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Modelling Australian stock market volatility

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Certification

I, Karunanayake Athukoralalage Indika Priyadarshani, declare that this thesis, submitted in fulfillment of the requirements for the award of Doctor of Philosophy, in the School of Economics, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Karunanayake Athukoralalage Indika Priyadarshani

26 August 2011

To my loving husband Piyal, kids, Imandi and Tinuka

List of Candidate's Publications

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Table of Contents

List of Tables

List of Figures

Abbreviations

ADC	Asymmetric Dynamic Covariance
ADVECH	Asymmetric DVECH
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AORD	All Ordinaries Index
ARCH	Autoregressive Conditional Heteroskedastic
AVIX	Australian Market Volatility Index
BIS	Bank for International Settlements
CCC	Constant Conditional Correlation
DBEKK	Diagonal Version of BEKK
DCC	Dynamic Conditional Correlation
DVECH	Diagonal Version of VECH
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
FGARCH	Factor GARCH
FTSE100	Financial Times Stock Exchange Index
GDP	Gross Domestic Product

GFC	Global Financial Crisis
GLS	Generalized Least Square
HIC	Hannan-Quinn Information Criterion
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
NBER	National Bureau of Economic Research
OECD	Organisation for Economic Co-operation and Development
OGARCH	Orthogonal GARCH
S&P 500	Standard and Poor’s Index
SIC	Schwarz Information Criterion
STI	Straits Times Index
UK	United Kingdom
US	United States
VAR	Vector Autoregression Model
VECM	Vector Error Correction Model

Abstract

This thesis examines the interplay between the Australian stock market and other interrelated international stock markets to evaluate the volatility contained within and across these markets. In particular, this thesis aims to: (1) shed some light into the asymmetry of volatility effect across different international stock markets; (2) assess the volatility transmission dynamics across international stock markets during different financial crises by comparing and contrasting the similarities and dissimilarities of those crises; and (3) examine the interaction between stock market volatility and the volatility of economic growth across a number of countries evaluated.

Based on an extensive literature review, this thesis demonstrates that the asymmetry associated with volatility effects spread across various stock markets and Australia have not been fully investigated. A Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model for weekly stock market data of Australia, Singapore, the United Kingdom (UK), and the United States (US) for the period spanning from January 1992 to June 2010 is adopted in this thesis. Firstly, the estimated results from the empirical analysis identifies that negative shocks in each market plays an important role in increasing both variances and covariances within and across these stock markets in contrast to positive shocks. Of note, for smaller markets (Australia and Singapore) the asymmetry coefficients in covariances are generally higher than the asymmetry coefficients in the variance equations, suggesting the volatility of these smaller stock markets will increase following negative shocks from other markets. Second, the findings from this study confirm that negative shocks from

highly correlated markets can involve higher time-varying covolatility between those two markets. Thus, investors will be highly unlikely to benefit from diversifying their financial portfolio by investing their funds within these four markets only.

The second issue that has received little attention in the literature is how volatility between Australia and different international stock markets varies during two different financial crises. This thesis focuses on the 1997–98 Asian crisis and the 2008–09 Global Financial Crisis (GFC). A MGARCH model is augmented with two dummy variables to capture exact timing and possible effects on the volatility of stock markets of Australia, Singapore, the UK, and the US, from the two crises. There exists a significant influence arising from both crises on volatility in all four markets. Although both crises impacted on increasing own-volatility in these four markets, only the recent GFC contributed to increase the cross-volatilities across these four markets.

Finally, it is found that the nature of the relationship between stock market and the output growth are mixed in relation to the interaction effect of volatility across stock market returns and growth rates of Gross Domestic Product (GDP). This thesis also employs the diagonal version of BEKK (Baba, Engle, Kraft, and Kroner, see Engle and Kroner, 1995) model using quarterly data from 1959 to 2010 for four Anglo-Saxon economies (namely Australia, Canada, the US, and the UK). The results from this empirical analysis indicate that although statistically significant own-mean spillover effects exist in all eight series, the cross-mean spillover effects exist: (1) from the US stock market to the Australian stock market; (2) from the US GDP growth to the US stock market; and (3) from the US GDP growth to GDP growth rates of all four countries. These empirical results confirm that the US stock market predominately influences the Australian stock market while the US economy impacts upon Australian economic growth.

