.571***	29.52
b_{12}	0.232***	5.16	-0.032***	-7.26	-0.312***	-22.28	-0.258***	-8.89	-0.267***	-14.95	0.210***	3.14	-0.045	-1.29
b_{21}	-0.170**	4.58	0.009	1.62	-0.058*	1.74	-0.230***	-9.58	0.137**	2.23	0.106***	5.33	0.018	1.56
b_{22}	0.804***	25.08	0.919***	143.93	0.829***	75.36	0.776***	59.69	0.792***	97.97	0.908***	278.66	0.794***	48.61

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for MA-PHI, a_{12} represents transmission of innovations from MA to PHI, while a_{21} represents transmission of innovations from PHI to MA.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for MA-PHI, b_{12} represents persistence in conditional volatility transmission from MA to PHI, while b_{21} represents persistence in conditional volatility transmission from PHI to MA.

Table 5.2 Parameter estimates of BEKK model for pre-crisis period from 8th January 1992 to 1st July 1997

Parameters	HK-JP		HK-SG		HK-MA		HK-PHI		HK-KOR		HK-IND		HK-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.285***	10.37	0.267***	9.08	0.180***	4.81	0.251***	8.77	0.250***	8.65	0.287***	9.77	0.257***	9.62
a_{12}	-0.003	-0.12	0.352***	9.44	0.056	1.63	-0.017	-0.61	0.054	1.61	0.098**	2.10	-0.048	-1.60
a_{21}	-0.049*	-1.92	0.103***	3.18	0.022	1.05	0.063**	2.31	0.079**	2.99	0.021	0.18	-0.034	-1.39
a_{22}	0.232***	9.91	0.297***	7.05	0.282***	7.37	0.291***	10.71	0.279***	6.71	0.257***	4.48	0.331***	11.66
b_{11}	0.938***	47.94	0.950***	97.75	0.933***	61.24	0.947***	39.35	0.952***	84.33	0.951***	51.89	0.953***	104.64
b_{12}	-0.015	-0.19	0.450***	8.82	-0.079	-1.44	0.008	0.09	0.087**	2.12	0.057	1.25	-0.014	-1.25
b_{21}	-0.186***	-3.29	0.237**	2.19	-0.060	-1.13	0.165***	4.55	-0.098*	-1.75	-0.097	1.50	-0.012	-1.30
b_{22}	0.960***	54.69	0.910***	30.23	0.971***	109.54	0.942***	36.92	0.895***	30.06	0.958***	48.26	0.928***	79.14

Parameters	JP-MA		JP-SG		JP-PHI		JP-KOR		JP-IND		JP-THA		MA-SG	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.271***	8.18	0.287***	10.83	0.275***	11.01	0.263***	11.02	0.235***	10.11	0.210***	10.91	0.202***	8.91
a_{12}	0.025	1.59	-0.063**	-2.54	-0.041	-1.46	-0.115***	-3.55	-0.067**	-2.06	-0.047	1.16	0.012	0.37
a_{21}	0.011	1.22	0.239***	7.18	-0.052	1.63	-0.081***	-3.02	0.172***	3.89	0.048	1.52	0.031	0.99
a_{22}	0.224***	13.70	0.294***	7.99	0.237***	7.60	0.307***	8.67	0.451***	11.70	0.307***	10.29	0.212***	4.92
b_{11}	0.947***	67.16	0.939***	99.05	0.946***	113.82	0.914***	34.34	0.964***	104.81	0.974***	198.24	0.968***	148.7
b_{12}	0.010	1.47	0.030***	3.45	0.024	1.26	-0.253***	-2.72	0.059*	1.67	0.030**	1.98	-0.026	-1.62
b_{21}	0.003	0.69	0.106***	4.17	-0.029	-1.61	-0.279***	-2.98	-0.269***	-3.17	-0.028***	-4.43	0.061***	4.52
b_{22}	0.969***	165.0	0.889***	28.27	0.926***	70.47	0.844***	25.05	0.958***	78.32	0.919***	55.17	0.964***	78.14

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for HK-JP, a_{12} represents transmission of innovations from HK to JP, while a_{21} represents transmission of innovations from JP to HK.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for HK-JP, b_{12} represents persistence in conditional volatility transmission from HK to JP, while b_{21} represents persistence in conditional volatility transmission from JP to HK.

Table 5.2 Parameter estimates of BEKK model for pre-crisis period from 8th January 1992 to 1st July 1997 (cont'd)

Parameters	MA-PHI		MA-KOR		MA-IND		MA-THA		SG-PHI		SG-KOR		SG-IND	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.231**	9.60	0.223***	13.21	0.255***	12.35	0.229***	12.73	0.275***	4.13	0.284***	7.85	0.255***	4.90
a_{12}	0.189***	3.69	0.010	0.30	0.062	1.63	0.024	0.66	0.063	1.57	-0.074	-1.62	0.072	1.54
a_{21}	0.207***	9.97	0.023	1.32	0.051	1.37	-0.001	-0.08	0.098***	4.67	0.017	0.37	0.105	1.62
a_{22}	0.276***	5.39	0.340***	9.09	0.237***	6.56	0.334***	10.67	0.272***	5.76	0.326***	8.81	0.253**	6.32
b_{11}	0.966***	141.4	0.967***	187.68	0.968***	185.4	0.957***	35.30	0.901***	16.36	0.881***	25.67	0.932***	26.72
b_{12}	-0.335***	-7.97	0.003	0.04	-0.057	-1.59	-0.236***	2.84	-0.076	-1.52	0.086	1.64	0.196	1.62
b_{21}	0.410***	16.41	0.012	0.23	0.042	1.61	-0.021	0.39	-0.087	-1.61	0.009	0.27	-0.048	-0.43
b_{22}	0.947***	48.99	0.877***	38.64	0.962***	75.96	0.888***	26.45	0.947***	54.29	0.884***	37.57	0.958***	70.88

Parameters	SG-THA		PHI-KOR		PHI-IND		PHI-THA		KOR-IND		KOR-THA		IND-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.255***	7.13	0.292***	9.14	0.278**	5.41	0.274***	6.83	0.323***	9.25	0.308***	7.18	0.221***	5.06
a_{12}	-0.101**	-2.10	0.026	0.81	0.060	1.36	0.096***	2.77	0.016	0.52	0.041	1.57	0.077***	2.95
a_{21}	-0.027	-1.27	-0.008	-0.24	0.056	1.13	-0.102***	3.53	-0.059	-0.91	0.051**	1.96	0.078	0.92
a_{22}	0.340***	11.21	0.325***	8.59	0.369***	5.29	0.259***	6.04	0.471***	4.83	0.275***	10.64	0.268*	6.01
b_{11}	0.913***	38.71	0.942***	73.57	0.923***	43.97	0.951*	75.12	0.898***	42.80	0.858***	22.30	0.970***	96.28
b_{12}	-0.057*	-1.69	0.013	0.79	0.199**	4.18	-0.314***	-8.48	0.054	1.32	-0.233***	-2.25	0.155**	2.46
b_{21}	-0.024***	-2.01	0.009	0.45	-0.163	1.54	0.254***	7.25	-0.041	-0.41	0.147*	1.73	0.065	1.34
b_{22}	0.915***	57.35	0.882***	35.41	0.629***	4.37	0.953***	52.00	0.514***	9.87	0.931***	45.01	0.951***	55.35

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for MA-PHI, a_{12} represents transmission of innovations from MA to PHI, while a_{21} represents transmission of innovations from PHI to MA.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for MA-PHI, b_{12} represents persistence in conditional volatility transmission from MA to PHI, while b_{21} represents persistence in conditional volatility transmission from PHI to MA.

Table 5.3 Parameter estimates of BEKK model for crisis period from 2nd July 1997 to 31thDecember 1998

Parameters	HK-JP		HK-SG		HK-MA		HK-PHI		HK-KOR		HK-IND		HK-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.443***	10.32	0.177*	1.86	0.397***	6.18	0.361***	5.23	0.411***	4.89	0.384***	7.42	0.398***	5.61
a_{12}	0.062	1.55	-0.086	-1.02	0.051	0.52	0.145***	3.14	0.154**	2.04	0.291***	4.07	-0.006	-0.09
a_{21}	-0.209***	-5.55	0.131**	2.07	0.079	1.54	0.106	1.52	0.015	0.24	-0.047	-0.73	0.030	0.51
a_{22}	0.289***	4.13	0.361***	3.22	0.328***	5.91	0.373***	13.80	0.375***	6.35	0.309***	3.78	0.319***	6.93
b_{11}	0.872***	24.25	0.814***	8.23	0.551***	16.17	0.825***	17.18	0.817***	4.04	0.883***	30.28	0.869***	13.54
b_{12}	-0.223***	-2.95	-0.334**	-2.02	-0.290***	-4.02	0.299***	6.06	-0.195**	-2.06	-0.121**	-2.52	-0.159**	2.52
b_{21}	0.364**	1.96	0.493***	2.76	0.371***	6.08	-0.115	-1.60	-0.265***	-2.60	0.069	-1.58	0.054	0.91
b_{22}	0.887***	12.24	0.867***	8.75	0.861***	11.08	0.881***	48.94	0.886***	25.51	0.939***	25.32	0.894***	31.77

Parameters	JP-MA		JP-SG		JP-PHI		JP-KOR		JP-IND		JP-THA		MA-SG	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.311***	3.51	0.488***	4.58	0.267***	4.11	0.210**	2.01	0.436***	4.26	0.331***	5.41	0.337**	2.51
a_{12}	-0.352**	-2.30	-0.194***	-3.18	-0.077*	-1.66	0.052*	-1.67	-0.394**	-2.27	0.267***	2.68	-0.075	1.61
a_{21}	0.039	0.92	-0.102	-1.49	0.067	1.22	-0.128***	4.42	0.075	1.62	0.036	1.28	-0.218**	-5.54
a_{22}	0.482***	5.98	0.475***	7.42	0.287**	2.36	0.388***	7.62	0.218**	2.28	0.213***	4.32	0.423***	7.16
b_{11}	0.895***	16.85	0.752***	12.73	0.899***	28.44	0.924***	19.13	0.904***	4.02	0.901***	18.60	0.859***	17.20
b_{12}	0.581***	7.38	-0.290***	-5.27	-0.114**	-2.02	-0.075	-0.22	-0.412***	-2.97	0.427*	1.82	0.109	1.29
b_{21}	0.100	1.17	0.142**	2.48	0.010	0.30	-0.249***	-2.63	0.117	1.04	0.260*	1.66	-0.281**	2.11
b_{22}	0.874***	29.00	0.776***	12.38	0.808***	7.52	0.917***	17.17	0.928***	3.98	0.943***	15.29	0.888***	19.52

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for HK-JP, a_{12} represents transmission of innovations from HK to JP, while a_{21} represents transmission of innovations from JP to HK.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for HK-JP, b_{12} represents persistence in conditional volatility transmission from HK to JP, while b_{21} represents persistence in conditional volatility transmission from JP to HK.

Table 5.3 Parameter estimates of BEKK model for crisis period from 2nd July 1997 to 31thDecember 1998 (cont'd)

Parameters	MA-PHI		MA-KOR		MA-IND		MA-THA		SG-PHI		SG-KOR		SG-IND	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.464***	7.18	0.326***	5.18	0.373***	4.38	0.393***	6.49	0.475***	4.07	0.460***	5.89	0.477***	6.04
a_{12}	0.031	0.78	0.011	0.25	0.076	1.47	0.112*	1.68	0.174*	1.69	0.336**	3.89	0.050	1.52
a_{21}	0.264**	1.86	0.286***	4.53	0.109	1.62	0.171**	1.90	0.105	0.81	0.007	0.16	-0.098*	-1.75
a_{22}	0.493***	5.41	0.324***	6.59	0.259***	3.03	0.219***	3.67	0.280***	2.88	0.305***	6.25	0.414***	5.31
b_{11}	0.869***	17.79	0.612***	8.18	0.802***	4.51	0.846***	9.51	0.790***	12.74	0.689***	10.30	0.699***	5.17
b_{12}	-0.051	-1.56	-0.169**	-2.02	0.201***	2.69	-0.229***	-2.93	0.106	1.45	0.433***	3.57	0.109	1.41
b_{21}	-0.082	-1.37	-0.394***	-5.06	0.103	1.59	0.297***	3.14	0.101	1.27	-0.107	-1.03	0.102	0.93
b_{22}	0.664***	5.56	0.916***	24.10	0.901***	8.11	0.881***	11.18	0.944***	23.60	0.888***	63.08	0.872***	7.42

Parameters	SG-THA		PHI-KOR		PHI-IND		PHI-THA		KOR-IND		KOR-THA		IND-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.464***	6.82	0.392***	4.71	0.470**	4.79	0.336***	5.16	0.349***	5.36	0.315***	5.83	0.297***	4.59
a_{12}	0.065	0.69	0.169**	2.28	0.310***	3.52	0.102*	1.90	0.143***	2.81	0.064	1.29	-0.168	-1.36
a_{21}	-0.098	-1.62	-0.102	-1.62	0.272***	4.12	-0.056	-0.98	-0.072	-1.43	-0.074	-1.51	0.089	1.06
a_{22}	0.307	0.93	0.313***	4.03	0.324***	4.38	0.239***	4.34	0.253***	4.18	0.262***	4.14	0.327***	2.94
b_{11}	0.897***	13.30	0.853***	14.68	0.886***	5.98	0.941***	14.77	0.911***	26.90	0.914***	51.64	0.959***	20.33
b_{12}	0.318***	4.24	-0.101***	-3.25	-0.255*	1.90	0.223***	4.36	0.108	1.47	-0.031*	-1.68	0.155	1.61
b_{21}	0.088	1.40	0.030	1.61	-0.348***	-5.53	-0.079	-1.57	0.025	0.23	-0.016	-0.67	-0.090	-0.68
b_{22}	0.723***	10.13	0.951***	52.08	0.890***	7.29	0.451**	2.51	0.892***	21.82	0.893***	24.66	0.652***	2.72

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for MA-PHI, a_{12} represents transmission of innovations from MA to PHI, while a_{21} represents transmission of innovations from PHI to MA.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for MA-PHI, b_{12} represents persistence in conditional volatility transmission from MA to PHI, while b_{21} represents persistence in conditional volatility transmission from PHI to MA.

Table 5.4 Parameter estimates of BEKK model for post-crisis period from 1st January 1999 to 6th March 2003

Parameters	HK-JP		HK-SG		HK-MA		HK-PHI		HK-KOR		HK-IND		HK-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.203***	3.16	0.193***	5.24	0.235***	6.33	0.134***	3.14	0.170***	3.67	0.215***	5.85	0.199***	2.78
a_{12}	-0.113*	-1.72	0.109***	2.54	0.087	1.62	0.214***	7.21	-0.217***	-15.5	0.118*	1.66	-0.135	-1.61
a_{21}	-0.168**	-1.79	0.077	1.57	-0.044	-0.99	0.180***	4.91	0.084***	6.46	-0.102	-1.09	0.056	1.49
a_{22}	0.249***	5.31	0.316***	5.72	0.340***	7.22	0.369***	3.72	0.114***	4.03	0.258***	6.36	0.323***	5.19
b_{11}	0.962***	41.56	0.966***	86.82	0.937***	77.05	0.814***	24.92	0.928***	34.37	0.951***	70.83	0.921***	30.85
b_{12}	0.290***	6.04	-0.376***	-17.09	0.054	1.63	0.313***	12.52	-0.105***	-5.77	0.127***	2.99	0.141	1.63
b_{21}	-0.357***	-6.86	-0.246***	-18.92	-0.043	-1.43	0.365***	9.35	-0.044	-1.63	0.094	1.56	-0.108	-1.63
b_{22}	0.922***	33.14	0.850***	15.85	0.868***	27.93	0.861***	23.91	0.944***	34.96	0.526***	6.82	0.885***	15.05

Parameters	JP-MA		JP-SG		JP-PHI		JP-KOR		JP-IND		JP-THA		MA-SG	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.210***	5.15	0.271***	6.69	0.242***	6.27	0.262***	6.71	0.254***	6.98	0.221***	4.37	0.353***	6.53
a_{12}	-0.076**	-1.83	-0.026	-0.80	-0.062	-1.55	0.297***	3.19	-0.196***	-3.41	0.051	1.06	0.062	1.59
a_{21}	0.115***	3.22	-0.021	-0.84	0.049	1.36	-0.071**	-2.78	0.059	1.57	0.066	1.62	-0.057	-1.52
a_{22}	0.296***	5.19	0.293***	7.32	0.319***	7.97	0.133***	7.29	0.437***	8.24	0.272***	7.59	0.216***	5.23
b_{11}	0.934***	40.61	0.919***	43.76	0.913***	31.48	0.921***	62.39	0.933***	55.96	0.910	33.30	0.916***	16.68
b_{12}	-0.189**	-2.15	0.264***	6.32	-0.166***	-3.22	0.341**	2.35	0.149	0.83	0.065***	2.84	-0.047	-0.35
b_{21}	0.277**	2.21	0.109***	2.74	0.016	0.13	-0.189***	-4.26	-0.124	-1.46	0.037	1.34	-0.109	-1.33
b_{22}	0.914***	23.79	0.867***	27.50	0.884***	29.39	0.946***	25.56	0.665***	5.54	0.938***	42.60	0.864***	15.30

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for HK-JP, a_{12} represents transmission of innovations from HK to JP, while a_{21} represents transmission of innovations from JP to HK.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for HK-JP, b_{12} represents persistence in conditional volatility transmission from HK to JP, while b_{21} represents persistence in conditional volatility transmission from JP to HK.

Table 5.4 Parameter estimates of BEKK model for post-crisis period from 1st January 1999 to 6th March 2003 (cont'd)

Parameters	MA-PHI		MA-KOR		MA-IND		MA-THA		SG-PHI		SG-KOR		SG-IND	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.326**	2.39	0.352***	7.18	0.278***	5.14	0.314**	2.15	0.260***	3.42	0.305***	4.38	0.261***	6.15
a_{12}	0.051	1.19	-0.148**	-2.01	-0.025	-0.44	0.066	1.54	0.103	1.59	0.206*	1.73	0.167**	2.11
a_{21}	0.087	1.59	-0.060***	-2.91	0.047	1.06	0.103***	2.59	-0.109	1.57	-0.058*	-1.69	0.072	1.56
a_{22}	0.335**	2.64	0.244***	4.13	0.394***	7.29	0.283***	5.71	0.391***	2.78	0.376***	6.59	0.364***	5.43
b_{11}	0.923***	6.99	0.890***	8.38	0.661**	4.59	0.938***	14.38	0.900***	24.50	0.867***	26.52	0.842***	30.85
b_{12}	-0.103	-1.25	0.101	1.60	-0.079	-1.60	-0.202***	-3.25	-0.230***	-5.78	0.208***	2.49	0.221**	2.18
b_{21}	0.106	1.61	-0.067	1.58	0.096	1.62	-0.342***	11.79	0.101***	2.93	-0.086*	1.67	0.030	0.95
b_{22}	0.866***	14.59	0.863**	8.19	0.641***	4.45	0.861***	10.68	0.863***	13.35	0.796***	11.52	0.737***	8.49

Parameters	SG-THA		PHI-KOR		PHI-IND		PHI-THA		KOR-IND		KOR-THA		IND-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.275***	5.42	0.357*	6.92	0.363***	9.31	0.320***	6.74	0.390**	5.07	0.364***	7.36	0.340***	7.23
a_{12}	0.111*	1.86	0.099	1.09	0.007	0.11	0.112*	1.85	-0.115***	-2.81	0.044	-1.61	0.065	1.62
a_{21}	0.087**	1.96	-0.060*	-1.72	0.050	1.13	0.104***	3.26	0.269***	7.07	0.197**	2.49	0.216**	4.17
a_{22}	0.350***	7.15	0.342***	9.13	0.419***	7.75	0.325***	7.73	0.283**	2.48	0.338***	4.82	0.349***	8.01
b_{11}	0.916***	12.34	0.923***	35.81	0.906***	39.77	0.902***	33.4	0.920***	34.04	0.917***	57.86	0.688***	9.22
b_{12}	-0.341***	-2.64	-0.214***	-3.83	0.058	0.88	0.135***	3.58	-0.140***	-5.02	0.025	0.29	0.031	0.73
b_{21}	0.199*	1.66	0.153***	10.29	-0.060	-1.22	-0.251***	-10.51	-0.107	-1.57	-0.337***	-6.35	0.299***	15.15
b_{22}	0.915***	12.50	0.778***	24.05	0.584***	6.48	0.737***	21.37	0.752**	2.51	0.875***	21.78	0.840***	9.37

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for MA-PHI, a_{12} represents transmission of innovations from MA to PHI, while a_{21} represents transmission of innovations from PHI to MA.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for MA-PHI, b_{12} represents persistence in conditional volatility transmission from MA to PHI, while b_{21} represents persistence in conditional volatility transmission from PHI to MA.