In terms of second order moments (1) the own-volatility shocks exist for all eight series except for Australian and Canadian GDP growth series; (2) the covolatility shocks between stock markets and GDP growth rates are also positive and significant with the exception being the covolatility shocks between the Canadian GDP growth and other stock markets; (3) the covolatility across GDP growth rates is also positive and significant except for the covolatility shocks between the Canadian GDP growth and GDP growth rates of other countries; and (4) unlike own-volatility and covolatility shocks (ARCH effect), both the own-volatility and covolatility spillovers (GARCH effect) within and across all eight series are positive and statistically significant indicating a strong relationship across stock market and the GDP growth series from different countries on increasing corresponding covolatilities.

In general, this thesis has made three significant contributions evaluating dynamics of stock market volatility transmission across different stock markets with particular focus on the Australian stock market. First, this thesis extends previous findings by identifying and quantifying the asymmetric volatility effects that exist within and across international stock markets. Second, this research is the first study to evaluate varying volatility implications on volatility transmission across international stock markets during different financial crises by comparing and contrasting their similarities and differences. Lastly, no previous study has simultaneously assessed the interaction effect of volatility across stock market returns and GDP growth rates of different countries.

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CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

In finance, volatility is a measure of fluctuations of asset prices. According to Schwert (1990a), finance researchers use percentage changes in prices or rate of returns to measure the volatility of a financial market. Furthermore, in response to new information, price of stocks can change quickly; thereby volatility of stock markets is an indication of high liquidity of the market (Schwert, 1990a). On the other hand, Bauwens *et al*. (2003, 2006) stated that financial volatilities move together over time across assets and markets which mean that the volatility of one asset or market can lead the volatility of other assets or markets.

In addition, the interaction between stock markets has increased markedly over recent decades with the integration of national economies through international trade, capital flows, foreign direct investment, and the spread of technology (Chan *et al.*, 1997). The importance of understanding these cross-market interactions arises from several sources. Brailsford (1996) states that the transmission of international stock market volatility is significant for the pricing of securities, trading strategies, hedging strategies, and regulatory strategies within, and across the markets. Both Shamsuddin and Kim (2003) and In (2007) also argue that the knowledge of market interdependency is extremely important in determining diversification of international investments.

Therefore, a growing interest has emerged in recent years examining the determinants of volatility transmission across international stock markets. Past studies have stressed *inter alia*, asymmetric volatility effects, financial crises, and GDP growth as significant factors influencing individual stock market volatility and volatility spillovers across different markets. Thus, this thesis will identify and quantify the factors affecting cross-country spillovers in both stock market returns and volatilities, with a special focus on the Australian stock market. Specifically, this thesis will focus on the asymmetric nature of stock market volatility transmission mechanisms, the interaction between stock markets during financial crises, and, the effect of economic growth.

First, with regard to asymmetry of volatility effects, according to Bollerslev *et al.* (1994), Patterson (2000), and Brooks (2008) stock market volatility is greater following a large price fall compared to a price rise of the same magnitude. Similarly, Koutmos and Booth (1995), Brooks and Henry (2000) and Ng (2000) observed that not only the magnitude of unanticipated shocks but also the sign of the shocks arising in one stock market impact on the volatility of other stock markets. Even though this issue is becoming more topical there are limited empirical studies capturing such potential asymmetries which may exist in the volatility transmission mechanism (for example, Koutmos and Booth, 1995, Kroner and Ng, 1998, Brooks and Henry, 2000, de Goeij and Marquering 2004, 2005, 2008). Therefore, in the context of different international stock markets, the asymmetry of volatility effect is not fully identified and quantified in the literature.

Another important influence on stock market returns and volatility is financial crises. In this regard, Schwert (1989a) confirms that volatility of a stock market increases during financial crises periods. Many empirical studies such as

Theodossiou *et al*. (1997), Ellis and Lewis (2001), and Caporale *et al.* (2006), find that the magnitude and the severity of the shocks arising in one stock market during the financial crises periods influence the stock market volatility transmission across different markets. Furthermore, these volatility transmission patterns vary from market to market due to the influence of financial crises. Theodossiou *et al*. (1997) for example, provides evidence that volatility in Japan and the UK stock markets were the same during both the pre and post October 1987 crash while US volatility was higher prior to the October 1987 crash period. In addition, Ellis and Lewis (2001) observe that stock market volatility in Australia and New Zealand was greater in late 1998 rather than the 1997-98 period when the main events of the Asian financial crisis occurred. A noteworthy aspect of those financial crises is how volatility transmission dynamics vary across different international stock markets pre and post, as well as during, different financial crises periods. There also remains a void in the literature distinguishing the nature of different financial crises in terms of causes, the geographical location where it initiates and how rapidly it spreads to other countries.

Finally, according to Ritter (2005), since the relationship between stock market returns and economic growth is significant for investors to manage their portfolio, the release of macroeconomics news can be utilized to identify stock market trends. However, there is no consensus on the nature of the relationship between stock market volatility and the volatility of economic growth. For instance, Diebold and Yilmaz (2008) find a unidirectional influence from GDP volatility to stock market volatility. In contrast, others have reported empirical evidence of a bidirectional relationship between stock market volatility and the volatility of GDP growth. In this case, Leon and Filis (2008) argue that the relationship between stock market and GDP is negative from GDP to the stock market whereas it is positive from the stock market to GDP. Ahn and Lee (2006), on the other hand, identify that high volatility in the stock market is followed by increased volatility in the output sector and *vice versa*. Although it is important for investors to identify varying volatility implications across different international stock markets due to GDP growth in the wake of regional or global economic crises, no study has so far examined this issue in a multi-country context.

Therefore, the purpose of this thesis is to focus on these three issues to identify and quantify varying implications on the nature of volatility transmission dynamics through application of advanced econometric techniques.[1] In this regard, the current study uses both weekly and quarterly data from the Australian stock market and four other countries. Namely, Canada, Singapore, the UK, and the US.[2]

The Australian stock market is of particular interest in this study as it is one of the major financial markets in the Asia Pacific region. According to Standard and Poor's, (September, 2009) it is the second largest market in the Asia Pacific region and the seventh largest in the world in terms of total market capitalisation. In addition, a review of existing empirical works reveals that no

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[1] A detail review of recent development of financial econometric techniques for analysing dynamics of financial market volatility transmission and their applications in the context of this study is presented in Chapter 3.

[2] The reasons for selecting these countries in the present thesis have discussed in Chapter 4 and Chapter 6.

study has conducted a comprehensive analysis evaluating how asymmetric volatility effects, financial crises, and GDP growth influence the stock market integration between Australian and other international stock markets.[3] Besides Australia, use of other stock market data will allow an analysis of the interplay with other major stock markets from North America, Europe, and the Asia Pacific regions.

The findings from this study will be important for investors when allocating their funds on portfolio diversification across these markets. As suggested by Kroner and Ng (1998), in portfolio diversification, it is riskier to invest in two assets if they are highly positively correlated than to invest in two assets that are less correlated. Therefore, an investor will be highly unlikely to benefit from diversifying their financial portfolio by acquiring stocks from international stock markets with a high degree of time-varying co-volatility. In addition, policy makers and macroeconomists will benefit from better understanding of systematic financial-sector risk in the wake of information flow during global financial and economic turmoils. Thus, policy makers may take appropriate policy actions to reduce the risks likely to affect stock market volatility as well as economic growth.

1.2. Research Questions and Significance of the Research

The current thesis contributes to the literature by addressing the following questions on cross-market volatility spillovers between the Australian stock market and international stock markets.

[3] More details on Australian stock market and its volatility are discussed in Chapter 2.

i. Are there any influence from past stock returns of Australia and other markets towards the future Australian stock returns?

The aim of this research question is to identify and quantify the influence from past stock returns on the present state of the Australian market as well as the influence from other major international markets towards Australian stock returns.

ii. How do shocks originating in other markets affect the Australian stock market compared to shocks originating in the domestic market?

This question examines the variations of the Australian stock market volatility due to the unanticipated shocks stemming from the Australian stock market as well as other markets. In other words, this aspect of the current study will identify whether the country-specific shocks increase the volatility in the Australian stock market more than the shocks arising from other markets. Therefore, this will identify which stock market(s) influence the Australian stock market volatility the most and which stock market influence the least.

iii. Do asymmetric volatility effects significantly influence - the Australian stock market?