Table 5.5 Parameter estimates of BEKK model for recovery period from 7th March 2003 to 8th March 2007

Parameters	HK-JP		HK-SG		HK-MA		HK-PHI		HK-KOR		HK-IND		HK-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.155***	4.63	0.156***	5.01	0.153***	5.52	0.169***	5.15	0.169***	5.65	0.142**	2.55	0.210***	7.51
a_{12}	-0.027	-0.18	0.124***	3.04	-0.019	-0.58	0.204***	2.73	0.085*	1.93	0.039	0.62	-0.184**	-3.06
a_{21}	0.174*	1.68	0.340***	5.63	0.097	1.52	-0.015	-0.34	-0.104***	-3.09	-0.049	-1.56	-0.009	-0.47
a_{22}	0.228***	5.11	0.214***	6.86	0.256***	7.35	0.272***	2.73	0.250***	7.88	0.214***	5.21	0.264***	6.88
b_{11}	0.937***	89.04	0.968***	80.92	0.959***	92.5	0.945***	22.63	0.966***	100.4	0.959***	110.6	0.738***	13.97
b_{12}	0.146*	1.86	-0.268***	-6.99	0.295***	11.34	-0.181***	-2.45	0.218***	13.62	0.136**	2.30	-0.300***	-4.28
b_{21}	0.229**	2.18	0.389***	6.96	0.271***	6.15	-0.054	-0.68	0.374***	31.16	-0.263***	-11.43	0.080	1.58
b_{22}	0.925***	40.02	0.946***	88.60	0.948***	68.61	0.858***	11.11	0.934***	89.38	0.927***	52.73	0.670***	12.43

Parameters	JP-MA		JP-SG		JP-PHI		JP-KOR		JP-IND		JP-THA		MA-SG	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.210***	4.93	0.210**	2.54	0.176***	4.35	0.234***	12.53	0.231***	4.85	0.225***	5.14	0.245***	8.17
a_{12}	0.027	1.24	-0.071**	-2.05	-0.086*	1.70	0.077*	1.84	0.082*	1.75	-0.042	-0.84	0.174**	3.89
a_{21}	0.085	1.61	0.195**	2.26	0.048*	1.65	0.046	1.21	-0.011	-0.28	0.003	0.10	0.047**	2.04
a_{22}	0.233***	6.36	0.228***	5.54	0.273***	3.42	0.245***	6.51	0.225***	5.61	0.258***	3.40	0.207***	4.76
b_{11}	0.940***	45.61	0.938***	51.95	0.886***	17.51	0.950***	53.55	0.900***	24.78	0.953***	54.13	0.936***	88.44
b_{12}	0.060***	5.01	0.098*	1.88	-0.182***	3.09	0.038**	2.02	0.075**	2.46	-0.042	-1.39	0.250***	2.74
b_{21}	0.097***	4.04	-0.088	-1.62	-0.093	-1.61	0.036*	1.76	-0.074*	-2.26	0.032	1.41	0.196***	3.15
b_{22}	0.952***	54.86	0.954***	70.20	0.843***	7.71	0.924***	44.47	0.959***	34.73	0.786***	11.28	0.928***	68.00

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for HK-JP, a_{12} represents transmission of innovations from HK to JP, while a_{21} represents transmission of innovations from JP to HK.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for HK-JP, b_{12} represents persistence in conditional volatility transmission from HK to JP, while b_{21} represents persistence in conditional volatility transmission from JP to HK.

Table 5.5 Parameter estimates of BEKK model for recovery period from 7th March 2003 to 8th March 2007 (cont'd)

Parameters	MA-PHI		MA-KOR		MA-IND		MA-THA		SG-PHI		SG-KOR		SG-IND	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.250***	7.69	0.273***	7.71	0.256***	6.82	0.253***	8.08	0.225***	5.45	0.185***	5.15	0.207***	4.75
a_{12}	0.209***	3.04	0.027	0.39	0.145*	1.69	0.064	1.60	0.147*	1.79	0.026	0.46	0.172***	3.05
a_{21}	-0.030**	-1.87	0.007	0.41	-0.029*	-1.65	-0.043	-1.22	-0.109***	-5.34	0.045	1.60	0.071	1.62
a_{22}	0.292***	4.09	0.275***	6.86	0.261***	6.82	0.250***	5.34	0.206***	2.57	0.281***	7.96	0.257***	5.71
b_{11}	0.961***	86.75	0.938***	45.51	0.950***	95.06	0.962***	99.78	0.961***	71.69	0.950***	60.84	0.969***	67.55
b_{12}	-0.267*	1.68	-0.046*	1.77	-0.257**	-4.51	0.132***	5.44	-0.156*	-1.68	-0.027***	-2.70	-0.335***	-2.91
b_{21}	0.148***	3.25	0.018*	1.66	0.087*	1.73	0.032**	2.13	-0.039	-0.96	0.026***	2.85	0.278***	6.05
b_{22}	0.832***	6.98	0.918***	58.14	0.916***	37.59	0.859***	10.99	0.929***	24.54	0.936***	81.68	0.910***	30.46

Parameters	SG-THA		PHI-KOR		PHI-IND		PHI-THA		KOR-IND		KOR-THA		IND-THA	
	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat	Estimates	Tstat
a_{11}	0.233***	4.76	0.257***	4.64	0.250***	3.33	0.210***	4.69	0.231***	5.89	0.255**	2.50	0.286***	9.82
a_{12}	-0.143***	-2.62	-0.037	-0.98	0.071*	1.76	-0.087	-1.47	0.111**	2.56	-0.131**	-2.09	-0.047	-1.01
a_{21}	0.039	1.59	0.023	0.63	0.125*	1.83	-0.028	-0.87	-0.039	-0.74	0.015	0.40	-0.005	-0.21
a_{22}	0.308***	5.46	0.321***	9.05	0.251***	5.97	0.299***	4.56	0.194***	3.60	0.397***	5.58	0.305***	6.35
b_{11}	0.950***	53.45	0.946***	24.01	0.721***	6.28	0.920***	27.18	0.881***	31.78	0.936***	50.75	0.865***	43.71
b_{12}	0.255***	3.35	0.300***	5.26	0.379***	2.96	0.134	1.61	0.052**	2.32	-0.061**	-2.11	-0.120	1.61
b_{21}	0.076	1.57	-0.189***	-2.68	-0.283**	-2.13	-0.006	-0.18	-0.119**	-2.23	-0.005	-0.14	-0.115***	5.75
b_{22}	0.811***	9.89	0.957***	40.43	0.868***	32.82	0.779***	10.46	0.975***	51.61	0.765***	14.66	0.416**	7.37

Note: The estimates are based on equations (5.1) to (5.3) in the text. a_{ij} and b_{ij} terms are the elements of the ARCH and GARCH coefficient matrices A and B in equation (5.3). ***, ** and * indicate that null hypothesis can be rejected at 1%, 5% and 10% level, respectively.

a_{12} measures transmission of innovations from market 1 to market 2. For example, for MA-PHI, a_{12} represents transmission of innovations from MA to PHI, while a_{21} represents transmission of innovations from PHI to MA.

b_{12} measures transmission of persistence in conditional volatility from market 1 to market 2. For example, for MA-PHI, b_{12} represents persistence in conditional volatility transmission from MA to PHI, while b_{21} represents persistence in conditional volatility transmission from PHI to MA.

5.4 Empirical Results

The conditional variance covariance equations incorporated in this multivariate BEKK-GARCH methodology effectively capture the volatility and cross volatility spillovers between Asian stock markets. These quantify the effects of the lagged own and cross innovations and lagged own and cross volatility persistence on the present own and cross volatility of the eight Asian markets. Tables 5.1 to 5.5 present the estimated coefficients for the bivariate variance covariance matrix of equations for the full sample period and four sub-periods using RATS 6.0 software. From these results it is possible to see how the stock volatility transmission channels change over time.

5.4.1 Volatility transmission in the full sample period

Table 5.1 shows volatility spillovers for the whole sample period. Own-volatility spillovers (a_{11}, a_{22}) in all markets are large and significant, indicating the presence of strong ARCH effects. The own-volatility spillover effects are generally larger than the cross-volatility spillovers. This would suggest that past volatility shocks in each individual market have a greater effect on future volatility than past volatility shocks in other markets.

The cross-market volatility spillover effects are more complicated and require to analysis market by market.

Hong Kong. As far as modelling the volatility is concerned, it is necessary to differentiate between the effects of the innovations and the variance (matrices A and B respectively). With respect to innovations (interpreted as 'news'), the Hong Kong stock market is significantly affected by news originating from the Japanese, Singapore and Philippine markets (a_{21} is significant), while news generated from Hong Kong has an effect on Singapore and Thailand (a_{12} is significant). This could mainly because the market in Hong Kong opens and closes after the markets in Japan and the Philippines but before the market in Thailand[22]. An examination of

[22] Hong Kong opens at the same time as Singapore.

the lagged variances shows that past volatility in Hong Kong has significant impact on future volatility in Singapore, Malaysia, Korea, Indonesia and Thailand (b_{12} is significant). while, with the exception of Singapore and the Philippines, other Asian markets have no significant influence on volatility of Hong Kong (b_{21} is insignificant) . This result suggests that Hong Kong is a very influential market in Asia.

Japan. The Japanese market shows bidirectional cross-market spillover of innovations with Singapore and Korea, indicating the sensitivity of Japan to news generated in Singapore and Korea and vice verse. In addition, past innovations in Japan have an effect on future volatility in Hong Kong and Malaysia. For volatility persistence transmission (b_{12}, b_{21}), bidirectional volatility persistence transmission exists with the Singapore, Philippines and Korea. In addition, there is unidirectional persistent volatility transmission from Japan to Malaysia, which implies that Malaysia is dominated by Japan.

Malaysia. The results for Malaysia show that it is directly affected by news generated in Japan and Korea. In addition, Malaysia has a bidirectional cross-market spillover relationship with Indonesia. This result is quite understandable since market open/close in Malaysia is later than in Japan and Korean but almost at the same time as Indonesia. The volatility transmission from lagged variances shows that Malaysia receives volatility from Hong Kong, Japan, Singapore and Korea, but does not transmit volatility to these countries. This indicates that Malaysia is dominated by the developed markets of this sample. Moreover, it has also been found that Malaysia has bidirectional cross-volatility persistence relationships with Indonesia and Thailand. This result may reflect similarities between Malaysia, Indonesia and Thailand arising from their joint membership of ASEAN.

Singapore. It is interesting to note that the market in Singapore has bidirectional volatility spillover relationships with Hong Kong, Japan and Korea for both innovations and volatility persistence. This may be due to the similarity of market microstructure and regulatory systems in Singapore and other countries (particularly

Hong Kong)[23]. On the other hand, Singapore is also affected by innovations and volatility persistence from the Philippines, transmitting volatility to Malaysia and Indonesia, and sharing bidirectional volatility persistence relationship with Thailand.

Korea. There are many bi-directional information spillover relationships between Korea and other markets. For example, with respect to innovations, it shares bi-directional cross-market volatility relationships with Japan, Singapore, the Philippines and Indonesia. With respect to cross-market volatility persistence, it has bi-directional transmission relationships with Japan, Singapore, Indonesia and Thailand. Meanwhile, Korea receives volatility from Hong Kong and the Philippines, and transmits volatility to Malaysia. The large number of bi-directional relationships found between Korea and other markets indicate that Korea has a very close relationship with other Asian markets.

Philippines. With respect to the Philippines, news generated by the Philippines market can affect Hong Kong, Singapore and Indonesia, but the Philippines market is itself affected by the news generated in Thailand. In addition, it shares a bi-directional informational spillover relationship with Korea. The pattern of volatility transmission through lagged variances shows that the Philippine market transmits volatility to Hong Kong, Singapore and Korea. It also has significant and reciprocal volatility transmission linkages with Japan, Indonesia and Thailand. Thus, excluding Thailand, no market transmits volatility uni-directionally to the Philippines. This is mainly because the Philippine market is the first to close in this sample of Asian stock markets and its information is therefore likely to be important for markets which open later.

Indonesia. Volatility transmission is weak between the Indonesian and Hong Kong, Japan and Thailand, suggesting weak linkages. However, Indonesia has strong bi-directional cross-market volatility spillover effects with Malaysia, the Philippines and Korea, and is affected by innovations and volatility persistence from Singapore.

[23] Rhee and Chang (1993) investigate the microstructure of Asian equity markets. They find that the overall regulatory structures in Hong Kong and Singapore are consistent. Further, they also find that Hong Kong and Singapore stock exchanges have adopted the same trading systems.

This suggests that Indonesia is easily affected by volatility emanating from these countries.

Thailand. The Thai market is significantly affected by news from Korea and Hong Kong but significantly affects the Philippines. Thailand is the last market to close and is therefore easily affected by markets that close earlier. However, Thai information is useful for the Philippine market, which is the first to open on the following day. Thailand receives volatility persistence from Hong Kong, and it also has significant and reciprocal persistent volatility spillover linkages with Malaysia, Singapore, the Philippines and Korea. This may suggest that Thailand has close economic relationships with Malaysia, the Philippines and Korea.

To conclude, the results of the whole sample period suggest that there is an influence of opening/closing times on volatility spillover in terms of innovations. In addition, Hong Kong and Japan are very influential markets in Asia, while emerging markets seem to have bi-directional volatility persistence transmission relationships with each other. However, these conclusions must be modified somewhat in the light of sub-period results analysed below, since the results discussed so far do not account for the possibility of changes in direction of volatility transmission due to major events such as the financial crisis. Arago and Fernandez (2007) conclude that the impact of major events should be considered in this type of research, since these could reduce volatility persistence and influence the pattern of transmission. For this reason, the BEKK model is applied to each sub-period. More important, it is possible to examine how critical events can change the information and volatility transmission channels in Asian stock markets.

5.4.2 Volatility transmission in the sub-sample periods

Tables 5.2 to 5.5 shows volatility spillover effects for the sub-periods.

Hong Kong. During the pre-crisis sample period (shown in Table 5.2), the Hong Kong market is significantly affected by news generated from Japan, the Philippines and Korea (a_{21} is significant) while news from Hong Kong affects Indonesia (a_{12} is significant). Further, Hong Kong can affect and be affected by news from Singapore (both a_{12} and a_{21} are significant). This phenomenon is probably due to the different trading times of Asian stock markets. The Japanese, Philippines and Korean stock markets open/close earlier than Hong Kong. Thus, information generated from these markets should affect Hong Kong. The Indonesian market open/close occurs later than in Hong Kong and hence Indonesia is affected by news generated in Hong Kong. The Singapore market has the same trading times as Hong Kong and there should therefore be bi-directional linkages. The pattern of volatility transmission through lagged variances shows that Hong Kong receives volatility from Japan and has bi-directional volatility spillovers with Singapore and Korea. This indicates that Hong Kong had a volatility persistence relationship with developed Asian markets during the pre-crisis period. On the other hand, there is little spillover of volatility persistence between Hong Kong and the emerging markets of the sample.

During the crisis period (shown in Table 5.3), significant changes in the pattern of volatility transmission become evident. The Hong Kong stock market was significantly affected by news generated from the Japanese and Singapore markets. Meanwhile, news in Hong Kong market had an impact on the crisis-hit countries: the Philippines, Korea and Indonesia. Further, Hong Kong had bi-directional volatility persistence transmission relationships with Japan, Singapore, Malaysia and Korea, and transmited volatility uni-directionally to the Philippines, Indonesia and Thailand. This indicates that Hong Kong became more influential for other Asian stock markets during the crisis period, especially for severely crisis-affected countries. An explanation for this phenomenon might be the relative size of the Hong Kong market and its financial importance in Asia. In terms of market capitalization, the Hong Kong market is far larger than the emerging Asian markets of the sample. It is likely that information in the Hong Kong market became very important for Asian emerging markets during the crisis, implying easy transmission of volatility from Hong Kong to emerging markets during this period.

During the post-crisis period (shown in Table 5.4), Hong Kong still retained its relatively dominant role in Asia and its volatility transmission pattern was similar to that of the crisis period. However, it is noticeable that the volatility transmission between Hong Kong and Malaysia is weak during this period. One possible explanation could be the capital controls imposed by the Malaysian government in response to the crisis.

During the recovery period, Hong Kong was affected by news generated from Japan, Singapore and Korea, while its news in turn affected Singapore, the Philippines, Korea and Thailand. Moreover, the pattern of its volatility transmission through lagged variances is bi-directional in all cases (b_{12} and b_{21} are significant) except for the Philippines and Thailand. The increased significant and reciprocal linkages between Hong Kong and other stock markets indicate greater financial integration between Hong Kong and most other Asian equity markets.

Japan. The Japanese stock market has bi-directional volatility spillover relationships with many Asian countries during the pre-crisis period – for example, significant bi-directional volatility spillover effects with Singapore, Korea and Indonesia, in both innovations and volatility persistence. In addition, the volatility of the Japanese market significantly affected the conditional volatility of Hong Kong during the pre-crisis period. The volatility feedback linkages between Japan and some other Asian markets may be due to the presence of feedback traders. That is, due to the prominent economic position of Japan, traders in other countries focus not only on domestic news but also on news from Japan when assessing their risks. This could cause feedback relationships in volatility spillovers.

During the crisis period, past innovations in Japan had significant effects on volatility in all Asian markets (a_{12} is significant in all cases). Moreover, Japan had volatility feedback linkages in cross-volatility persistence with Hong Kong, Singapore and Thailand (b_{12} and b_{21} are significant). Japan also transmitted volatility to Malaysia, the Philippines and Indonesia and received volatility from Korea. This clearly shows that most of the emerging markets in the sample were dominated by the Japanese stock market during the crisis period. This result could be interpreted as an outcome of the cross-market hedging behaviour of market participants within these emerging markets. Given the sharp falls in stock prices in these markets during the financial crisis, the investors would want to hedge by moving part of their funds to a safer harbour – Japan. Thus, investors in emerging markets not only pay more attention to risks related to Japanese news but also need time to evaluate the impact of this news on their asset prices. This would imply that past volatility shocks in Japan have significant effects on future volatility in emerging markets.

During the post-crisis period, the volatility transmission patterns of Japan are not much different from the patterns observed during the crisis. Japan transmitted its volatility uni-directionally to most of the emerging markets of the sample while the volatility channels from the majority of these markets to Japan are weak. Additionally, the volatility spillover channels between Japan and the developed markets of the sample are found to be bi-directional during the post-crisis period. This suggests that investors in Japanese markets responded differently to news generated from developed and emerging markets.

During the recovery period, it can be observed that volatility spillovers between Japan and other markets were bi-directional in almost all cases (either through innovations transmission or through persistent volatility transmission. This is evidence of increased interdependence between the equity volatilities of Japan and those of other Asian equity markets in recent years.

Malaysia. There is only weak volatility transmission between Malaysia and the two major developed markets of Hong Kong and Japan, during the pre-crisis period. This is shown by insignificant coefficients on cross-innovations and cross-volatility persistence (a_{12}, a_{21}, b_{12}, b_{21}). There are cross-volatility persistence spillovers from Singapore and the Philippines to Malaysia and significant volatility spillovers from Malaysia to the Philippines and Thailand (volatility spillovers between Malaysia and the Philippines are bi-directional). This result underlines the impact of volatility within either Malaysia or the Philippines on the dynamics of both markets. In addition, the strong volatility transition from Singapore to Malaysia suggests that an information event that alters expectations of returns in Singapore will influence demand and trading in Malaysia, but not the other way round. Meanwhile, the evidence of strong volatility spillovers from Malaysia to Thailand indicates that an information event that alters expectations of returns in Malaysia will influence demand and trading in Thailand.