This feature of the current research further evaluates the fluctuations of the Australian stock market volatility due to the asymmetric volatility effect in the Australian stock market as well as other markets. More specifically, this will enable the identification of whether a price fall or bad news emanating from one stock market will affect the Australian stock market greater than a price increase or good news of the same magnitude.

iv. How do stock market returns and the volatility of international stock markets affect the Australian stock market during global financial crises?

The purpose of this research question is to identify any possible influence from financial crises on the cross-market volatility spillovers between the Australian stock market and international stock markets. Furthermore, this aspect compares and contrasts the impact on systematic patterns of return and volatility transmission during two recent financial crises periods; namely, the recent GFC and 1997-98 Asian crisis.

v. How does domestic and foreign economic growth influence cross-market volatility spillovers between Australian and international stock markets?

This aspect of the study is expected to identify the relationship between stock market volatility and economic growth volatility. The link between macroeconomic performance and the stock market is important because as Arnold and Vrugt (2006) stated, macroeconomic variables affect both expected cash flows and discount rates, and thereby affect stock prices.

By analysing these issues, the current thesis contributes to the literature in several significant ways. First, this particular thesis fills the gap in the literature by providing a comprehensive evaluation of how an asymmetry in one stock market influences the volatility of other stock markets, distinguishing relative importance of regional verses world markets. In the Australian context, although few studies argue that not only magnitudes but also sign of the international stock market shocks can influence the Australian stock market returns, the present study is the first study to quantify the extent of asymmetry of volatility effect from international stock market to the Australian market.

The second important contribution is to explore how magnitude and sources of volatility shocks emanating in financial crises affect the cross-market volatility spillovers. Special attention will be focussed on the recent GFC and the Asian crisis. The cause of these two crises was similar in that over-leveraging, hence bad debts played an important common role in initiating these crises. However, they originated in different geographic origins. According to the Bank for International Settlements (BIS, 1999, 2009), the Asian crisis engulfed the global market with the collapse of Thai-baht while the recent GFC originated from the collapse of the US subprime mortgage market. Therefore, this enables us to identify whether cross-country spillovers in volatility were similar for the two financial crises with regards to their fundamental similarities and differences in terms of how and where they originated. In this regard, this study becomes the first study in the literature evaluating how magnitude and sources of volatility shocks emanating in two different financial crises affect the cross-market volatility spillovers.

The third contribution of this thesis is to examine how the nature of stock market volatility transmission across different international markets varies due to the influence of GDP growth. Although some studies such as Errunza and Hogan

(1998), Ahn and Lee (2006), and Diebold and Yilmaz (2008) used multi-country data, their analysis focused on one single country at a time to evaluate the relationship between stock market volatility and output growth. Therefore, findings of those studies did not provide any evidence on how GDP growth volatility of one country can influence the stock market volatility and covolatility of other countries. Hence, this thesis is the first study to evaluate how the nature of stock market volatility transmission dynamics varies over time with the economic growth of different countries. This is important for macroeconomic management as linkages between economies and financial markets increase with globalization. In addition, as Levine (1996) explained the ability to trade securities may facilitate investment and promote capital allocation efficiently, thereby increase long-term economic growth. Therefore, policymakers should consider reducing obstacles such as tax, legal, and regulatory barriers to stock market development.

Finally, the present thesis applies more sophisticated econometric techniques to evaluate asymmetric of volatility effects, financial crises, and GDP growth influence from international stock markets towards the Australian stock market. Therefore, methodologically, this study becomes the first study to employ different MGARCH models to; (1) compare and contrast the varying volatility implications across stock markets during two different financial crises and (2) investigate how GDP growth of various countries influence different stock market returns and volatilities.

1.3. Summary and the Structure of the Thesis

The current thesis consists of seven chapters. An introduction to the thesis is given in Chapter 1. The remaining chapters of this thesis are organized in the following way. Chapter 2 provides a review of literature related to the Australian stock market returns and volatility. This chapter, first, provides an overall background of the Australian stock market. Then, it evaluates the empirical work on the Australian stock market under four main themes: (1) the asymmetry of volatility effects that may present in the Australian stock market; (2) the behaviour of Australian stock market during financial crises period; (3) the relationship between the Australian stock market and GDP growth rates; and (4) the Australian stock market integration with other international stock markets.

Chapter 3 presets a comprehensive review of MGARCH models. This chapter includes theoretical framework and the extensions of three main MGARCH models viz. MGARCH of models Bollerslev *et al*. (1988), which is also known as VECH, BEKK and Constant Conditional Correlation (CCC) models with parameter estimation methods and diagnostic tests for MGARCH models. Finally, Chapter 3 concludes with a discussion of empirical application of these MGARCH for evaluating the asymmetry of volatility effects that may exist in the volatility transmission across different international stock markets, capturing varying volatility implications across stock markets during financial crises periods and studying the dynamics of volatility transmission across different stock markets and GDP growth rates.

Chapter 4 empirically tests the asymmetry of volatility effects that may exist in the volatility transmission process across four highly integrated stock markets: Australia, Singapore, the UK, and the US. The Diagonal Version of VECH (DVECH) model augmented with Glosten *et al.* (1993) dummy series is employed to test the asymmetry of volatility effects within and between each of the two stock markets.

Chapter 5 examines the dynamics of volatility transmission across different international stock markets during two financial crises – i.e. 1997-98 Asian crisis and 2008-09 GFC. To capture the influence of these two crises this study incorporates two dummy variables for the DVECH model.

Chapter 6 investigates the volatility transmission mechanism across stock markets and GDP growth rates of four Anglo-Saxon countries (Australia, Canada, the UK and the US). Since there are eight time series in this study, the Diagonal Version of BEKK (DBEKK) model is employed to reduce the number of parameters while guaranteeing positive definite of variance and covariance matrix.

Finally, Chapter 7 summarises the main findings from previous chapters with key policy implications. This chapter also discusses the specific contributions made by this thesis and its limitations. Suggestions for further studies are also set out in this chapter.

CHAPTER TWO

LITERATURE REVIEW OF AUSTRALIAN STOCK MARKET VOLATILITY

2.1. Introduction

As outlined in Chapter 1, the purpose of this study is to examine the dynamics of volatility transmission between Australian and stock markets of other major economies, both regionally and globally. The analysis focuses on the asymmetric volatility effect, financial crises, and GDP growth, as influences affecting volatility spillovers across these stock markets. Therefore, the structure of this chapter reflects these main themes. Section 2.2 presents empirical studies on the asymmetric volatility effect in the Australian stock market. Section 2.3 provides some evidence on the behaviour of the Australian stock market returns and volatility during periods of financial crises followed by a review of literature on the interaction between the Australian stock market return and GDP growth in Section 2.4. Finally, the integration of the Australian stock market with other international stock markets is discussed in Section 2.5 followed by summary and conclusion in Section 2.6.

2.2. The Asymmetric Volatility Effect in the Australian Stock Market

In recent years, the dynamics of international stock market volatility transmission has emerged as a growing topic of interest. A number of empirical studies find asymmetric volatility to be a crucial factor. The asymmetry of volatility effect is generally associated with a greater increase in the volatility of the stock market following an unexpected price fall compared to a price increase of the same magnitude (Bollerslev *et al.*, 1994, Patterson, 2000, Brooks, 2008). Furthermore, this asymmetry of volatility effects is due to changes in stock prices and these changes tend to be negatively correlated with changes in stock volatility. According to Kroner and Ng, (1998) the explanation for this asymmetric effect is related to a leverage effect and an increase in the information flow following bad news. If the leverage effect is the underlying reason, an increase in the debt: equity ratio of a company increases the risk of holding stocks following a price fall of stocks. On the other hand, when the information flow increases following bad news, it will increase the relative rate of information across firms affecting the covariances across stock returns. In terms of the asymmetry issue, “bad news” refers to negative returns while during financial crises “bad news” refers the information with adverse effects across integrated stock markets. Few examples Schwert (1989b) and Nelson (1991) reported this asymmetric volatility behaviour of stock returns using US data; Reyes (2001) estimated an asymmetric impact on volatility in the Tokyo Stock Exchange; Henry (1998) captured asymmetry of volatility using Hong Kong Stock market data; Sentana (1995) used the UK and the US data to identify the asymmetric impact in the stock market returns; Zakoian (1994) empirically tested the asymmetry of volatility behaviour of French stock data.