During the crisis period, Malaysia is significantly affected by news generated from Japan, Singapore, the Philippines and Korea, while news from Malaysia does not affect other markets in Asia except Thailand. The pattern of volatility transmission through lagged variances shows that Malaysia receives volatility from Japan and transmits volatility uni-directionally to Indonesia. Meanwhile, Malaysia has bi-directional volatility persistence transmission relationships with Hong Kong and Korea.

Furthermore, a particular characteristic of the Malaysian market is that its volatility transmission channels with other markets are extremely weak during the post-crisis period. Malaysia only has volatility persistence transmission relationships with Japan and Thailand during the post-crisis period. This result provides some evidence to support the claim that Malaysian market became slightly segregated from the region after the crisis. As argued earlier, one possible explanation could be the way in which the Malaysian government responded to the crisis by imposing capital controls. During the recovery period, however, there is bi-directional transmission of both news and volatility persistence between Malaysia and its regional counterparts. An increased degree of market openness may be a reason for this increase in bilateral spillovers.

Singapore. For the Singapore market, the pre-crisis results shown in Table 5.2 confirm significant bi-directional news and volatility persistence spillovers between Singapore and the two major developed markets (Hong Kong and Japan). In addition, volatility in the Singapore market is affected by news from the Philippines market which opens/closes just before it. The Thai market opens/closes after the Singapore market and therefore the significant 'news' spillovers are transmitted from Singapore to Thailand. The results also show that Singapore can transmit volatility to Malaysia. During the crisis period, Singapore begins to play a leading role among Asian stock markets. There are uni-directional innovations spillovers from Singapore to Hong Kong, Malaysia, the Philippines and Korea, and uni-directional volatility persistence spillovers from Singapore to Korean and Thailand.

One important thing to notice is that, although Singapore has significant impact on many emerging markets during the crisis period, it is still affected by news generated from Japan.

During the post-crisis and recovery periods, Singapore still affects the volatility of other markets and more bi-directional spillover relationships can be found. For example, during the post-crisis period, bilateral volatility spillovers are found with all Asian counterparts except Malaysia and Indonesia. Further, significant unidirectional volatility persistence spillovers are transmitted from Singapore to Indonesia during the post-crisis period. During the recovery period, there are bi-directional volatility spillovers with Hong Kong, Malaysia, Korea and Indonesia, as well as unidirectional spillovers from Singapore to the Philippines and Thailand. From this analysis it can be concluded that Singapore is a regional leader for Asian emerging markets, with its leadership becoming stronger during the crisis. This leadership persists after the crisis, and the number of bilateral volatility persistence relationship increases.

Korea. Korea shows increasing volatility transmission after the crisis. In the pre-crisis period Korea only has volatility spillover relationships with Hong Kong, Japan and Thailand, but these spread to all other markets from the onset of the crisis. Before the crisis, the conditional volatility of Korea is affected by news (innovations) from Japan and Thailand, while news of Korea in turn affects the volatilities of Hong Kong and Japan. Korea also has persistent volatility feedback linkages with these three markets before the financial crisis. During the crisis, Korea is no longer affected by news from Thailand but is affected by news from Hong Kong, Singapore and the Philippines. Bilateral volatility persistence spillovers are found with Hong Kong and Malaysia, during the crisis, while unidirectional volatility persistence spillovers occur from Singapore and the Philippines and to Japan and Thailand. These results show that the volatility transmission channels of Korea are completely changed by the financial crisis. For the innovations spillover relationship with Hong Kong, the spillover channel is even reversed. This suggests that the crisis substantially influenced the economic and financial policies imposed by the Korean government. After the crisis, there is an increase in a number of bilateral spillover relationships are found between Korea and other countries. Thus, during the post-crisis period, there are significant bi-directional spillovers either of innovations or of volatility persistence between Korea and the other markets, with the exception of Thailand. The post-crisis and recovery periods have similar results, with bilateral spillovers between Korea and all other markets except Thailand. These results reflect the increased openness of the financial market in Korea after the crisis, with Korea both affecting and being affected by foreign market volatility.

Philippines. The Philippine stock market affects all markets except Japan and Korea before the crisis, and is affected only by Malaysia and Thailand, probably because the Philippine market opens and closes before other markets. However, the pattern of volatility transmission changes from the onset of the crisis. During the crisis period, significant unidirectional innovations and volatility persistence spillovers are transmitted from Hong Kong and Japan to the Philippines. This reversed spillover relationship suggests that volatility spillovers are no longer solely determined by market trading times but are also affected by the quality of markets (market capitalisation, number of stock listed and trading volume) since the onset of the financial crisis. Further, although the Philippine market is dominated by two major developed markets, it still exerts influence on most other markets during the crisis period. Significant unidirectional spillovers can be found from the Philippines to Korea, Malaysia and Thailand.

During the post-crisis period, the Philippine market is still affected by the conditional volatility of Japan, but its volatility spillover relationships with other markets are changed. That is, bi-directional linkages emerge with countries where uni-directional linkages or no linkages at all, occurred previously. For example, there is bi-directional innovations spilllovers with Hong Kong and bi-directional volatility persistence transmission between the Philippines and Hong Kong, Singapore, Korea and Thailand during the post-crisis period. This suggests that market trading times become less important in determination of volatility spillover effects after the crisis. Instead, investors and market traders may find that information on volatility in every Asian stock market is helpful in predicting volatility in any one. The post-crisis and recovery period results are quite similar. Japan and Hong Kong are the only two countries to affect the Philippines uni-directionally in volatility persistence transmission. There are more bilateral spillovers of either innovations or volatility persistence between the Philippines and other Asian markets after the crisis. Thus, it can be concluded that the Philippine market is highly linked to other Asian markets after the crisis, particularly during the recovery period.

Indonesia. The results show significant strong impact on Indonesia of spillovers from Japan and Hong Kong for pre-crisis, crisis and post-crisis periods, with only weak volatility spillovers from Indonesia to Japan and Hong Kong. As explained earlier, this might be due to the size differential in the markets. In terms of investment flows, the Japanese and Hong Kong markets are far larger than the Indonesian stock market. Consequently, volatility spillovers from Indonesia to Japan and Hong Kong are weak. Moreover, the volatility spillovers beween Indonesia and other markets vary over time. During the pre-crisis period, excluding Japan and Hong Kong, Indonesia is only affected by the Philippines and only affects Thailand. However, during the crisis period it is affected by Korea and Malaysia, affecting Singapore, and shares bi-directional volatility spillovers with the Philippines. During the post-crisis period, it is affected by Hong Kong, Japan, Singapore, Korea and Thailand but does not itself affect any market with the exception of Korea. In general, it is clearly shown that Indonesia is a small market in Asia and does not have much influence on other markets before the recovery period. However, during the recovery period Indonesia has an influence on the larger markets, with bilateral volatility persistence spillover relationships with Hong Kong, Japan, Malaysia, Korea and the Philippines. When taken with the results of other markets, this is evidence to support the claim that inter-linkages between Asian stock markets increased rapidly during the recovery period, consistent with increased cooperation following the crisis.

Thailand. It is clear that the conditional volatility of the Thai market is dominated by the volatilities of many Asian countries before and during the financial crisis. Thailand receives uni-directional volatility spillovers (in terms of lagged conditional variance, shown by significant b_{ij}) from Malaysia, the Philippines and Indonesia before the financial crisis, and from Hong Kong, Singapore, Korea and the Philippines during the crisis. This phenomenon is partly because the Thailand market opens/closes after most of the other markets in the sample, so that significant spillover takes place from these markets to Thailand. However, this pattern of volatility transmission changed, with many Asian stock markets becoming sensitive to volatility from Thailand after the crisis. For example, news generated from Thailand significantly affect the conditional volatilities of Malaysia, Korea and Indonesia during the post-crisis period. Additionally, Thailand shares bi-directional volatility persistence spillover relationships with Singapore, Malaysia and the Philippines, and transmits volatility to Korea. It is only influenced by Japan during the post-crisis period. Since the financial crisis started in Thailand and engulfed the region very quickly, investors in other Asian markets may have learned to consider news from Thailand as an important indicator to guide their trading, thereby increasing the influence of Thailand after the crisis. It is also interesting to note that Singapore generally acts a leader for the Thai market both before and after the crisis, with increasing influence in the recovery period. This is supported by evidence of innovations and volatility persistence spillovers from Singapore to Thailand across sub-periods, in particular the recovery period. Furthermore, it is also found that Thailand is influenced by Hong Kong and Korea; shares bi-directional volatility persistence spillover relationship with Malaysia; influences Indonesia during the recovery period.

5.5 Tests of Model Fitness

The most widely used diagnostics to detect ARCH effects are probably the Ljung-Box test. Following Hosking (1980), a multivariate version of the Ljung-Box test is given by :

$$MLBQ = T^2 \sum_{j=1}^{m} (T-j)^{-1} tr\{C_{yt}^{-1}(0) C_{yt}(j) C_{yt}^{-1}(0) C'_{yt}(j)\}$$

Where y_t is the vector of observed returns and $C_{yt}(j)$ is the sample autocovariance matrix of order j. m is the maximum lag length. Under the null hypothesis of no serial correlation in y_t, $MLBQ$ is distributed asymptotically as a $\chi^2(N^2 m)$. N is the number of variables. This test is used to detect misspecification in the conditional mean or the variance matrix H_t. To detect misspecification in the conditional mean,

y_t is replaced by estimated standardized residuals $z_t = H_t^{-1/2}\varepsilon_t$, and to detect misspecification in the conditional variance, y_t is replaced by estimated squared standardized residuals, z_t^2 , referred to as $MLBQ^2$ test. The statistical model provides a good fit to empirical data if a test of remaining serial correlation and ARCH-structure comes out insignificant.

The multivariate Ljung-Box test results in Table 5.6-5.10 show no evidence of autocorrelation in the standardised residuals and squared standardised residuals (all of the p-values are greater than 0.05). Therefore, we can conclude that our statistical models provide an overall good fit to the data.

Table 5.6 Tests of Model Fitness for full sample period from 8th January 1992 to 8th March 2007

	HK-JP	HK-SG	HK-MA	HK-PHI	HK-KOR	HK-IND	HK-THA
MLBQ	50.01 [0.13]	50.34 [0.11]	47.90 [0.15]	54.34 [0.06]	46.64 [0.18]	50.57 [0.11]	43.34 [0.29]
$MLBQ^2$	52.32 [0.08]	42.45 [0.28]	31.44 [0.76]	32.21 [0.73]	30.74 [0.79]	46.51[0.17]	26.72 [0.91]
	JP-MA	JP-SG	JP-PHI	JP-KOR	JP-IND	JP-THA	MA-SG
MLBQ	52.19 [0.08]	41.85 [0.34]	28.18 [0.90]	35.29 [0.63]	44.43 [0.25]	35.88 [0.61]	44.62 [0.25]
$MLBQ^2$	46.14 [0.17]	34.59 [0.62]	23.51 [0.96]	29.74 [0.82]	51.79 [0.08]	14.84 [0.99]	47.27 [0.14]
	MA-PHI	MA-KOR	MA-IND	MA-THA	SG-PHI	SG-KOR	SG-IND
MLBQ	47.08 [0.17]	47.41 [0.17]	35.17 [0.64]	34.93 [0.65]	44.42 [0.25]	52.87 [0.07]	47.04 [0.17]
$MLBQ^2$	41.26 [0.33]	49.47 [0.11]	35.86 [0.57]	41.49 [0.32]	38.74 [0.43]	45.35 [0.19]	51.79 [0.09]
	SG-THA	PHI-KOR	PHI-IND	PHI-THA	KOR-IND	KOR-THA	IND-THA
MLBQ	37.88 [0.52]	42.35 [0.33]	51.11 [0.09]	42.16 [0.94]	41.71 [0.35]	50.20 [0.11]	52.86 [0.07]
$MLBQ^2$	18.76 [0.99]	36.32 [0.55]	36.95 [0.51]	13.50 [0.99]	52..42 [0.08]	37.74 [0.48]	45.33 [0.19]

Note: p-values are in parentheses. Lag length is set to 10.

Table 5.7 Tests of Model Fitness for pre-crisis period from 8th January 1992 to 1st July 1997

	HK-JP	HK-SG	HK-MA	HK-PHI	HK-KOR	HK-IND	HK-THA
MLBQ	42.78 [0.31]	33.44 [0.72]	40.32 [0.41]	41.42 [0.36]	50.41 [0.11]	38.75 [0.11]	34.82 [0.66]
$MLBQ^2$	39.88 [0.38]	47.13 [0.15]	40.19 [0.37]	53.43 [0.06]	49.35 [0.11]	53.41 [0.06]	40.98 [0.34]
	JP-MA	JP-SG	JP-PHI	JP-KOR	JP-IND	JP-THA	MA-SG
MLBQ	35.88 [0.61]	39.33 [0.45]	30.59 [0.83]	36.83 [0.57]	55.11 [0.06]	34.36 [0.68]	33.27 [0.73]
$MLBQ^2$	20.28 [0.99]	17.19 [0.99]	41.47 [0.33]	53.95 [0.06]	13.18 [0.99]	29.18 [0.85]	26.13 [0.93]
	MA-PHI	MA-KOR	MA-IND	MA-THA	SG-PHI	SG-KOR	SG-IND
MLBQ	45.85 [0.21]	37.69 [0.53]	35.60 [0.63]	29.38 [0.87]	44.46 [0.25]	49.63 [0.12]	55.65 [0.05]
$MLBQ^2$	52.49 [0.07]	34.14 [0.65]	31.30 [0.77]	31.98 [0.74]	44.81 [0.21]	50.20 [0.10]	46.59 [0.16]
	SG-THA	PHI-KOR	PHI-IND	PHI-THA	KOR-IND	KOR-THA	IND-THA
MLBQ	23.13 [0.98]	36.61 [0.58]	43.39 [0.29]	26.00 [0.94]	40.23 [0.42]	41.81 [0.35]	31.78 [0.79]
$MLBQ^2$	26.08 [0.93]	45.15 [0.20]	34.35 [0.64]	55.54 [0.05]	26.31 [0.92]	52.01 [0.08]	38.42 [0.45]

Note: *p*-values are in parentheses. Lag length is set to 10.

Table 5.8 Tests of Model Fitness for crisis period from 2nd July 1997 to 31th December 1998

	HK-JP	HK-SG	HK-MA	HK-PHI	HK-KOR	HK-IND	HK-THA
MLBQ	47.04 [0.18]	35.22 [0.72]	38.00 [0.52]	37.17 [0.36]	49.61 [0.12]	31.91 [0.78]	40.43 [0.41]
$MLBQ^2$	48.05 [0.13]	52.82 [0.06]	46.57 [0.17]	39.82 [0.39]	44.40 [0.22]	25.04 [0.95]	42.98 [0.27]
	JP-MA	JP-SG	JP-PHI	JP-KOR	JP-IND	JP-THA	MA-SG
MLBQ	41.19 [0.37]	37.29 [0.55]	24.52 [0.96]	46.27 [0.20]	36.80 [0.57]	46.68 [0.18]	29.85 [0.85]
$MLBQ^2$	44.24 [0.22]	27.28 [0.90]	23.14 [0.97]	33.73 [0.67]	23.65 [0.96]	40.87 [0.34]	35.86 [0.57]
	MA-PHI	MA-KOR	MA-IND	MA-THA	SG-PHI	SG-KOR	SG-IND
MLBQ	22.40 [0.98]	28.84 [0.88]	34.90 [0.66]	40.87 [0.39]	27.42 [0.92]	35.16 [0.64]	24.67 [0.96]
$MLBQ^2$	31.46 [0.76]	24.57 [0.95]	31.30 [0.77]	31.98 [0.48]	33.65 [0.67]	26.48 [0.92]	28.62 [0.86]
	SG-THA	PHI-KOR	PHI-IND	PHI-THA	KOR-IND	KOR-THA	IND-THA
MLBQ	29.52 [0.86]	44.61 [0.25]	19.43 [0.99]	34.15 [0.69]	36.25 [0.59]	29.16 [0.87]	25.08 [0.96]
$MLBQ^2$	47.24 [0.14]	21.22 [0.98]	45.65 [0.18]	45.98 [0.17]	18.36 [0.99]	34.37 [0.64]	47.33 [0.15]

Note: *p*-values are in parentheses. Lag length is set to 10.

Table 5.9 Tests of Model Fitness for post-crisis period from 1st January 1999 to 6th March 2003

	HK-JP	HK-SG	HK-MA	HK-PHI	HK-KOR	HK-IND	HK-THA
MLBQ	41.30 [0.37]	49.33 [0.12]	46.49 [0.41]	40.36 [0.41]	47.40 [0.17]	44.96 [0.20]	42.53 [0.32]
MLBQ^2	50.23 [0.10]	30.24 [0.81]	52.31 [0.08]	38.24 [0.46]	39.08 [0.42]	35.61 [0.58]	41.37 [0.32]
	JP-MA	JP-SG	JP-PHI	JP-KOR	JP-IND	JP-THA	MA-SG
MLBQ	31.90 [0.78]	37.61 [0.53]	29.51 [0.86]	23.21 [0.97]	44.71 [0.24]	34.88 [0.65]	49.51 [0.12]
MLBQ^2	52.30 [0.07]	46.11 [0.17]	26.05 [0.92]	42.49 [0.28]	38.63 [0.44]	52.07 [0.06]	47.64 [0.14]
	MA-PHI	MA-KOR	MA-IND	MA-THA	SG-PHI	SG-KOR	SG-IND
MLBQ	44.19 [0.26]	33.79 [0.70]	51.06 [0.10]	31.01 [0.81]	47.19 [0.17]	29.92 [0.85]	43.74 [0.28]
MLBQ^2	10.61 [0.99]	27.89 [0.88]	39.98 [0.38]	49.80 [0.12]	14.60 [0.99]	33.46 [0.67]	30.90 [0.78]
	SG-THA	PHI-KOR	PHI-IND	PHI-THA	KOR-IND	KOR-THA	IND-THA
MLBQ	32.57 [0.75]	53.13 [0.07]	40.28 [0.42]	47.09 [0.17]	53.45 [0.06]	52.83 [0.07]	43.33 [0.29]
MLBQ^2	38.88 [0.43]	28.27 [0.87]	21.46 [0.98]	17.48 [0.99]	44.33 [0.22]	41.42[0.33]	34.33 [0.64]

Note: *p*-values are in parentheses. Lag length is set to 10.

Table 5.10 Tests of Model Fitness for recovery period from 7th March 2003 to 8th March 2007

	HK-JP	HK-SG	HK-MA	HK-PHI	HK-KOR	HK-IND	HK-THA
MLBQ	28.26 [0.89]	38.50 [0.49]	41.01 [0.38]	39.41 [0.45]	19.36 [0.99]	20.58 [0.99]	32.41 [0.76]
MLBQ^2	22.45 [0.97]	31.73 [0.75]	49.32 [0.11]	41.73 [0.32]	38.04 [0.46]	36.07 [0.55]	15.27 [0.99]
	JP-MA	JP-SG	JP-PHI	JP-KOR	JP-IND	JP-THA	MA-SG
MLBQ	34.05 [0.69]	39.63 [0.44]	36.18 [0.59]	22.34 [0.98]	24.26 [0.96]	31.92 [0.78]	27.24 [0.92]
MLBQ^2	40.14 [0.37]	39.26 [0.41]	24.46 [0.95]	21.07 [0.98]	50.44 [0.09]	10.28 [0.99]	50.33 [0.10]
	MA-PHI	MA-KOR	MA-IND	MA-THA	SG-PHI	SG-KOR	SG-IND
MLBQ	38.49 [0.49]	21.63 [0.98]	25.43 [0.95]	25.55 [0.95]	41.79 [0.35]	27.63 [0.91]	25.99 [0.94]
MLBQ^2	37.82 [0.74]	36.97 [0.51]	32.73 [0.71]	34.33 [0.64]	45.17 [0.20]	39.22 [0.41]	46.98 [0.15]
	SG-THA	PHI-KOR	PHI-IND	PHI-THA	KOR-IND	KOR-THA	IND-THA
MLBQ	39.01 [0.46]	37.24 [0.55]	39.89 [0.43]	41.89 [0.34]	37.66 [0.53]	43.61 [0.28]	30.47 [0.83]
MLBQ^2	21.18 [0.98]	37.82 [0.47]	38.40 [0.45]	25.38 [0.98]	50.83 [0.09]	17.62 [0.99]	26.25 [0.92]

Note: *p*-values are in parentheses. Lag length is set to 10.