In an Australian context, Kearns and Pagan (1993) observed that the asymmetric volatility effect in Australian stock returns was lower compared to the

US stock returns.[4] Other recent empirical studies also documented that the asymmetric impact was not presented in the Australian stock data. For example, Mian and Adam (2001) identified that the Australian intraday return volatilities during the period from 1993 to 1997 did not indicate asymmetry in its response to positive and negative stock returns. While these two studies were similar in findings they were different in methodological approach. Kearns and Pagan (1993) divided the returns into two groups: (1) the value was higher than the previous month by certain amount *x* and (2) the value is lower than the previous month by the amount *x*. Then they examined the changes of variances, while Mian and Adam (2001) used a more sophisticated GARCH approach, where a dummy variable was used to capture the magnitude of the effect from positive and negative shocks on the conditional variance.

However, Dowling and Muthuswamy (2005) and Frijns *et al.* (2010) using traditional regression analysis methods documented contradictory findings for volatility asymmetry in Australian stock data.[5] Dowling and Muthuswamy (2005) reported no asymmetry in the Australian Market Volatility Index (AVIX), which was constructed using daily data of S&P/ASX200 Index Options from November 1999 to September 2002. In contrast, more recently Frijns *et al.* (2010) found that the Australian stock market data indicated a significant asymmetric relationship between changes in the AVX and S&P/ASX 200 returns using daily stock market

[4] For this study, Kearns and Pagan (1993) used monthly data from 1875 to 1987.

[5] Dowling and Muthuswamy (2005) and Frijns *et al*. (2010) performed a regression of the volatility index change on lead, lags, and contemporaneous S&P/ASX 200 returns and incorporate absolute value of contemporaneous return to detect any asymmetry relationship between market volatility index and S&P/ASX 200 returns. In addition to these variables, Frijns *et al*. (2010) included lagged value of the change in market volatility index to control first-order autocorrelation.

data from January 2002 to December 2006.[6] Therefore, it appears that there is no consensus on the presence of asymmetry of volatility effect in the Australian stock returns. It must be noted that those studies attempted to capture the asymmetric volatility effect based on the negative shocks or negative returns of the Australian stock data only.

How good (positive shocks) and bad (negative shocks) news originating in another county's stock market affects volatility in the Australian stock market was not addressed. In this regard, Brooks and Henry (2000) incorporated Japanese and US stock market data in addition to Australian data from January 1980 to June 1998 into an asymmetric BEKK model. According to Brooks and Henry (2000), although it is difficult to explain how asymmetric spillovers of international stock returns transmitted from one market to the other, both the magnitude and the sign of the unanticipated shock arising in stock market returns of Japan and the US indicated an influence on the volatility of Australian stock market. However, they did not identify which stock market influenced the other markets the greatest or least. This feature is important for investors with Australian stocks to decide when one stock market in their portfolio is trading downwards how it affects other stocks in their portfolio. Thus, significant gaps remain in the empirical literature relating to the asymmetric effect of good and bad news arising from international stock markets on the volatility of the Australian stock market.

The empirical studies capturing the asymmetry dynamics in the Australian stock market are summarised in Table 2.1.

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[6] AVX is the volatility index for the Australian data using S&P/ASX 200 returns constructed by Frijns *et al.* (2010) similar to Dowling and Muthuswamy (2005).

Table 2.1 Empirical Evidence on the Asymmetric Volatility Effect in the Australian Stock Market