5.6 Summary, Implications and Conclusions

The transmission of volatility and shocks between eight major Asian stock markets has been examined in this chapter. In particular, the effects of the financial crisis on volatility transmission channels have been analyzed. In order to achieve these goals, a bivariate VAR-BEKK GARCH model is applied to estimate volatility spillovers between markets. The empirical findings can be summarised as follows.

(1) There is significant transmission of shocks and volatility between Asian stock markets, though the nature of these spillovers varies significantly. This finding implies that investors and market traders should keep a close eye on all Asian stock markets, because news originating in one market will eventually have an impact on other markets, and suggests the existence of cross-market hedging and sharing of common information by investors.

(2) During the pre-crisis period, the evidence is consistent with the view that market trading time is an important factor in determination of volatility spillover effects. That is, the volatility of the index in a particular market is mostly affected by the indices of markets that open/close before it.

(3) During the crisis and post-crisis periods, market trading time appears to become a less important determinant of volatility spillover effects, giving way to quality of markets (market capitalisation, number of stock listed and trading volume). This is supported by the observation that cross-market links in conditional variance tend to become uni-directional following the financial crisis, running from the developed to the emerging markets

(4) During the recovery period, there is an increase in a number of bi-directional variance feedback relationships for all markets – a finding that is strongly consistent with a growing degree of Asian equity market integration over recent years.

(5) Hong Kong and Japan play a dominant role in Asian stock markets. The basic evidence for this leadership lies in the uni-directional spillover from Hong Kong and Japan to most of other stock markets.

(6) Singapore emerges as leader for the emerging markets of the sample. This is supported by the evidence of uni-directional spillovers from Singapore to the emerging markets. Singapore is itself affected by the Hong Kong and Japanese markets.

(7) Malaysia appears to have become more isolated from the region after the crisis. This could reflect the capital control policies of the Malaysian government.

(8) Korea was relatively isolated before the crisis but developed significant bi-directional spillover relationships with its major Asian counterparts after the crisis. This suggests that the crisis substantially influenced the economic and financial policies imposed by the Korean government.

(9) Indonesia is a small market in the region, with little influence on other markets.

(10) The Philippine market plays an important role in exporting volatility to other Asian markets during the pre-crisis period, probably because it closes earlier than other markets studied.

(11)The Thai market is dominated by most other Asian markets before the crisis, probably because it opens/closes after most other markets. The influence of Thailand on other markets is greater after the crisis.

The empirical results from this study highlight the complex nature of Asian equity market linkages. Each market is characterised by quantifiable volatility (risk) linkages with the others, suggesting both that market participants (investors and policymakers) should pay attention to the linkages and that the linkages are there because these participants in fact act on news from other markets. These involve volatility spillovers that are relevant to portfolio allocation decisions, financial system stability and monetary policy transmission.

The results also show that cross-border linkages in variance are an significant determinant of domestic volatility. Knowledge of complex volatility transmission patterns can therefore help investors to improve the valuation and forecasting power of models for domestic assets. For the purpose of portfolio diversification, investors can reduce their portfolio risk by combining financial assets from markets that are more isolated from volatility spillovers. However, the results for the recovery period indicate that benefits from diversification may have become more limited for traders in Asian stock markets in more recent years, due to stronger market links.

Furthermore, market risk is of particular importance for the stability of the financial system. The market risk to which investors are exposed depends on both the volatility and the co-volatility of returns in different markets. Increased volatility in a single market might not be a serious threat to investor portfolios since this increased risk exposure could be effectively diversified. However, the existence of volatility linkages that cause difficulties in diversifying portfolio risks create a more significant threat to systemic financial stability. Volatility linkages increase the probability of system instability and therefore are monitored by financial regulators. The linkages found here suggest that Asian stock markets became exposed to high systemic risk, during the financial crisis. Further, the stronger volatility linkages between Asian equity markets in recent years imply that these markets have become exposed to higher risks of system instability. That is, any further financial crash in one Asian equity market, is likely to become a regional crisis in a short time. This suggests that domestic regulators should be aware of risks from other Asian markets when assessing/regulating domestic market risks.

Finally, volatility spillovers between Asian stock markets could also have implications for effective monetary policy, since volatility spillovers from abroad may influence domestic financial stability. In other words, there could be a need for the integration of monetary policy and financial system supervision. For example, regional cooperation of regulatory institutions and monetary policies can control capital flows with the aim of protecting domestic equity markets from shocks spilling over from other Asian markets. The empirical findings for the Malaysian market demonstrate the effect of the policy to stop capital flight. However, recent studies show that this policy is ineffective and harmful to the economy (Abdelal and

Alfaro, 2003). Therefore, regulators and policy markers also need to assess the potential risks of imposing capital controls (and indeed of monetary policy in general), in order to secure the stability and long-term development of the financial system in Asia.

Chapter 6 Dynamic Conditional Correlation Analysis of Asian Stock Market Interdependence

6.1 Introduction

The previous chapters have investigated Asian stock market interdependence and linkages by examining the lead/lag relationships of stock returns and volatilities. Those studies mainly focused on the causal links across the markets and examined the dynamic transmission of return and volatility over time, from one market to another. However, 'causal links' analysis cannot identify contemporaneous interactions between stock markets even though their movements seem to directly influence one another. For this reason, this chapter analyzes the contemporaneous interactions between Asian stock markets through examining the dynamic movements in the conditional correlations (time-varying correlation) in stock returns.

Understanding and careful estimation of time-varying correlation is crucial for portfolio diversification. According to the CAPM, investors can reduce the risks of their portfolios by allocating their investments to different classes of assets that respond in different ways to the same event. In other words, diversification benefits can be achieved because portfolio performance depends not only on the return and risk characteristics of the assets being held in the portfolio, but also on the correlation between the asset returns. That is, the lower is the correlation between assets returns, the higher are the diversification benefits. Thus, diversifying portfolios across Asian markets is beneficial to investors only if these markets do not move together. The nature of co-movement between Asian stock markets is therefore central to opportunities for portfolio diversification and hedging – if investors understand the interaction dynamics between Asian stock markets in advance, then successful hedging activities can be implemented in time. Asset allocation decisions must therefore be based on the dynamic behaviour of cross-market returns correlations in Asian equity markets.

The 1997-98 Asian financial crisis provides a particular stimulus for investigating co-movement between Asian stock markets. The increase in cross-country correlations during the financial crisis may be evidence of contagion. It is possible that time-varying correlation could be used to measure the degree of crisis contagion, with higher correlations in turn reducing diversification opportunities. Some researchers identify financial contagion by providing evidence of significant increases in cross-country correlations between stock returns or volatilities (Sachs, Tornell and Velasco, 1996). Forbes and Rigobon (2002) define contagion as a significant increase in cross-market co-movement and interdependence as a continuing high degree of co-movement. Billio and Venice (2002) discuss the robustness of two methods in the existing literature to analyse the presence of contagion. The first method is introduced by Forbes and Rigobon (2002), focusing on the correlation coefficients among market returns (correlation analysis) and attempting to correct for the bias due to the changing volatility (i.e.heteroskedasticity). The second method is the DCC test proposed by Rigobon (2002), which considers the entire variance-covariance matrix of market returns and allows for the presence of heteroskedasticity, simultaneous equations and omitted variables. Billio and Venice (2002) find that all the tests are highly affected by the choice of observation period. Furthermore, they show that test results are also highly affected by time zone, which could mean that the tests misdiagnose contagion.

The world bank gives three different definitions of contagion. In broad definition, contagion is the cross-country transmission of shocks or general cross-country spillover effects. In restrictive definition, contagion is the transmission of shocks to other countries or cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behaviour. In very restrictive definition, contagion occurs when cross-country correlations increase during 'crisis times' relative to correlations during 'tranquil times'. (world bank webpage). If investors and policymakers can understand the nature of co-movement between stock markets, they may be better able to manage the contagion risk resulting from potentially harmful volatility spillovers across markets at times of financial crisis. However, one should note that there is a conceptual problem of defining contagion as an increase in correlations (the correlations may increase for other reasons).

In this chapter, the main objective is to investigate the inter-relationships of Asian stock markets through the evolution of time-varying correlations. Understanding how correlations change over time and when they will be strong or weak is the motivation here. The correlation matrix is estimated by using a recently proposed representative of the class of multivariate GARCH models, the so-called dynamic conditional correlation DCC model (Engle, 2002). Dynamic conditional correlation increases modelling flexibility by dropping assumptions about constancy in the means and variances of variables and in the relationships among them. The DCC model does this by calculating a current correlation between variables of interest as a function of past realisations of both the volatility within the variables and correlations between them. The relationship between variables can thus be seen to evolve over time in a manner that not only depends on whether and to what degree the variables moving in the same direction, but also on variance/covariance history of the series.

Several specific questions will be addressed in this chapter. It is first asked how the cross-correlations of Asian stock markets vary over time and how various types of information events affect these correlations. Second, it is well established that stock return correlations are not constant over time, with many previous studies finding evidence that high volatility causes high correlation. For example, Solnik, Boucrelle and Fur (1996) shows that correlation will increase in periods of high market volatility among industrialized countries, Calvo and Reinhart (1996) report correlation shifts during the Mexican crisis, Campbell, Koedijk and Kofman. (2002) finds increasing cross-market correlations in bear markets while Longin and Solnik (2000) find that correlations tend to decline in bull markets and increase in bear markets. This motivates the question as to whether correlations between paired Asian stock markets increase during periods of high market volatility. Third, it is interesting to consider whether contagion occurred in Asian markets during the financial crisis period. It is therefore natural to ask whether cross-market correlations increase during the financial crisis period, since such an increase is consistent with the existence of contagion.

This chapter proceeds as follows. A brief literature review is presented in Section 6.2, methodological issues are discussed in Section 6.3 and empirical results are reported in Section 6.4. The final section contains the concluding remarks.

6.2 Literature Review

There are a number of theoretical and empirical studies that have employed a wide variety of methods to model the co-movement between international stock markets and searched for the reasons behind the phenomenon. The focus has been mostly on correlations and stock returns/volatility spillovers between stock markets around the world. Since the literature is very large, only the most relevant work is reviewed in the following paragraphs.

The earliest paper investigating stock market co-movements and the benefits of international diversification can be traced to Grubel (1968), who assumed that US investors held both domestic assets and foreign assets from eleven industrial countries over the period 1959 to 1966. According to his findings, US investors could have achieved higher risk-adjusted returns by investing part of their portfolios in foreign equity markets, because of low correlations between the selected countries. Levy and Sarnat (1970) examined international correlations during the period 1951 to 1967, showing that diversification benefits were not limited to securities issued by developed markets. More recently, Bekaert and Harvey (1997) find that correlations in emerging markets have increased slightly but remain relatively low, hence still providing portfolio diversification opportunities to international investors who invest in emerging markets.

In the spirit of the aforementioned papers, the recent literature focusing on the co-movement of international stock markets has grown rapidly, with the concept of co-movement now covering not only correlations but also stock return and volatility spillovers across international equity markets. Various empirical methods have been used to examine both short-term and long-term co-movements of international stock markets. For example, Chaudhuri (1997) employs cointegration tests and error correction models to examine long-run relationships between six Latin American markets and the US, finding evidence of a cointegrating relationship and significant causality between these markets. Cha and Cheung (1998) establish spillovers in return relationships and examine linkages between Asia-Pacific equity markets using vector autoregression (VAR) models, finding a number of interrelationships within the Asia-Pacific region. Darrat and Zhong (2005) use multivariate price cointegrating systems to find a long-run equilibrium relationship between Asia-Pacific stock markets, which implies limited gains from long horizon international diversification. Further, there is much research examining the presence of spillovers in volatility. In one of the first of these studies, Hamao *et al.* (1990), use univariate ARCH/GARCH type models to uncover significant volatility spillovers between markets in London, New York and Tokyo. Recent studies extend the earlier analyses by using multivariate GARCH models, in particular BEKK (Baba-Engle–Kraft–Kroner, 1990) and Constant Conditional Correlation (CCC – Bollerslev, 1990) models. For example, Worthington and Higgs (2004) provide evidence of volatility transmission between nine developed and emerging Asia-Pacific markets using the multivariate BEKK-GARCH model. Booth *et al.* (1997) examine volatility spillovers in Scandinavian stock markets using a CCC model. Lee (2009) finds significant volatility spillovers between six Asian stock markets by using a multivariate GARCH process with constant conditional correlation.

In this literature, correlations are estimated using moving average, cointegration, univariate GARCH and multivariate GARCH techniques. However, some of these have been subject to criticism. For example, a weakness of the moving average specification is that it gives equal weight to all the observations used in the moving average calculations. With respect to multivariate GARCH models, a range of studies, including Bera and Kim (1996), Tsui and Yu (1999) and Tse (2000), argue that the constant conditional correlation assumption is too restrictive and that the multivariate BEKK-GARCH model is computationally deficient, requiring the estimation of too many coefficients at the same time. A solution to these problems is the dynamic conditional correlations (DCC) model proposed by Engle (2002). This new approach represents a significant departure from the methodologies of the previous literature, overcoming several limitations. First, the DCC approach breaks the unrealistic assumption of the Bollerslev (1990) model that the conditional correlations are constant. Second, it has the computational flexibility of univariate

GARCH without the complexity of the multivariate BEKK-GARCH model. Third, the DCC-GARCH model estimates correlation coefficients of the standardized residuals and thus accounts for heteroskedasticity directly (Chiang, Jeon and Li, 2007). Fourth, dynamic conditional correlations can capture contemporaneous interactions between stock markets and therefore fulfil the research interest aim.

Although the DCC approach appears highly suitable, its application to Asian financial markets is quite limited, having been mostly applied to European and Latin American stock markets. For instance, Egert and Kocenda (2007) use the DCC-GARCH model to study co-movements between three developed (France, Germany and UK) and three emerging (Poland, the Czech Republic and Hungary) European stock markets. They find very little evidence of positive co-movement between the developed and emerging markets. Kearney and Poti (2006) examine the five largest Euro-zone stock markets (France, Germany, Italy, the Netherlands and Spain), finding a rise in correlation between these markets and little expected benefit from Euro-zone diversification strategies. Gupta (2008) investigates time-varying correlations between Australia and seven emerging markets (Brazil, Chile, Greece, India, Korea, Malaysia and the Philippines), finding low correlations within emerging markets pairs and between the emerging markets and Australia. They conclude that there are unrealized gains to be made by Australian investors from diversifying into emerging markets. Arouri, Bellalah and Nguyen (2007) focus on the extent of stock markets linkages between the main Latin American markets and a world index. They show that there is an increase correlation between the main Latin American markets and the world index. Multivariate DCC-GARCH applications to Asian stock markets are very few. Yang (2005) examines the relationship between Japan and the Asian 'Four Tigers' (Taiwan, Singapore, Hong Kong and South Korea). He finds that correlations between Japan and the 'Four Tigers' fluctuated widely and were negative during the Asian crisis period, concluding that the Japanese market was less affected than others by the crisis. Chiang *et al.* (2007) applies a dynamic conditional correlation model and examines pair-wise conditional correlation coefficients between the stock returns of Thailand (they assume Thailand to be the origin of the financial crisis) and those of Indonesia, Malaysia, the Philippines, Korea and Hong Kong, during the period 1996-2003. They identify two phases of the Asian crisis. The first stage shows an increase in correlation (from the second half of 1997-1998) and the second stage shows a continued high correlation (1998-1999).

More recently, researchers have started to search for determinants of international stock market co-movements. Gupta (2008) finds that different countries have different legal frameworks and labour markets, and are at different stages of development. Potential gains from diversification across countries arise through these differences. Empirical studies by Li, Sarkar and Wang (2003) and Schmuler (2004) indicate that there are still benefits to be realised in diversifying internationally because world financial markets are still not fully integrated. They conclude that the great differences in real economic structure between emerging and developed markets are reflected in the correlations of their financial markets, so that diversification benefits in a portfolio drawn from emerging markets are still large.

The work reported in this chapter contributes to the related literature in several ways. First, it adds evidence to the debate on the value of diversification through Asian stock markets (which are mainly emerging markets). Second, it directly infers cross-market linkages from stock data using a multivariate dynamic conditional correlation (DCC) model rather than using the VAR approach of past studies. The latter approach captures casual linkages but does not quantify the co-movements. Third, the approach differs from Yang (2005) and Chiang *et al.*(2007) by examining pair-wise correlations between all the sampled countries, rather than examining the co-movement between one pre-specified country and all others taken together. Finally, the work adds to the literature by investigating changes in cross-market co-movements and discusses the reasons behind these changes.

6.3 Modelling the Dynamic Conditional Correlations

The multivariate DCC-GARCH model developed by Engle (2002) specifies the return equation as

$$R_t = \gamma_0 + \gamma_1 R_{t-1} + \varepsilon_t, \tag{6.1}$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \tag{6.2}$$

Here $R_t = (R_{1,t}, R_{2,t}, ..., R_{n,t})^{'}, \varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, ...\varepsilon_{n,t})^{'}$, $n = 8$, R_t is an $(n \times 1)$ vector of the stock returns and ε_t is an $(n \times 1)$ vector of zero mean return innovations conditional on the information available at time *t*-1. An AR (1) term is included in the mean equation because of the autocorrelation of stock returns which was found in almost all countries, as reported in the previous chapters. Note that in some previous studies a conditional variance term has been added to the mean equation to control for risk-return tradeoffs. However, Lundblad (2007) and Arouri *et al.* (2007) have concluded that mean-variance tradeoffs are only positively significant over very long-term horizons, while in this work (reported in chapter 4) there is no evidence of any significant impact of conditional volatility on stock returns. Accordingly, the in-mean effect of conditional volatility is excluded from the model and the focus is only on short-term co-movements between Asian stock markets.

It has been well documented, stock returns are characterised by fat tailed or leptokurtic distributions, with many alternatives being proposed in the literature. For this chapter, the specification uses the Student-*t* conditional error distribution[24]. That is, the conditional distribution of the innovation $\varepsilon_t | I_{t-1} \sim N(0, H_t)$ is replaced by $\varepsilon_t | I_{t-1} \sim f_{student-t}(\varepsilon_t; v)$, where

$$f_{student-t}(\varepsilon_t; v) = \frac{\Gamma[(n+v)/2]}{(\pi v)^{n/2}\Gamma(v/2)} |H_t|^{-1/2} [1 + v^{-1}\varepsilon_t^{'} H_t^{-1} \varepsilon_t]^{-(n+v)/2} \tag{6.3}$$

and v is the degree of freedom parameter.

The conditional covariance matrix can be decomposed as

$$H_t = D_t V_t D_t \tag{6.4}$$

where $D_t = diag\{\sqrt{h_{ii,t}}\}$ is the $n \times n$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{ii,t}}$ on the diagonal. V_t is the

[24] The Student-*t* distribution is used because the GED distribution is not available in the Oxmetrics software.

$n \times n$ time varying correlation matrix, containing conditional correlations.

According to Engle (2002), the DCC-MVGARCH model involves two-stage estimation of the conditional covariance matrix H_t. In the first stage, univariate GARCH models are fitted for each of stock return series and estimates of $\sqrt{h_{ii,t}}$ are obtained. The asymmetry described in chapter 2 is allowed for by considering unvariate TAR-GARCH (1,1) specifications:

$$h_{ii,t} = \omega_0 + \alpha_1 \varepsilon_{i,t-1}^2 + \alpha_2 S_{t-1} \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \text{ with } S_{t-1} = \begin{cases} 1 & if \quad \varepsilon_{t-1} < 0 \\ 0 & otherwise \end{cases} \tag{6.5}$$

In the second stage, standardized residuals ($z_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$) obtained from the first stage are used to estimate the parameters of the conditional correlation. The DCC model of Engle (2002) specifies the dynamics of the correlation matrix as follows:

$$V_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{6.6}$$

$$Q_t = (q_{ij,t}) \tag{6.7}$$

$$(diag(Q_t))^{-1/2} = diag\left(\frac{1}{\sqrt{q_{11,t}}}, \ldots\ldots \frac{1}{\sqrt{q_{nn,t}}} \right) \tag{6.8}$$

$$q_{ij,t} = \overline{\rho}_{ij}(1-a-b) + a q_{ij,t-1} + b z_{i,t-1} z_{j,t-1} \tag{6.9}$$

Here $Q_t = (q_{ij,t})$ is the time-varying covariance matrix of the standardized residuals, z_t. $\overline{\rho}_{ij}$ is the unconditional correlation matrix of z_t while a and b are non-negative scalar parameters satisfying $a + b < 1$. Engle (2002) shows that the estimators a and b can be obtained by maximizing two likelihood functions[25]. The key element of interest in V_t is $\rho_{ij,t} = q_{ij} / \sqrt{q_{ii,t} q_{jj,t}}$, $i, j = 1,2,\ldots,n, i \neq j$. Expressing the correlation coefficient more clearly,

[25] The details of obtaining a and b are shown on Oxmetrics 5 -G@ARCH 5 by Laurent (2006), page 202.

$$\rho_{12} = \frac{(1-a-b)\overline{\rho}_{12} + aq_{12,t-1} + bz_{1,t-1}z_{2,t-1}}{\sqrt{[(1-a-b)\overline{\rho}_{11} + aq_{11,t-1} + bz_{1,t-1}^2]}\sqrt{[(1-a-b)\overline{\rho}_{22} + aq_{22,t-1} + bz_{2,t-1}^2]}} \tag{6.10}$$

which represents the conditional correlation between two stock markets.

The advantage of the model can be summed up by Kerney and Poti (2006), "the model preserves the simple interpretation of the univariate GARCH models, while providing a consistent estimate of the correlation matrix". The models have GARCH type dynamics for both the conditional correlations and conditional variances.

6.4 Empirical Results

6.4.1 Estimates of the Model

Table 6.1 Constant correlation coefficient test

	statistic value	P-value
LM test	220.305***	0.000
χ^2-test	39.85***	0.000

Note: ***, ** and * represent 1%, 5%, and 10% significant level respectively.

Before estimating the DCC model two parameter constancy tests were carried out, with results shown in Table 6.1. The first test involves an LM statistic, developed by Tse (2000). The second test involves a χ^2 statistic, developed by Engle and Sheppard (2001). Both tests show rejection of the constant correlation coefficient hypothesis, so the DCC-TGARCH model is applicable.

Table 6.2 displays estimation results for the DCC (1,1)-TGARCH (1,1) model. For the return equation, the AR (1) term in the mean equation, γ_1, is significantly positive for all markets except Japan. This result is in agreement with the findings of Chapter 3, where it was argued that positive autocorrelation can be explained by non-synchronous trading, or more precisely, non-synchronous observations of trade prices of stocks in the index (Boudoukh, Richardson and Whitelaw, 1994; Ogden, 1997). That is, when computing returns on an index, the value of the index is computed at some fixed time *t*, generally based on the last trade price observed for each stock at any time up to time *t*. However, since trading does not occur continuously, for some stocks the last trade may have happened at an earlier point in the interval between time *t*-1 and time *t*, while for other stocks the last trade may have occurred just prior to time *t*. As a result, the computed value of the index reflects a mixture of past and contemporaneous prices. Hence, a positive autocorrelation in index returns occurs because some measured returns in the interval (*t*-1, *t*) reflect information in the interval (*t*-2, *t*-1).

For the variance equation, the coefficients (α, β) of both shock-squared terms and lagged variance are highly significant, which indicates the presence of time-varying volatility and validates the choice of a GARCH (1, 1) specification. In particular, the sum of α_1, α_2 and β are fairly close to one, indicating high persistence in the conditional variances. Furthermore, the coefficient of asymmetry effects (α_2) is positively significant in all markets except Indonesia, which indicates the existence of asymmetry features in a majority of the sampled stock markets. This finding also confirms that it is appropriate to use a TGARCH model rather than a symmetric GARCH model. Two explanations have been offered for this asymmetry effect: (i) leverage and (ii) volatility feedback. The 'leverage' explanation, introduced in previous chapters, means that volatility increases when the stock price falls. The reason is that a negative stock return leads to a higher debt-to equity ratio for the firm (financial leverage) so that there is a subsequent increase in the risk of the firm (volatility as a measure of risk). In the 'volatility feedback' explanation (Campbell and Hentschell, 1992), an anticipated increase in the perceived risk induces a high risk premium on the stock so the stock price must fall immediately. Put differently, if the expected stock return increases when its volatility increases, the stock price must fall on impact when volatility increases. Time-varying risk-premia may therefore contribute to the return-volatility relationship. Notice that in the leverage effect hypothesis, the stock return causes volatility while the volatility feedback hypothesis implies that the causality runs the other way around (Selcuk, 2005).

Table 6.2 DCC-TGARCH model estimation results (08/01/1992-08/03/2007)

	Return Equations		Variance Equations				
	γ_0	γ_1	ω_0	α_1	α_2	β	Persistence
Hong Kong	0.062**	0.072***	0.042***	0.039***	0.081***	0.906***	0.986
	(2.36)	(3.69)	(3.26)	(4.31)	(3.37)	(67.48)	
Japan	-0.002	-0.013	0.071***	0.024**	0.107***	0.895***	0.973
	(-0.08)	(-0.73)	(3.15)	(2.29)	(4.43)	(55.17)	
Singapore	0.036*	0.098***	0.051	0.061**	0.089*	0.869***	0.975
	(1.65)	(4.53)	(1.33)	(2.03)	(1.92)	(13.42)	
South Korea	0.038	0.036*	0.027*	0.033**	0.057**	0.928***	0.991
	(1.27)	(1.93)	(1.65)	(2.46)	(2.74)	(40.50)	
Malaysia	0.041**	0.147***	0.011**	0.052***	0.064***	0.909***	0.993
	(2.06)	(6.60)	(2.14)	(4.31)	(2.93)	(60.69)	
Philippine	0.003	0.175***	0.128**	0.075**	0.114***	0.834***	0.967
	(0.11)	(7.26)	(1.99)	(2.06)	(3.35)	(15.28)	
Indonesia	0.088***	0.251***	0.021*	0.092***	0.013	0.892***	0.990
	(2.99)	(10.79)	(1.81)	(3.21)	(0.71)	(34.54)	
Thailand	0.022	0.122***	0.187**	0.077***	0.062**	0.841***	0.950
	(0.66)	(5.46)	(1.89)	(4.62)	(2.31)	(24.18)	
Log-likelihood	-39304.68		a	0.005 (5.57)***		b	0.991 (465.7)***

Notes: The persistence level of the variance is calculated as the summation of the coefficients in the variance equations ($\alpha_1 + 0.5\alpha_2 + \beta$). The t-statistics are in parentheses. ***, ** and * denote statistical significance at 1%, 5%, and 10% levels with critical values of 2.58, 1.96 and 1.65, respectively.

Figure 6.1 Correlations of Japan vs. Asian 'Three Little Dragons'

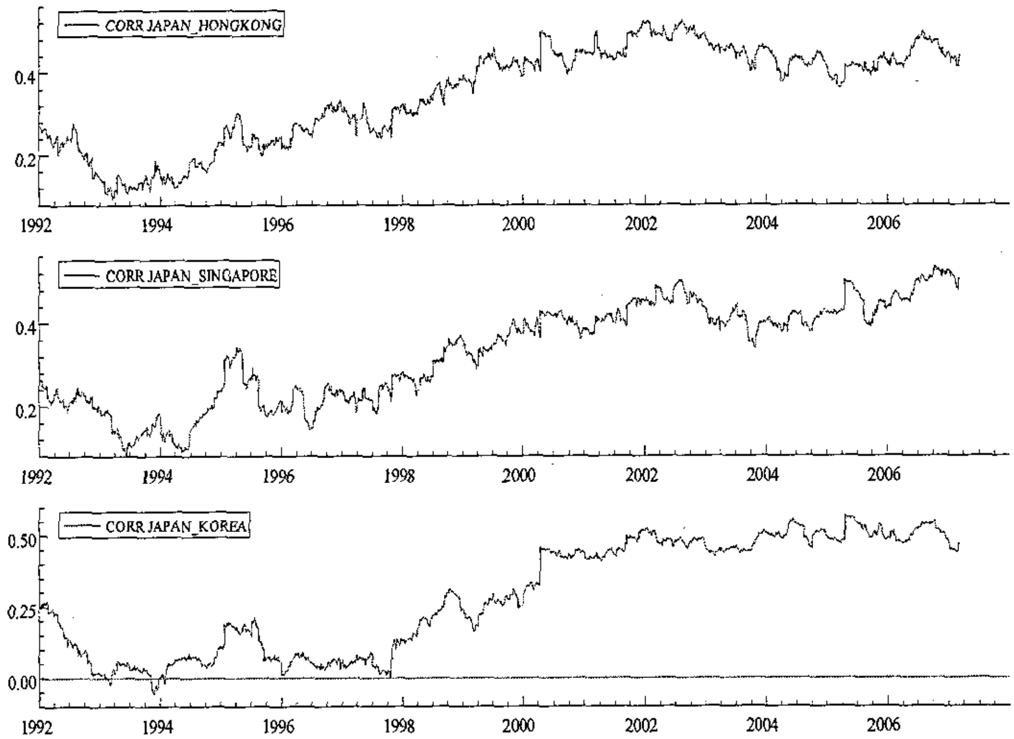


Figure 6.2 Correlations of Japan vs. Asian 'Four Southeast Tigers'

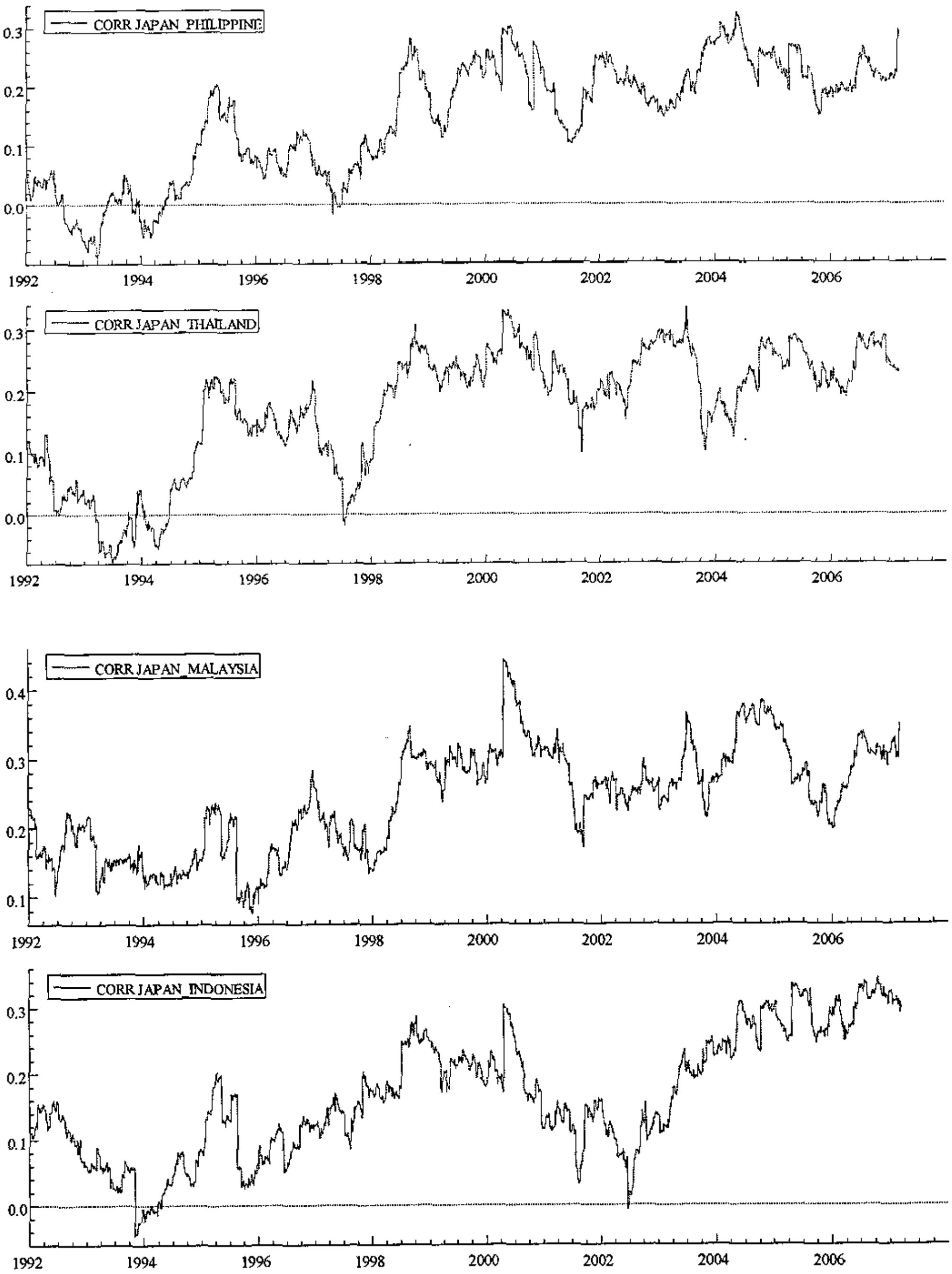


Figure 6.3 Correlations among the 'Three Asian Little Dragons'

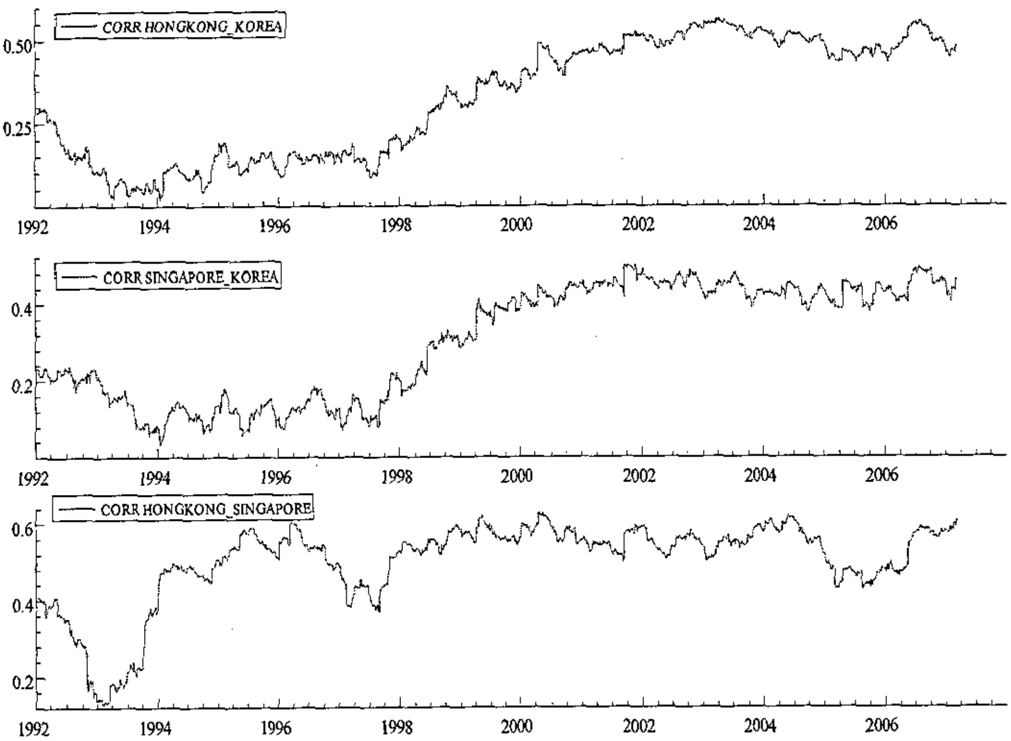


Figure 6.4 Correlations among the 'Four Southeast Asian Tigers'

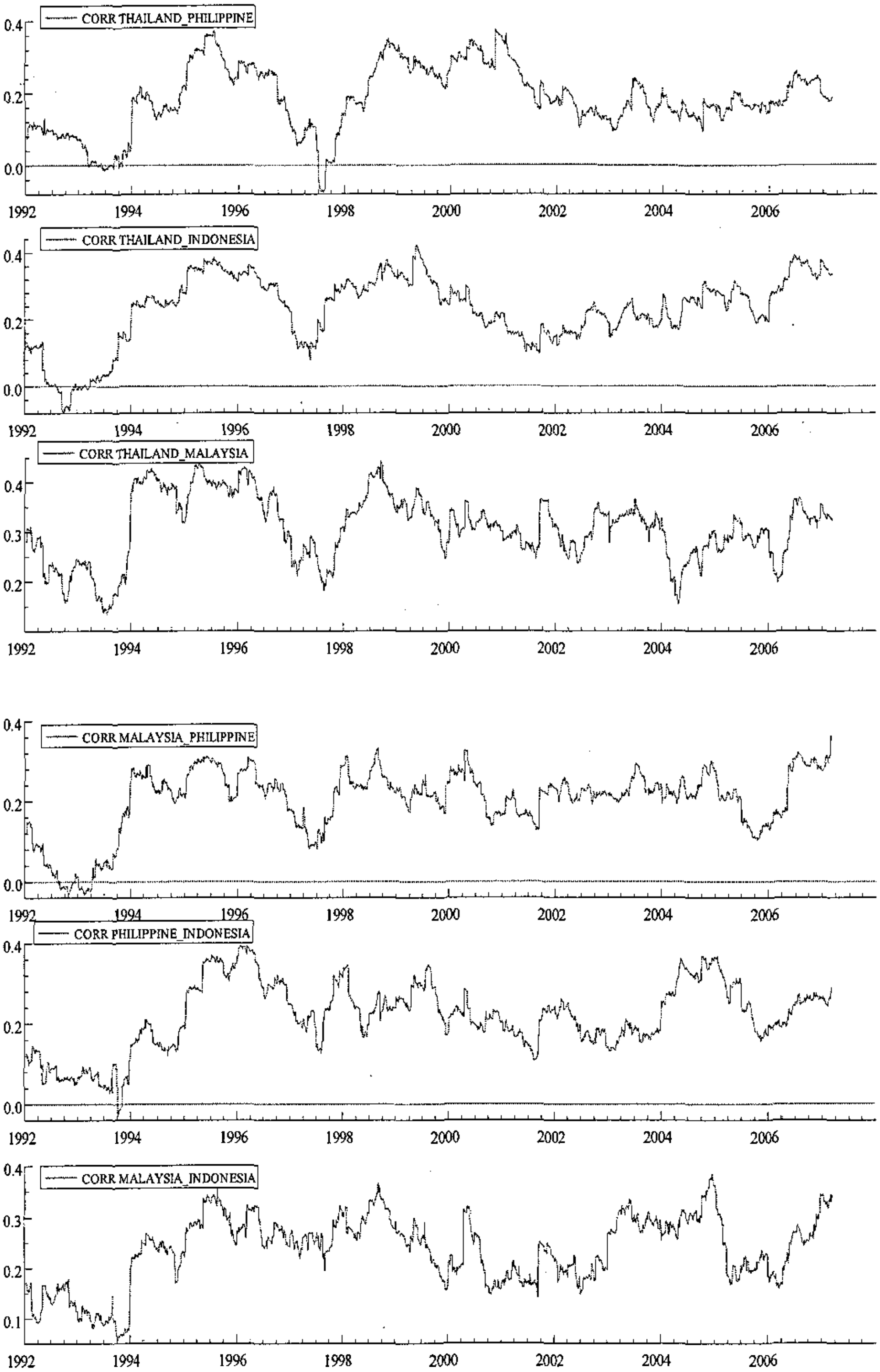


Figure 6.5 Correlations of 'Three Asian Little Dragons' vs. 'Four Southeast Asian Tigers'

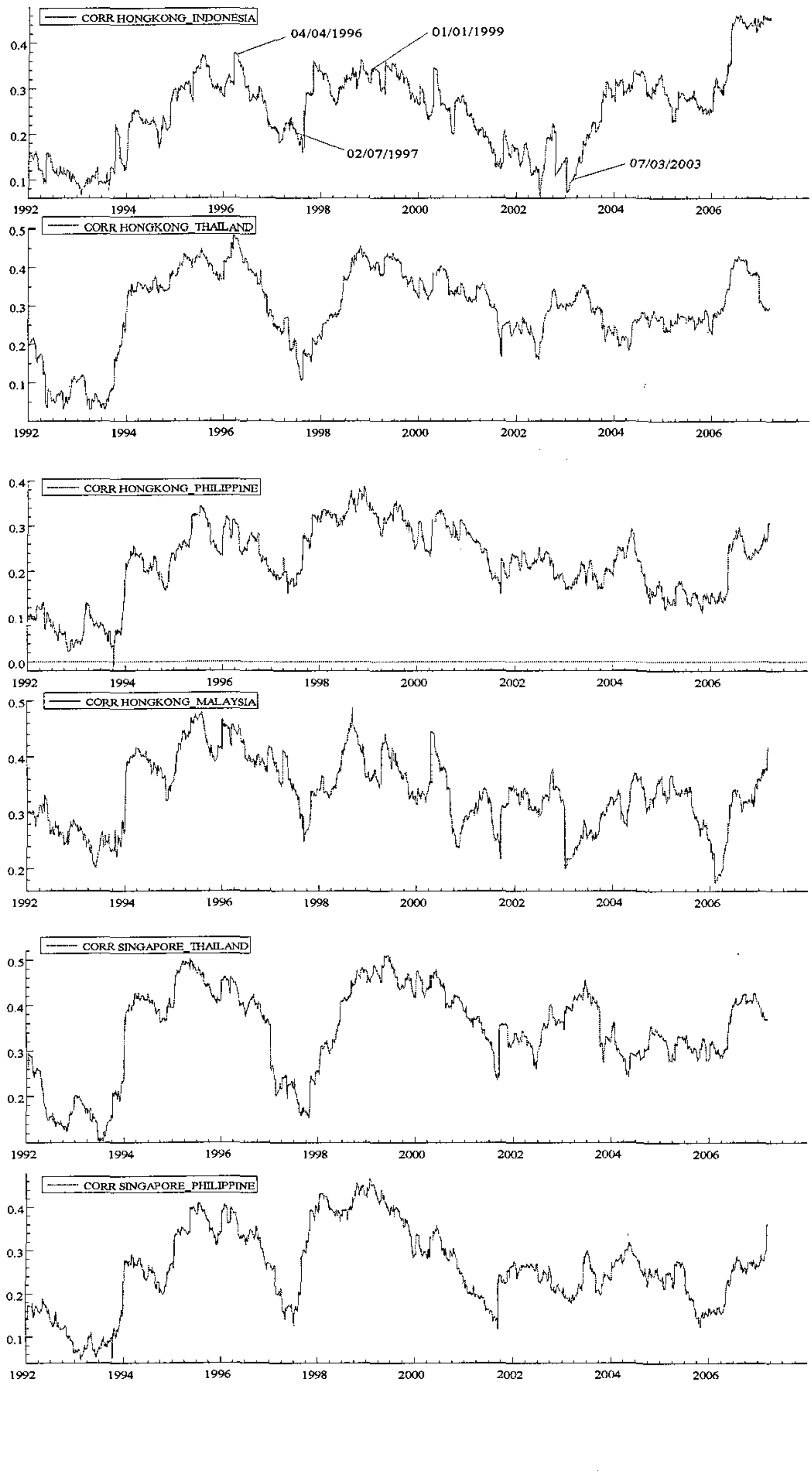
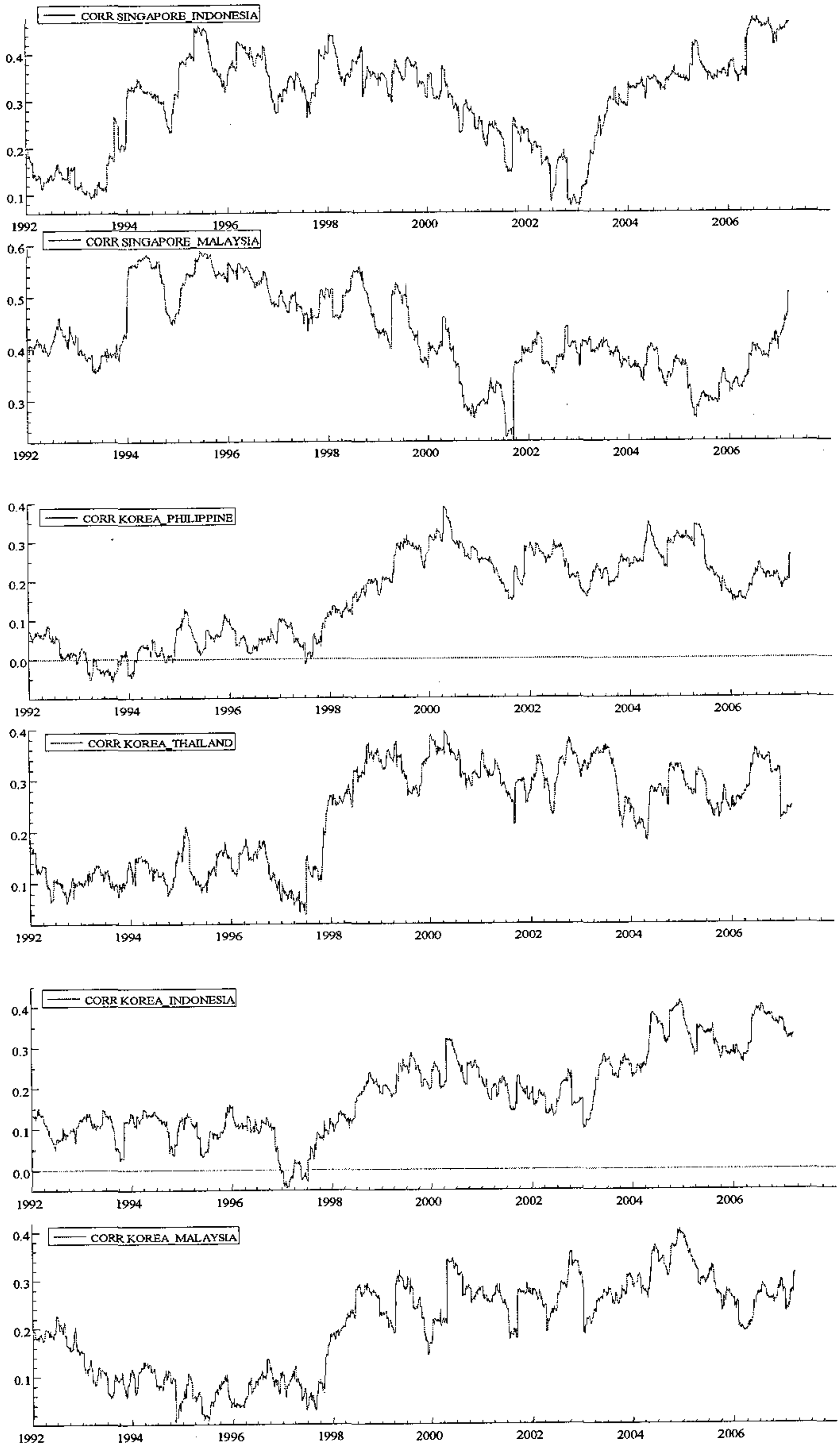


Figure 6.5 'Three Asian Little Dragons' vs. 'Four Southeast Asian Tigers' (cont'd)



6.4.2 Graph analysis of dynamic conditional correlation coefficients

Figures 6.1 to 6.5 plot the pair-wise dynamic conditional correlation coefficients within Asian stock markets during the period 1992 to 2007. All figures exhibit varying patterns in the correlation dynamic path, which seems to be one of major benefits of using of the DCC-GARCH modelling strategy. The most interesting pattern is a clear upward trend in correlation from 1994 onwards, presumably resulting from market liberalization. The lowest average correlation between all studied markets can be found between 1992 and 1993. Interestingly, there is sudden increase in conditional correlation following the Asian financial crisis in 1997-1998 for almost all pairs of countries. The increased correlation in period of crisis may be a symptom of contagion. This point will be further investigated in section 6.4.4. It is also case that correlation values are sometimes negative (e.g. Japan/Philippines, Japan/Thailand, Japan/Indonesia, Thailand/Philippines, Thailand/Indonesia, Malaysia/Philippines Korea/Indonesia) strengthening the potential diversification gains from investing in these stock markets.

Additionally, some graphs of pairwise conditional correlations exhibit quite similar moving patterns. For example, the conditional correlation moving patterns of Japan/Hong Kong, Japan/Singapore and Japan/Korea are quite similar to each other, as are the graphs of Korea/Hong Kong and Korea/Singapore. Similar patterns can also be seen within the group of emerging markets (Thailand, Malaysia, the Philippines and Indonesia). For comparison, the graphs of those conditional correlations that show similar moving patterns are grouped together. This gives five main categories, shown in Figures 6.1 to 6.5. Similar correlation moving patterns implies similarity between the behaviour of financial markets. For example, Hong Kong, Singapore and Korea are well known as three of the four 'Asian Little Dragons'[26]. These three countries opened their financial markets in the 1980s and developed their economies earlier than other Asian countries. Thus, they are all relatively developed and could perhaps be expected to behave in similar ways. This finding is supported by the evidence of similar time-varying conditional correlation moving patterns between Japan and these three markets, shown in Figure 6.1. On

[26] Four "Asian Little Dragons" are Hong Kong, Singapore, Korea and Taiwan. Taiwan is not included because there are too many unexpected shocks in its stock index which may have political causes. The market co-movement of Taiwan with other Asian stock markets is not strong.

the other hand, Thailand, Malaysia, the Philippines and Indonesia officially opened their financial markets in the 1990s, developing their financial markets later than the 'Asian Little Dragon' countries. Hence, they are called 'emerging' markets. Although they developed their financial markets late, the fast growth of their economies has created the 'East Asian miracle' and has attracted the attention of investors all over the world. For this reason, they are also called the 'Four Southeast Tigers'. The behaviour of these four Southeast emerging markets could be similar, partially explaining why similar moving patterns of conditional correlations are observed among them, as shown in Figure 6.4.

It is also evident that the conditional correlations are very volatile. The changes in correlations is normally driven by major events, to be analyzed in the next section. Specifically, the analysis focuses on the dynamics of investor behaviour underlying the time-varying correlations shown in the Figures.

The first important feature is that correlations of all Asian markets fell during the period of 1992 to 1993. This may have occurred partly because of an increase in crude oil prices following lowered production in the period around the Gulf War[27]. Most Asian economies are highly dependent on oil imports, so a significant increase in oil prices is likely to increase investor uncertainty about the future of these economies. Thus, some investors and fund managers may have reduced their holdings of Asian stocks or waited for better investment opportunities. This behaviour could have caused the observed declining correlations between the sampled markets. In contrast to the declining correlations of the period 1992-1993, the years of 1994 and 1995 generally show a large increase in correlations. This may be the result of market liberalization. with markets opening up and becoming more liberalized and integrated with other countries in the region, one would expect increases in the correlations between the countries of the region. In addition, capital inflows into the Asian region during this period would have contributed to this phenomenon. It has been shown that the 1994 Mexico crisis led to a flood of 'hot money' from Latin America to Asia (Saxena and Wong, 1999), partly because Asian emerging markets were more attractive investment climates – their goods and labour

[27] Raymond and Rich (1997), Burton and Thornhill (2001) studied the relationship between the oil price and GDP. They found that oil crisis has a big impact on Asian countries' economy.

markets are generally perceived as being more liberal than those in Latin America (IMF, 1996). These factors all contributed to the large capital inflows into the Asian markets between 1994 and 1995, leading to increasing correlations between Asian stock markets.

During the period 1996 to 1999 there is a reversal in correlations for most country pairs, especially for emerging market pairs (see Figure 6.4 and Figure 6.5). This can be interpreted as the impact of the financial crisis in 1997-1998. This interesting correlation movement may perhaps be explained by contagion/herding behaviour. It is evident that most correlation coefficients started to decline around 1996 (some in the second half of 1995), in the year before the crisis. An interpretation is that problems would have been signalled by Asian financial market fundamentals even before the financial crisis started and that investors would have observed this. Following the well known 'home bias' phenomenon (investors prefer to invest a disproportionately large share of their equity portfolio in home country stock markets)[28]. Investors may have responded by withdrawing funds to reinvest domestically. This action could have caused increasing isolation between Asian stock markets (markets becoming more subject to domestic shocks) and hence a fall in correlations before the crisis started. The realisation by investors that the crisis was general would have led to panic withdrawal of funds from all markets simultaneously. According to Kaminsky and Reinhart (2000), the equity outflow was about US $ 28 billion between 1996 and 1998, with average net selling about 9% for each crisis-hit country in the first two quarters following the outbreak of the crisis. During this process, there would have been a realisation by increasing numbers of investors that the crisis would affect the whole of Asian economic development, leading to a convergence of market consensus and an increase in conditional cross-market correlations from the second half of 1997 that peaked at the end of 1998. This is consistent with the existence of contagion, and it is likely that news in any country would quickly affect other countries, with investors generally making uniform investing decisions. Such a process would also produce

[28] Home bias is partly explained by the fund managers' perception of 'informational advantage'. The more they believe themselves better informed about home assets than foreign investors, the more they invest in these assets.
Home bias is also explained by 'relative return optimism'. For example, the higher the performance predict for the domestic market relative to foreign markets, the higher the degree of home bias of domestic fund managers.

the persistently high correlation coefficients throughout 1999 that are shown in Figures 6.2 and 6.5 for many pairs of countries (Japan/Thailand, Japan/Malaysia, Japan/Indonesia, Hong Kong/Indonesia, Singapore/Thailand, Korea/Philippine, Korea/ Indonesia). Thus, all investors may have become sensitised to all information from all sources following the crisis, with shocks more likely to be seen as regional rather than country-specific. Shocks from one country would be transmitted to other countries very quickly. This causes persistently high correlations.

From the beginning of 2000 to 2002, a sharp drop in correlation occurs for many market pairs, especially for pairings between the developed markets (Japan, Hong Kong, Singapore) and the emerging markets (Malaysia, Philippines, Indonesia and Thailand) as is evident from Figures 6.2 and 6.5. Correlations between the markets of the 'Four Southeast Asian Tigers' also decline, as shown in Figure 6.4. The decline in correlations between the developed and emerging markets can be explained as follows: after the storm of the financial crisis, investors become more rational in analyzing the market fundamentals of each country, withdrawing funds from the hardest-hit countries (the 'Four Southeast Asian Tigers') to less affected countries (Japan, Hong Kong and Singapore). This implies that developed markets become more internationally-focused and emerging markets more domestically - focused. This in turn implies, as observed, correlations should increased between developed markets and decrease between emerging markets. From 2003, the correlations are quite volatile but still high. This may reflect a lifting of barriers and the greater financial cooperation of recent years, even though the fundamentals of the individual Asian stock markets may differ.

Another interesting observation from the results is that the relationship between Korean market and other Asian markets was relatively stable before the financial crisis occurred. This could perhaps be attributed to its 'political economy' policy[29]. Many Korean corporations are owned by the Korean government and therefore the

[29] Cho (1992) states that in Korea government not only affects activities of the firm directly, but also intervenes the relations between the firms and other organizations. For example, firms usually expect to be independent when they determine the percentage of profits they distribute to stock holders as dividends, but the Korean government used to provide guidelines within which firms would pay dividends to their stock holders and how much the listed firms should pay. This policy target is to keep the financial stability of the firms.

Korean economy is partly planned rather than purely market-based. The stable correlation coefficient between Korea with other Asian countries before the crisis is consistent with the assumption that Korean government policy was to maintain stable economic relationships with other Asian economies. To quickly eliminate the negative impact of the crisis on the Korean economy, the Korean government policy was to increase exports and have more financial cooperation with other Asian countries (Lee, 2004), leading to a post-crisis surge in correlation between the Korean market and other markets. Another interesting finding is that Hong Kong and Singapore have very similar patterns of correlation with other countries. This suggests that the financial market structure of these two markets is very similar. This is good news for some investors because they can get similar benefits from investment in either market.

6.4.3 Descriptive statistics of correlation coefficients in different phases of the financial crisis

Descriptive statistics of pair-wise conditional correlation series (summarized in Tables 6.3 to 6.7) reveal the evolution of dynamic conditional correlations in different stages of the financial crisis. Statistics for the whole sample period are shown in Table 6.3, where it can be seen that the time-varying correlations are relatively low, averaging only 20% to 30%. This implies that all investors can benefit considerably from diversification across Asian stock markets. Further, it can be seen that average time-varying correlations between developed markets and emerging markets are smaller than the average for correlations within the developed markets. This suggests that significant diversification benefits are available from investment in both developed markets and emerging markets. However, the conditional correlations vary considerably, both over time and across pairs of countries. For example, the highest conditional correlation is between Hong Kong and Singapore (50%) and the lowest is between Japan and the Philippines (14.5%). The maximum values are roughly 50% for Hong Kong/Japan, Hong Kong/Malaysia, Hong Kong/Korea, Hong Kong/Thailand, Japan/Singapore, Singapore/Korea, Singapore/Indonesia, Singapore/Thailand. But the minimum values are very close to zero for these same pairings. This suggests that investors must be careful in selecting countries for portfolio diversification to be aware of the substantial variation in these correlations over time.

The majority of past studies claim that the co-movement of stock markets is stronger during the crisis period than during normal or tranquil periods. Such variation in correlations is also shown here. This time-variation is explored further in this section by comparing average conditional correlations in different sub-periods. This allows better understanding of the dynamic pattern of correlations and shows whether cross-market co-movement is higher in the crisis period. Statistics for the first sub-period are shown in Table 6.4. The average pair-wise correlation coefficients are extremely low during this period, with 17 out of 28 correlation coefficients below 20%. For some country pairs (Japan/the Philippines, Japan/Korea, Japan/Thailand, Malaysia/Korea, Japan/Thailand, the Philippines/Korea), the coefficients are very close to zero, indicating the relative independence of the sampled markets before the crisis. Inter-market co-movements in the crisis period are seen to be higher than during the pre-crisis period, with an increase in correlations for all pairs of Asian countries shown in Table 6.5. For the post-crisis period correlations fall in 17 out of 28 cases, although they remain higher than pre-crisis levels. During the recovery period, the correlation levels are not much different from the levels during the post-crisis period. It can therefore be concluded that the Asian crisis caused an increase in intra-regional correlations, indicating a rising integration of the Asian stock markets.

Table 6.3 Statistics of dynamic conditional correlations for whole sample period

	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
Mean	0.348	0.336	0.500	0.220	0.323	0.252	0.291
Maximum	0.524	0.486	0.626	0.387	0.566	0.461	0.482
Minimum	0.093	0.173	0.128	-0.011	0.020	0.063	0.030
Standard deviation	0.116	0.063	0.106	0.081	0.174	0.091	0.103
	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
Mean	0.239	0.327	0.145	0.285	0.164	0.171	0.425
Maximum	0.442	0.534	0.323	0.569	0.345	0.335	0.588
Minimum	0.076	0.081	-0.091	-0.056	-0.046	-0.076	0.220
Standard deviation	0.075	0.117	0.098	0.193	0.091	0.097	0.082
	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
Mean	0.202	0.201	0.235	0.308	0.261	0.303	0.299
Maximum	0.361	0.404	0.384	0.442	0.465	0.497	0.475
Minimum	-0.036	0.006	0.054	0.133	0.046	0.031	0.072
Standard deviation	0.079	0.095	0.067	0.067	0.094	0.146	0.099
	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
Mean	0.345	0.157	0.218	0.186	0.185	0.231	0.230
Maximum	0.511	0.387	0.396	0.376	0.414	0.396	0.422
Minimum	0.102	-0.057	-0.028	-0.074	-0.044	0.037	-0.076
Standard deviation	0.097	0.110	0.085	0.091	0.101	0.096	0.103

Table 6.4 Statistics of dynamic conditional correlations for pre-crisis period

	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
Mean	0.215	0.354	0.423	0.183	0.128	0.217	0.269
Maximum	0.333	0.479	0.604	0.344	0.300	0.379	0.482
Minimum	0.093	0.201	0.128	-0.010	0.020	0.065	0.030
Standard deviation	0.061	0.075	0.132	0.091	0.055	0.086	0.140

	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
Mean	0.166	0.197	0.044	0.079	0.083	0.080	0.485
Maximum	0.283	0.344	0.203	0.274	0.203	0.224	0.588
Minimum	0.076	0.081	-0.091	-0.056	-0.046	-0.076	0.354
Standard deviation	0.041	0.053	0.063	0.065	0.051	0.082	0.070

	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
Mean	0.168	0.098	0.214	0.311	0.233	0.136	0.279
Maximum	0.312	0.229	0.353	0.438	0.411	0.240	0.461
Minimum	-0.036	0.006	0.054	0.133	0.046	0.031	0.090
Standard deviation	0.106	0.047	0.080	0.090	0.108	0.048	0.110

	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
Mean	0.317	0.035	0.194	0.158	0.091	0.118	0.193
Maximum	0.502	0.128	0.396	0.373	0.158	0.209	0.387
Minimum	0.102	-0.057	-0.028	-0.015	-0.044	0.038	-0.076
Standard deviation	0.124	0.039	0.114	0.104	0.045	0.032	0.134

Table 6.5 Statistics of dynamic conditional correlations for the crisis period

	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
Mean	0.318	0.362	0.514	0.312	0.227	0.303	0.289
Maximum	0.389	0.486	0.597	0.387	0.362	0.363	0.457
Minimum	0.240	0.247	0.369	0.168	0.084	0.160	0.105
Standard deviation	0.041	0.055	0.060	0.050	0.074	0.046	0.103

	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
Mean	0.223	0.279	0.136	0.164	0.189	0.160	0.491
Maximum	0.346	0.371	0.282	0.311	0.286	0.308	0.557
Minimum	0.133	0.181	-0.002	0.001	0.084	-0.017	0.429
Standard deviation	0.065	0.046	0.077	0.091	0.050	0.094	0.033

	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
Mean	0.229	0.192	0.289	0.327	0.369	0.221	0.363
Maximum	0.332	0.293	0.366	0.442	0.456	0.331	0.441
Minimum	0.079	0.028	0.194	0.181	0.126	0.079	0.262
Standard deviation	0.059	0.080	0.034	0.074	0.081	0.071	0.039

	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
Mean	0.322	0.118	0.240	0.168	0.133	0.252	0.293
Maximum	0.483	0.206	0.345	0.351	0.238	0.371	0.379
Minimum	0.154	-0.013	0.125	-0.074	-0.028	0.037	0.133
Standard deviation	0.105	0.059	0.052	0.124	0.058	0.080	0.049

Table 6.6 Statistics of dynamic conditional correlations for post-crisis period

	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
Mean	0.454	0.330	0.561	0.259	0.449	0.223	0.323
Maximum	0.524	0.444	0.626	0.356	0.557	0.359	0.438
Minimum	0.348	0.200	0.498	0.150	0.294	0.063	0.158
Standard deviation	0.038	0.049	0.027	0.053	0.066	0.080	0.065
	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
Mean	0.286	0.409	0.202	0.398	0.157	0.234	0.379
Maximum	0.442	0.504	0.302	0.525	0.304	0.330	0.526
Minimum	0.169	0.290	0.100	0.162	-0.007	0.098	0.221
Standard deviation	0.048	0.046	0.048	0.095	0.062	0.041	0.066
	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
Mean	0.213	0.258	0.213	0.311	0.281	0.426	0.249
Maximum	0.326	0.357	0.321	0.389	0.465	0.497	0.391
Minimum	0.125	0.143	0.141	0.234	0.117	0.285	0.072
Standard deviation	0.036	0.045	0.041	0.035	0.081	0.044	0.088
	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
Mean	0.393	0.255	0.213	0.237	0.207	0.318	0.220
Maximum	0.511	0.388	0.347	0.376	0.320	0.396	0.422
Minimum	0.235	0.148	0.106	0.095	0.100	0.212	0.096
Standard deviation	0.065	0.049	0.051	0.071	0.046	0.034	0.077

Table 6.7 Statistics of dynamic conditional correlations for the recovery period

	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
Mean	0.432	0.306	0.536	0.194	0.498	0.310	0.290
Maximum	0.498	0.415	0.619	0.306	0.566	0.461	0.429
Minimum	0.363	0.173	0.427	0.108	0.430	0.104	0.182
Standard deviation	0.027	0.047	0.054	0.050	0.035	0.083	0.058
	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
Mean	0.297	0.439	0.230	0.498	0.272	0.236	0.365
Maximum	0.383	0.534	0.323	0.569	0.345	0.335	0.505
Minimum	0.196	0.336	0.149	0.435	0.123	0.099	0.263
Standard deviation	0.046	0.045	0.038	0.033	0.044	0.045	0.042
	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
Mean	0.228	0.286	0.267	0.292	0.237	0.434	0.353
Maximum	0.360	0.404	0.384	0.368	0.359	0.491	0.475
Minimum	0.103	0.191	0.159	0.154	0.123	0.377	0.117
Standard deviation	0.056	0.046	0.052	0.046	0.046	0.026	0.069
	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
Mean	0.342	0.236	0.250	0.178	0.311	0.285	0.267
Maximum	0.455	0.349	0.370	0.263	0.414	0.368	0.392
Minimum	0.242	0.142	0.149	0.095	0.138	0.180	0.166
Standard deviation	0.051	0.051	0.062	0.035	0.056	0.045	0.060

6.4.4 'Contagion effect' and relationship between volatility and correlation

This section examines whether high volatility values are associated with an increase in correlation values and tests whether there is a 'contagion effect' during the crisis period.

A multiple regression model is adopted to analyse the evolution of market correlations and examine the relationship between conditional correlations and the volatilities of the underlying markets. The regression model is as follows:

$$\rho_{ij} = c + \gamma Trend + \alpha_1 DM_{1t} + \alpha_2 DM_{2t} + \alpha_3 DM_{3t} + \lambda_1 \sigma_i + \lambda_2 \sigma_j + \upsilon_t \qquad (6.10)$$

Here $\rho_{ij}, \sigma_i, \sigma_j$ are the conditional correlations and conditional standard deviations of the stock market returns estimated from the DCC framework, λ_1 and λ_2 measure the relationship between correlations and volatilities and *Trend* is dummy variable for capturing the time trend. The *Trend* variable is added to the regression because of the clear upward trend in correlation seen in the graphical analysis. DM_{1t}, DM_{2t} and DM_{3t} are dummy variables for the crisis, post-crisis and recovery periods respectively. Significant positive (negative) coefficient values for these dummies mean higher (lower) correlations than the pre-crisis levels. Using these three dummy variables allows the dynamic characteristics of the correlation to be examined at different phases of the crisis and may reveal whether a 'contagion effect' was present during the crisis period. a 'contagion effect' is associated with a significant increase in cross-market co-movement during a crisis period. Thus, if DM_{1t} is positively significant, then a 'contagion effect' may exist.

Table 6.8 reports the results of the multiple regression estimation. The dummy variables for long-term trends in correlations are almost all positive and highly significant. The largest slope is 0.0001 (Hong Kong/Japan, Hong Kong/Singapore, Hong Kong/Indonesia, Hong Kong/Thailand, Japan/Philippines, Japan/Korea, Japan/Thailand, Singapore/Indonesia, Malaysia/Philippines, Philippines/Indonesia and Indonesia/Thailand), indicating an average increase in correlation of 0.01% per day or 1.03% per year.

The crisis dummies DM_{1t} are positive and significant in most cases, as expected. This indicates that there is a significant increase in cross-market co-movements during the crisis, compared to pre-crisis levels. Contagion at times of crisis would be likely to lead to sharply increased correlations between markets. Hence such observed increases at times of crisis is a possible indicator of contagion (although it does not prove the existence of contagion).

There are many studies that attempt to explain the contagion. Some claim that contagion is explained by financial links. Financial links exist when two economies are connected through the international financial system. One example of financial links is when leveraged institutions face margin calls. When the value of their collateral falls, due to a negative shock in one country, leveraged companies need to increase their reserves. Therefore, they sell part of their valuable holdings in countries that are still unaffected by the initial shock. This mechanism propagates the shock to other economies. Another example is when open-ended mutual funds foresee future redemptions after a shock in one country. They need to raise cash and consequently they sell assets in third countries.

Others provide a real links explanation. Real links are the fundamental economic relationships between economies. These links have been usually associated with international trade. When two countries trade between themselves or if they compete in the same foreign markets, a devaluation of the exchange rate in one country reduces the other country's competitive advantage. As a consequence, both countries will likely end up devaluing their currencies to re-balance their external sectors (the devaluation was therefore 'contagious'. Additionally, some studies argue that herding behaviour is the key element to understand contagion. The literature has emphasized that asymmetric information is the root of herding behaviour. Information is costly, so investors remain imperfectly informed about the countries in which they invest. Therefore, investors try to infer future price changes based on how the rest of the market is reacting. Relatively uninformed investors follow supposedly informed investors, so all the markets move jointly. Hence this type of herding behaviour causes contagion. To conclude, although one can assume that the factors mentioned above may lead to contagion, the problem is how to identify them and how to determine the relative importance of each component. Therefore, when we observe high correlations at times of crisis, this is consistent with contagion but does not prove it.

Furthermore, the post-crisis and recovery dummies, DM_{2t} and DM_{3t}, are also positively significant in most cases. This confirms the findings of the graphical and descriptive statistics analyses that the correlations after the crisis are higher than pre-crisis levels.

Finally, all volatility coefficients are positive and significant, except for Japan/Hong Kong. This indicates that when large shocks in Asian markets occur, they affect all Asian markets simultaneously. This situation can lead to a large correlation increase across markets which could be also referred to as a 'volatility contagion effect'. The association between high correlation values and extreme volatility in the underlying markets is bad news for portfolio managers because it reduces the benefits of portfolio diversification. Thus, investors will require the benefits of international diversification most when domestic market prices drop sharply, but this is likely to occur at a time when cross-market correlations are higher.

In this chapter, estimation of equation (6.10) is performed with slope dummies included (results are shown in Appendix 6.1, pp205-208)[30]. The conclusions are unchanged: contagion at times of crisis may occur and high volatility values are associated with an increase in correlation values.

[30] The equation with slope dummies is

$$\rho_{ij} = c + Trend + \alpha_1 DM_{1t} + \alpha_2 DM_{2t} + \alpha_3 DM_{3t} + \lambda_1\sigma_1 + \lambda_2\sigma_2 + \gamma_1 DM_{1t}\sigma_1 + \gamma_2 DM_{1t}\sigma_2 + \gamma_3 DM_{2t}\sigma_1 + \gamma_4 DM_{2t}\sigma_2 + \gamma_5 DM_{3t}\sigma_1 + \gamma_6 DM_{3t}\sigma_2 + \upsilon_t$$

Table 6.8 Tests of relationship between volatilities and correlations

(i) (j)	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
constant	0.230***	0.269***	0.293***	0.079***	0.078***	0.079***	0.123***
	(44.9)	(66.5)	(48.9)	(14.8)	(17.5)	(33.3)	(14.9)
Trend	0.0001***	8.80e-005***	0.0001***	9.16e-005***	6.41e-005***	0.0001***	0.0001***
	(36.4)	(23.1)	(25.1)	(20.1)	(16.2)	(21.6)	(24.0)
$DM_{1,t}$	0.022***	0.020***	0.061***	0.026***	0.028***	0.003	0.032***
	(5.95)	(4.22)	(8.41)	(4.31)	(4.94)	(0.57)	(5.94)
$DM_{2,t}$	0.088***	-0.142***	0.061***	0.046***	0.218***	0.106***	0.156***
	(21.5)	(-26.0)	(7.51)	(7.12)	(34.9)	(16.4)	(10.2)
$DM_{3,t}$	0.006	-0.217***	0.177***	0.168***	0.233***	0.142***	0.129***
	(1.16)	(-26.6)	(14.8)	(17.2)	(27.3)	(13.1)	(9.71)
σ_i	-0.002*	0.003	0.022***	0.025***	0.014***	0.022***	0.029***
	(-1.70)	(1.48)	(5.32)	(10.7)	(6.72)	(8.55)	(9.01)
σ_j	0.068***	0.027***	0.065***	0.011***	0.018***	0.043***	0.008**
	(15.8)	(18.7)	(12.3)	(4.41)	(8.53)	(19.3)	(2.39)

(i) (j)	Japan Malaysia	Japan Singapore	Japan Philippine	Japan Korea	Japan Indonesia	Japan Thailand	Malaysia Singapore
constant	0.166***	0.075***	0.071***	0.066***	-0.021*	0.076***	0.405***
	(26.1)	(13.3)	(9.70)	(6.65)	(-1.86)	(9.07)	(103.0)
Trend	3.43e-006	7.04e-005***	0.0001***	0.0001***	-3.79e-005***	0.0001***	7.04e-005***
	(0.67)	(16.1)	(19.4)	(17.7)	(-6.88)	(22.0)	(15.9)
$DM_{1,t}$	0.039***	0.039	0.023***	0.055***	0.077***	0.007	-0.105***
	(7.57)	(0.99)	(4.72)	(8.51)	(13.8)	(1.39)	(-18.1)
$DM_{2,t}$	0.119***	0.091***	0.058***	0.169***	0.069***	0.003	-0.199***
	(22.8)	(20.2)	(10.2)	(20.5)	(12.0)	(0.42)	(-34.9)
$DM_{3,t}$	0.138***	0.036***	0.052***	0.217***	0.173***	0.068***	-0.240***
	(18.7)	(5.79)	(6.46)	(20.2)	(21.5)	(7.38)	(-28.4)
σ_i	0.013***	0.061***	0.018***	0.063***	0.088***	0.075***	0.017***
	(2.76)	(10.3)	(3.50)	(6.83)	(11.7)	(8.15)	(11.7)
σ_j	0.009***	0.014***	0.013***	0.011***	0.018***	0.004**	0.024***
	(6.76)	(8.26)	(7.34)	(6.22)	(10.8)	(2.05)	(8.94)

(i) (j)	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
constant	0.049***	0.073***	0.135***	0.231***	0.139***	0.104***	0.140***
	(10.0)	(19.7)	(38.6)	(47.3)	(22.2)	(28.6)	(25.2)
Trend	0.0001***	2.95e-005***	8.50e-005***	8.06e-005***	6.91e-005***	1.43e-005***	0.0001***
	(27.9)	(8.51)	(21.8)	(18.9)	(12.1)	(4.36)	(24.6)
$DM_{1,t}$	0.111***	0.059***	0.021***	-0.113***	0.029***	0.047***	-0.121***
	(16.5)	(10.6)	(3.56)	(-18.0)	(3.82)	(9.51)	(-14.2)
$DM_{2,t}$	0.125***	0.168***	0.104***	-0.109***	0.063***	0.255***	-0.247***
	(19.1)	(30.6)	(10.7)	(-17.9)	(7.62)	(48.7)	(-29.6)
$DM_{3,t}$	0.191***	0.251***	0.117***	-0.171***	0.036***	0.268***	-0.224***
	(19.3)	(33.5)	(13.8)	(-18.7)	(3.11)	(37.6)	(-18.5)
σ_i	0.031***	0.051***	0.019***	0.031***	0.062***	0.004**	0.020***
	(18.7)	(4.38)	(13.3)	(20.7)	(15.4)	(2.09)	(5.23)
σ_j	0.008***	0.024***	0.008***	0.001	0.007***	0.013***	0.014***
	(3.35)	(15.7)	(4.77)	(0.27)	(2.33)	(8.45)	(3.31)

(i) (j)	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
constant	0.197***	-0.037***	0.089***	0.056***	0.069***	0.087***	0.036***
	(26.7)	(-9.46)	(16.2)	(7.86)	(18.7)	(22.2)	(5.44)
Trend	9.31e-005***	2.31e-005***	0.0001***	7.11e-005***	-1.68e-005***	1.70e-005***	0.0001***
	(15.0)	(7.12)	(25.0)	(12.2)	(-4.82)	(5.55)	(25.8)
$DM_{1,t}$	0.122***	0.005	0.005	-0.079***	0.004	0.088***	0.143***
	(14.4)	(1.12)	(0.79)	(-10.4)	(0.75)	(19.2)	(16.2)
$DM_{2,t}$	0.064***	0.157***	0.002	0.115***	0.111***	0.154***	0.221***
	(7.05)	(30.7)	(0.59)	(10.8)	(19.8)	(31.7)	(25.3)
$DM_{3,t}$	0.125***	0.153***	0.049***	0.105***	0.248***	0.131***	0.262***
	(12.3)	(21.9)	(13.0)	(9.96)	(32.6)	(19.7)	(20.6)
σ_i	0.053***	0.012***	0.006*	0.030***	0.011***	0.022***	0.063***
	(13.0)	(7.79)	(1.91)	(9.79)	(7.01)	(16.5)	(24.3)
σ_j	0.007**	0.028***	0.040***	0.011***	0.014***	0.006***	0.006**
	(2.19)	(19.9)	(16.8)	(3.65)	(9.09)	(4.19)	(1.97)

6.5 Implications

As shown in the previous sections, the pair-wise conditional correlation coefficients within Asian countries seem to be low and volatile. This leads to several important implications from the perspective of investors. First, the relatively low level of correlation implies the presence of potential benefits from portfolio diversification. Second, the swiftly changing pattern of correlations, especially during the times of crisis suggests that correlations are not stable, casting doubt on the wisdom of using estimated unconditional correlation coefficients in guiding portfolio decisions. On the other hand, the significant changes in the conditional correlation pattern also indicate the possibility of short-term trading possibilities. Third, differences between developed and emerging markets in their market behaviors provide opportunities for portfolio diversification between these two regions. For example, those intending to invest in Asian stock markets could reduce risks by diversifing their portfolios to Hong Kong and the Philippines simultaneously. Finally, since all volatility coefficients are positive and significantly linked to correlation coefficients, so that local shocks should affect two market stocks in a symmetric manner, international diversification benefits at least partially diminish just when they are required (such as during the financial crisis period).

6.6 Conclusions

In this chapter the multivariate dynamic conditional correlation model of Engle (2002) has been used to analyse the correlation dynamics of Asian stock markets. The significant DCC terms and the estimation of dynamic conditional correlations between each of eight variables indicate that the correlations are indeed time-varying. The results show upward trends in conditional correlations from 1994 onwards in almost all of the sampled markets. This suggests that the market liberalization process in Asian countries increased the co-movements of stock markets in the Asian region and thus reduced the diversification benefits. Further, there is evidence of wide variation in correlations over time, consistent with the special economic conditions, associated with the sub-periods of this study. In an analysis of these changes it is argued that lower correlations before the crisis reflect high oil prices and investor uncertainty about the future of Asian economies. When the crisis started, there is an increase in correlations, consistent with contagion. As investor behaviour converges, continued investor sensitivity to external shocks keeps the correlations at a high level. After the crisis, many of the Asian countries, particularly the 'emerging' countries become more isolated (as a result of capital flight to more developed markets) and the correlations decline in some cases, but remain generally higher than pre-crisis levels.

It has been argued that the apparent higher co-movement of the sampled stock markets in times of crisis is evidence of a 'contagion effect'. This indicates that the gains from international diversification by holding a portfolio consisting of stocks from different Asian countries declined during the crisis, since these markets were systemically affected. It was also argued that some Asian countries have similar behaviour in their correlation movement. This provides a channel to invest in similar market behaviour to obtain similar returns. Finally, it was found that bilateral correlations increase in periods of high market volatility. This feature is particular important for portfolio diversification since it tells investors that the benefits of diversification during periods of high volatility may be very low.

Appendix 6.1 Examination of 'contagion effect' and relationship between volatilities and correlations when slope dummies are included

(i) (j)	Hong Kong Japan	Hong Kong Malaysia	Hong Kong Singapore	Hong Kong Philippine	Hong Kong Korea	Hong Kong Indonesia	Hong Kong Thailand
constant	0.098***	0.303***	0.393***	0.163***	0.105***	0.163***	0.337***
	(18.1)	(71.5)	(79.9)	(25.8)	(18.6)	(33.5)	(38.9)
Trend	0.0001***	6.58e-005***	6.82e-005***	5.12e-005***	6.97e-005***	0.0001***	2.91e-005***
	(41.4)	(16.4)	(16.3)	(11.6)	(18.3)	(29.0)	(4.67)
$DM_{1,t}$	0.137***	0.009	0.112***	0.155***	0.217***	0.132***	0.032
	(9.41)	(0.57)	(6.25)	(7.95)	(10.4)	(5.99)	(1.08)
$DM_{2,t}$	0.064***	-0.187***	0.071***	0.176***	0.225***	0.395***	0.183***
	(6.71)	(-17.3)	(5.97)	(13.4)	(19.4)	(28.1)	(9.51)
$DM_{3,t}$	0.005	-0.279***	0.128***	0.293***	0.129***	0.309***	0.180***
	(0.34)	(-18.1)	(7.82)	(15.8)	(8.62)	(16.7)	(7.12)
σ_i	-0.027***	0.008***	0.013***	0.008***	0.029***	0.014***	0.010***
	(-14.9)	(2.64)	(2.92)	(2.75)	(11.2)	(4.19)	(2.64)
σ_j	0.105***	0.008***	0.065***	0.013***	0.054***	0.028***	0.048**
	(31.1)	(2.41)	(8.41)	(2.81)	(12.6)	(5.69)	(9.19)
$DM_{1,t}\sigma i$	0.027***	0.007	0.021**	0.002	0.056***	0.048***	0.052***
	(4.95)	(1.08)	(2.21)	(0.21)	(8.03)	(6.12)	(4.66)
$DM_{1,t}\sigma j$	0.115***	0.014***	0.055***	0.014	0.125***	0.016**	0.073***
	(14.6)	(3.85)	(5.18)	(1.58)	(15.2)	(2.15)	(5.51)
$DM_{2,t}\sigma i$	0.055***	0.009	0.083***	0.059***	0.032***	0.036***	0.026***
	(12.7)	(1.54)	(9.60)	(9.38)	(5.36)	(5.65)	(2.88)
$DM_{2,t}\sigma j$	0.103***	0.049***	0.061***	0.012**	0.056***	0.086***	0.089***
	(18.0)	(10.1)	(5.97)	(1.98)	(9.82)	(12.8)	(10.4)
$DM_{3,t}\sigma i$	0.036***	0.003	0.053***	0.135***	0.065***	0.096***	0.082***
	(3.65)	(0.23)	(3.02)	(10.2)	(4.91)	(5.86)	(4.45)
$DM_{3,t}\sigma j$	0.025***	0.181***	0.017	0.033*	0.022***	0.009	0.037***
	(3.56)	(14.3)	(1.28)	(1.89)	(2.88)	(1.14)	(4.76)

Appendix 6.1 (cont'd) Examination of 'contagion effect' and relationship between volatilities and correlations when slope dummies are included

(i)	Japan	Japan	Japan	Japan	Japan	Japan	Malaysia
(j)	Malaysia	Singapore	Philippine	Korea	Indonesia	Thailand	Singapore
constant	0.086***	0.065***	0.073***	0.030***	0.023***	0.084***	0.402***
	(15.0)	(9.87)	(9.00)	(3.68)	(4.26)	(9.96)	(89.3)
Trend	3.82e-005***	9.33e-005***	5.84e-005***	5.11e-005***	6.68e-005***	8.44e-005***	7.23e-005***
	(10.8)	(24.0)	(13.6)	(11.4)	(19.1)	(17.7)	(18.7)
$DM_{1,t}$	0.207***	0.060***	0.052***	0.308***	0.089***	0.189***	0.008
	(15.6)	(3.65)	(2.62)	(12.3)	(5.66)	(7.52)	(0.71)
$DM_{2,t}$	0.075***	0.106***	0.009	0.178***	-0.072***	-0.082***	-0.245***
	(8.19)	(9.89)	(0.73)	(12.2)	(-7.15)	(-7.62)	(-26.3)
$DM_{3,t}$	0.079***	0.151***	0.089***	0.331***	0.038***	0.049***	-0.347***
	(6.25)	(11.1)	(5.30)	(20.7)	(3.22)	(2.81)	(-26.6)
σ_i	0.075***	0.101***	0.009**	0.065***	0.037***	0.032***	0.026***
	(20.5)	(23.4)	(1.97)	(12.4)	(11.1)	(6.40)	(4.58)
σ_j	0.019***	0.007*	0.020***	0.015***	0.026***	0.032***	0.002
	(8.86)	(1.74)	(4.99)	(3.31)	(9.67)	(8.70)	(0.07)
$DM_{1,t}\sigma i$	0.151***	0.071***	0.043***	0.062***	0.010	0.110***	0.023***
	(17.9)	(7.99)	(4.31)	(5.67)	(1.48)	(10.6)	(2.97)
$DM_{1,t}\sigma j$	0.029***	0.014**	0.052***	0.051***	0.023***	0.029***	0.001
	(10.7)	(2.30)	(7.16)	(5.79)	(4.08)	(3.49)	(0.24)
$DM_{2,t}\sigma i$	0.072***	0.071***	0.029***	0.020***	-0.031***	-0.027***	0.012
	(11.7)	(9.61)	(3.86)	(2.59)	(-5.89)	(-3.38)	(1.56)
$DM_{2,t}\sigma j$	0.042***	0.011*	0.057***	0.005	0.029***	0.073***	0.027***
	(12.1)	(1.84)	(10.2)	(0.87)	(7.33)	(12.6)	(5.47)
$DM_{3,t}\sigma i$	0.079***	0.112***	0.022**	0.067***	0.008	0.039***	0.033***
	(10.9)	(12.1)	(2.41)	(5.78)	(1.20)	(4.09)	(3.34)
$DM_{3,t}\sigma j$	0.068***	0.004	0.059***	0.027***	0.022***	0.029***	0.114***
	(7.14)	(0.46)	(7.48)	(2.99)	(4.67)	(5.22)	(9.31)

Appendix 6.1 (cont'd) Examination of 'contagion effect' and relationship between volatilities and correlations when slope dummies are included

(i) (j)	Malaysia Philippine	Malaysia Korea	Malaysia Indonesia	Malaysia Thailand	Singapore Philippine	Singapore Korea	Singapore Indonesia
constant	0.076***	0.092***	0.158***	0.328***	0.179***	0.087***	0.189***
	(13.5)	(17.4)	(40.1)	(56.9)	(21.5)	(14.9)	(35.5)
Trend	0.0001***	3.91e-005	0.0001***	2.58e-005***	4.19e-005***	3.53e-005***	0.0001***
	(31.8)	(1.09)	(24.9)	(5.86)	(7.33)	(9.12)	(26.4)
$DM_{1,t}$	0.033***	0.257***	0.002	-0.009	0.227***	0.241***	-0.025
	(2.42)	(13.2)	(0.12)	(-0.49)	(11.1)	(11.7)	(-1.33)
$DM_{2,t}$	0.180***	0.070***	0.267***	-0.154***	0.133***	0.258***	-0.351***
	(18.1)	(6.83)	(24.6)	(-12.7)	(8.86)	(22.8)	(-27.7)
$DM_{3,t}$	0.334***	0.107***	0.252***	-0.105***	0.175***	0.222***	-0.214***
	(23.6)	(8.08)	(17.6)	(-10.5)	(8.83)	(16.4)	(-13.9)
σ_i	0.034***	0.017***	0.016***	0.015***	0.073***	0.031***	0.003
	(10.1)	(7.74)	(4.57)	(4.79)	(9.99)	(6.87)	(0.55)
σ_j	0.016***	0.035***	0.037***	0.041***	0.020***	0.056***	0.032***
	(3.58)	(10.6)	(7.82)	(10.09)	(3.13)	(13.5)	(6.09)
$DM_{1,t}\sigma i$	0.034***	0.021***	0.021***	0.012***	0.027***	0.025***	0.001
	(8.81)	(7.55)	(5.44)	(3.40)	(2.07)	(3.53)	(0.87)
$DM_{1,t}\sigma j$	0.032***	0.076***	0.029***	0.043***	0.024*	0.096***	0.004
	(4.09)	(12.9)	(4.09)	(5.21)	(1.79)	(11.9)	(0.41)
$DM_{2,t}\sigma i$	0.001	0.017***	0.051***	0.016***	0.021**	0.026***	0.020**
	(0.16)	(4.98)	(10.4)	(3.56)	(2.09)	(3.85)	(2.53)
$DM_{2,t}\sigma j$	0.031***	0.011***	0.005	0.058***	0.007	0.057***	0.085***
	(5.27)	(2.13)	(0.74)	(9.86)	(0.78)	(10.3)	(11.9)
$DM_{3,t}\sigma i$	0.138***	0.117***	0.167***	0.026**	0.054***	0.080***	0.059**
	(11.7)	(11.9)	(14.3)	(1.99)	(3.81)	(8.40)	(5.18)
$DM_{3,t}\sigma j$	0.030***	0.024***	0.046***	0.048***	0.097***	0.065***	-0.027***
	(3.73)	(4.06)	(6.67)	(8.46)	(8.07)	(8.85)	(-3.38)

Appendix 6.1 (cont'd) Examination of 'contagion effect' and relationship between volatilities and correlations when slope dummies are included

(i) (j)	Singapore Thailand	Philippine Korea	Philippine Indonesia	Philippine Thailand	Korea Indonesia	Korea Thailand	Indonesia Thailand
constant	0.310***	0.004	0.213***	0.209***	0.142***	0.149***	0.186***
	(39.6)	(0.74)	(33.8)	(26.5)	(27.6)	(26.4)	(27.8)
Trend	5.85e-005***	4.54e-005	0.0001***	4.98e-005	-1.74e-005***	3.34e-005***	0.0001***
	(10.6)	(1.38)	(20.4)	(0.96)	(-4.48)	(9.74)	(19.9)
$DM_{1,t}$	0.009	0.266***	-0.084***	0.029	0.202***	0.261***	0.031
	(0.41)	(14.1)	(-4.29)	(1.27)	(10.8)	(13.5)	(1.28)
$DM_{2,t}$	0.164***	0.039***	-0.338***	0.181***	0.044***	0.124***	0.361***
	(10.4)	(3.85)	(-26.9)	(12.1)	(4.01)	(11.3)	(23.6)
$DM_{3,t}$	0.227***	0.131***	-0.234***	0.106***	0.162***	0.142***	0.238***
	(12.1)	(10.3)	(-15.4)	(5.87)	(13.0)	(11.3)	(14.4)
σ_i	0.025***	0.027***	0.070***	0.002	0.010***	0.001	0.045***
	(4.05)	(8.86)	(13.7)	(0.41)	(2.80)	(0.34)	(10.1)
σ_j	0.035***	0.014***	0.066***	0.036***	0.005*	0.015***	0.053***
	(7.51)	(4.30)	(13.4)	(7.83)	(1.72)	(5.61)	(13.3)
$DM_{1,t}\sigma i$	0.036***	0.002	0.067***	0.037***	0.015**	0.046***	0.033***
	(3.46)	(0.34)	(7.92)	(3.87)	(2.04)	(7.07)	(3.99)
$DM_{1,t}\sigma j$	0.054***	0.069***	-0.031***	0.018*	0.011*	0.023***	0.060***
	(4.41)	(11.2)	(-3.88)	(1.71)	(1.74)	(3.47)	(6.01)
$DM_{2,t}\sigma i$	0.008	0.044***	0.080***	0.007	0.031***	0.034***	0.070***
	(0.89)	(10.2)	(12.1)	(0.93)	(6.68)	(7.93)	(10.4)
$DM_{2,t}\sigma j$	0.085***	0.061***	0.023***	0.128***	0.016***	0.011***	0.072***
	(10.8)	(14.2)	(3.37)	(17.9)	(3.49)	(2.64)	(11.0)
$DM_{3,t}\sigma i$	0.069***	0.023***	0.068***	0.056***	0.037***	0.052***	0.021***
	(5.57)	(3.88)	(7.55)	(5.78)	(5.78)	(9.27)	(2.78)
$DM_{3,t}\sigma j$	0.045***	0.003	-0.054***	0.044***	0.026***	0.007*	0.076***
	(4.06)	(0.49)	(-7.09)	(6.65)	(4.57)	(1.78)	(12.4)

Chapter 7 Conclusions

The main purposes of this thesis are: to investigate daily price dynamics between Asian stock markets, to examine the characteristics of return and volatility of each individual stock market and to study the impact of the 1997-98 Asian financial crisis on stock market relationships. In this chapter, I summarize the main findings, discuss the shortcomings of the present work and suggest further research in this area.

The selection of the sample period and its partition into sub-samples were addressed first in this research since these issues were critical both for studying the evolution of equity market linkages and for identifying the impact of the Asian financial crisis. Four sub-periods were defined, based on structural break points estimated from the test of Zivot and Andrews (1992) and key economic events in Asia. The announcement by the Thai Government of a managed float of the Baht and the call on the International Monetary Fund (IMF) for 'technical assistance' on 02/07/1997 are commonly considered as the triggers of the crisis. This evidence, in conjunction with the structural break points found in 1997 in all Asian stock markets, determines the first sub-sample or 'pre-crisis period', from 08/01/1992 to 01/07/1997. The second sub-sample, the 'crisis period' from 02/07/1997 to 31/12/1998, corresponds to the largest fluctuations in exchange rates and stock indices (Nagayasu, 2000) and net selling activity in Asian stock markets (Karolyi, 2002). After the financial crisis there is a further potential break point in 2003 that applies to the majority of the countries sampled, in addition, 2003 is considered to be the beginning of the economic recovery in Asia (report of the Asian Development Bank indicating the end of the economic recession). The third sub-sample or 'post-crisis period' therefore covers 01/01/1999 to 06/03/2003 (the earliest potential break point in 2003). The fourth sub-sample or 'recovery period' covers 07/03/2003 to 08/03/2007 and reflects recent events in Asian equity markets.

Various econometric methods were used to examine the characteristics and volatility of stock returns, and to investigate market linkages in the overall sample and the four sub- periods. The important findings of this research are summarized below.

First, with regard to price dynamics (examined in Chapter 3), cointegration analysis strongly points toward a long-run equilibrium relationship between the sampled Asian markets. Additionally, Granger causality and variance decomposition analyses reveal significant and substantial short-run relationships between these markets. These findings clearly show a high degree of integration between Asian equity markets.

The sub-period analyses revealed a number of additional findings.

(1) The level of long-run integration appears to have been stronger in the post-crisis and recovery periods than was the case in the pre-crisis period.

(2) Hong Kong played a dominant role in Asia during the 1990s but its influence was significantly diminished during the recovery period and it was replaced as the leading market by Singapore.

(3) The Japanese stock market started exerting its leading role after the financial crisis and this role has intensified in more recent years.

(4) Close relationships are found between the returns of Indonesia, the Philippines, Malaysia and Thailand. This is probably due to the similarity of the financial and regulatory structure of their markets.

(5) Malaysia, which imposed restrictions on cross-country investment after the financial crisis, became less responsive to innovations in foreign markets.

(6) The Korean stock market was the only market with a causal influence on both Hong Kong and Japan during the pre-crisis period. However, this relationship disappeared during the crisis and its aftermath.

(7) There are some disparities in the extent of market integration among the sampled markets. The large-capitalization developed markets (Japan, Korea, Singapore and Hong Kong) generally appear to Granger-cause the returns of some of the small-capitalization emerging markets (Malaysia, the Philippines and Indonesia). This finding poses challenges in designing a consistent regional policy for smaller Asian economies.

The analysis of the time series behavior of stock returns (Chapter 3) only provides an insight into the first moment dynamics for stock prices. In Chapter 4, the analysis was extended by using a univariate TAR-GARCH-M model to capture the second moment of stock prices (stock volatility). Several issues are specifically investigated in chapter 4, including volatility clustering, asymmetry properties, risk-return relationships and day-of-the-week effects in returns and volatility. Overall, the results suggest that volatility is time-varying and that volatility clustering appears to characterize Asian stock markets. Asymmetry effects are also found, indicating that negative shocks to returns (bad news) generate more volatility than positive shocks (good news) of equal magnitude in Asian equity markets. With regard to risk-return relationships, surprisingly, there is no convincing evidence to support a significant positive linear relationship between risk and return. On the contrary, a negative (albeit insignificant) risk-return trade-off is found during the crisis and post-crisis periods. This finding is inconsistent with most asset-pricing models and it seems possible that the financial crisis is responsible. Another general result in chapter 4 is the existence of day-of-the-week effects in returns and volatility. Returns are lower and volatility higher on Mondays, but mostly for the emerging markets of the sample. Lower returns on Mondays can be explained by the hypothesis of Miller (1988)[31] that there was a shift in the broker-investor balance in decisions to buy and sell. The excessive volatility on Mondays may be partly due to the existence of informed traders[32]. In general, the existence of day-of-the-week effects raises question about the efficiency of Asian emerging markets. On the other hand, the sub-period analysis shows little evidence of day-of-the-week effects after the financial crisis. This suggests improved post-crash market efficiency in Asian emerging markets.

Chapter 5 extends the analysis by using a multivariate GARCH-BEKK model. This model makes two major contributions. First, it can successfully capture the autoregressive second moment of the distribution of stock returns (time variation in the conditional variance of stock returns) and hence overcome the problems of VECM analysis (chapter 3), which only examine the first moment of returns. Second, it provides evidence of volatility dynamics between two price series and therefore overcomes the problems of univariate GARCH models (Chapter 4), which only allow volatility modelling of individual series. The multivariate GARCH-

[31] Chapter 4 gives details of the Miller hypothesis.

[32] French and Roll (1986) argue that informed investors trading on private information may cause the higher variance after the holidays – the 'informed trader hypothesis' (described in chapter 4).

BEKK model therefore adds to the investigation by allowing an examination of the mechanisms for volatility transmission between the sampled markets.

To summarize, Asian stock markets show the following volatility transmission characteristics.

(1) During the pre-crisis period, market trading time was an important factor in determination of volatility spillover effects. That is, the volatility of the index in a particular market was mostly affected by the indices of markets that open earlier.

(2) During the crisis and post-crisis periods, market trading time appears to become a less important determinant of volatility spillover effects, giving way to quality of markets (market capitalisation, number of stock listed and the effects of market regulation).

(3) During the recovery period, more bi-directional variance feedback is found for all markets – a finding that is strongly consistent with a growing degree of Asian equity market integration over recent years.

(4) Hong Kong and Japan play a dominant role in volatility transmission. This is probably due to their large trading volume and good quality of market microstructure. Therefore, they become an important indicator for the rest of Asian stock markets.

(5) Singapore behaves as a leader for the emerging markets of the sample. This is understandable since Singapore is a member of ASEAN but it also has a similar market microstructure with Hong Kong.

(6) Malaysia appears to have become more isolated from the region since the crisis. This seems partly due to the capital control policies of the Malaysian government.

(7) Korea was relatively isolated before the crisis but developed significant bi-directional spillover relationships with its major Asian counterparts after the crisis. This suggests that the crisis might substantially influence the economic and financial policies imposed by the Korean government.

(8) Indonesia is a small market in the region, with little influence on other markets.

(9) The Philippine market transmitted volatility to other Asian markets before and during the crisis period, possibly because it has the earliest close time.

(10)The Thai market was dominated by most other Asian markets before the crisis, probably because it opens/closes after most other markets. The influence of Thailand on other markets increased after the crisis.

In general, empirical findings derived from Chapter 5 highlight the complex nature of Asian equity market linkages. Each market is characterised by quantifiable volatility (risk) linkages with the others. An important implication of these findings is that domestic investors/regulators should be aware of risks from other Asian markets when assessing/regulating domestic market risks.

Chapter 6 reveals contemporaneous relationships between Asian stock markets by examining cross-market time-varying correlations. Since much previous research has shown that correlations between Asian equity markets tend to be time varying rather than constant, a DCC-TGARCH model is adopted to investigate the correlation dynamics of the sampled markets.

DCC (dynamic conditional correlation) analysis reveals correlations that are indeed time-varying. There are upward trends in conditional correlations from 1994 onwards in almost all of the sampled markets. This indicates that the market liberalization process in Asian countries has led to an increase in the co-movements of stock markets in the region and Asian stock market integration has increased due to financial liberalization in the early 1990s. When the crisis started, as anticipated, there was an increase in cross-market correlation. The apparent higher co-movement of the sampled stock markets in times of crisis is evidence of a 'contagion effect'. This suggests that the gains from international diversification by holding a portfolio consisting of stocks from different Asian countries declined during the crisis, since these markets were systemically affected.

Another important inference from the DCC analysis is that high correlation is associated with high volatility in Asian stock markets. This finding is particularly important for investors who diversify their portfolios across Asian equity markets since it shows that the benefits of diversification tend to be low in volatile market conditions.

Limitations and further possible directions implied by the findings of this thesis should not be ignored. They are summarized as follows. **First,** a possible limitation of this thesis is that the empirical studies are based on daily data of stock indices. Hence there may be intra-day effects that are not be captured by daily returns/prices and it is very possible that important intra-day linkages exist even where linkages are absent here. In future research, therefore, empirical studies based on intraday data should provide more accurate insights into price/volatility dynamics. **Second,** the methodology used in this study can be applied to an analysis of cross-country stock-bond market comovements to explore the relationships in different assets classes both at the country and international levels. **Third,** research that analyzes the factors and determinants of global stock market comovements, using intra-day data and focusing upon the evolution and stability of markets over time should continuously be investigated. This could be a positive and practical step for future research in international finance.

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