	Econometric Model	Data	Findings
1. Kearns and Pagan (1993)	• First, they divided the monthly returns into two groups based on the sign of the returns. • Second, they compared the current period value with the previous month's value to examine the changes of variances.	Monthly Australian stock market data from 1875 to 1987.	• The asymmetric impact in Australian stock returns was lower compared to the US stock market returns. • Furthermore, results indicated that increase in monthly returns of Australian stock market during their sample period increased the variances of stock returns.
2. Brooks and Henry (2000)	• Asymmetric BEKK model with VAR(1) structure (i.e. current period returns are based on one lag returns of each market). In addition, a dummy variable is incorporated for 1987 crash.	Weekly stock returns from Australia, the US, and Japan from 1 January 1980 to 22 June 1998.	• The Australian stock market becomes more volatile when the US markets are trending downwards. • The Asymmetric BEKK model provides evidence that the estimated variance and covariance matrix is time varying and asymmetric.
3. Mian and Adam (2001)	• Asymmetric univariate GARCH approach, where a dummy variable was used to capture the magnitude of effect from positive and negative shocks on the conditional variance.	Intraday 15-minute data of the All Ordinaries Index from January 1993 to January 1997.	• They identified that the Australian intraday return volatilities during their sample period did not indicate asymmetry in its response to positive and negative stock returns.
4. Dowling and Muthuswamy (2005)	• They carried out a regression of the AVIX index on lead, lags, and contemporaneous S&P/ASX 200 returns and incorporated absolute value of contemporaneous return to detect any asymmetry relationship between market volatility index and S&P/ASX 200 returns.	Daily data of S&P/ASX200 Index Options from November 1999 to September 2002.	• They did not detect any asymmetric effect in the AVIX index.
5. Frijns *et al.* (2010)	• They used the similar regression as Dowling and Muthuswamy (2005) performed. Additionally, Frijns, Tallau and Tourani-Rad (2010) incorporated lagged value of the change in market volatility index to control first-order autocorrelation.	Daily data of S&P/ASX 200 index from January 2002 to December 2006.	• They identified that the Australian stock market data indicated a significant asymmetric relationship between changes in the AVX and S&P/ASX 200 returns.

2.3. Australian Stock Market Returns and Volatility During Financial Crises

Besides the asymmetric volatility effect, the global and regional financial crises influence the stock market returns and volatility. According to the BIS (1999), the 1997-98 Asian financial crisis started in mid-1997 with the collapse of Thai-baht and spread within Asia until mid-1998. Subsequently the crisis engulfed Russia and other countries. However, the more recent GFC originated from the collapse of the US subprime mortgage market in June 2007 (BIS, 2009). Furthermore, the GFC sharply grew out of control following the Lehman Brothers collapse on 15 September 2008. Although, these two crises originated outside Australia, the aftermath of these two crises influenced both the Australian economy and the Australian stock market (Brown and Davis, 2009).

In the context of varying volatility implications on the Australian stock market from other international stock markets during financial crises and non-financial crises periods, Ellis and Lewis (2001) employed a Vector Autoregressive model (VAR) approach for stock returns and daily-realised volatility during the period from the beginning of 1994 to the end of 1999. To compare the behaviour of the Australian stock market during the 1997-98 Asian financial crisis and non-financial crisis periods, they divided their sample into following four sub samples: from 1 January 1994 to 30 April 1997 as “pre-crisis”, from 1 May 1997 to 31 August 1998 as “Asian crisis”, from 1 September 1998 to 31 December 1998 as “world crisis”, and finally the first eight months of 1999 as “post-crisis”. Furthermore, Ellis and Lewis (2001) revealed that the influence from the US stock market on increasing prices and volatility in the Australian market was greater in late 1998 (i.e. world crisis) than from mid1997 to mid 1998, when the main events of 1997-98 Asian financial crisis occurred. In addition, during other periods results did not indicate higher volatility in the Australian stock market.

Cheunga *et al.* (2010) on the other hand, investigated the relationship among several international financial markets during the 2007-09 GFC period. They employed a VAR, Granger causality test and cointegrated Vector Error Correction Model (VECM) for weekly stock returns of Australia, China, Hong Kong, Japan, Russia, the UK, and the US from 2003 to 2009. In addition to stock market data, Cheunga *et al.* (2010) incorporated the difference between 3-month T-bill interest rate and the 3-month London Interbank Offered Rate. Furthermore, they considered July 2007 as the starting point of the recent GFC. According to the findings of Cheunga *et al.* (2010), the US market shocks transmitted to other global financial markets at least two times during the 2007–09 GFC period. In particular, the influence from international financial markets towards the Australian stock market indicated that the US market returns and volatility influenced the Australian market the most.

However, a significant aspect with regard to financial crises is how volatility of different stock markets varies during different financial crises. In this regard, no evidence found in the literature comparing and contrasting the similarities and differences of volatility transmission dynamics by distinguishing the nature of different financial crises in terms of how they origin, the geographical origin where they initiates and how rapidly they spreads to other countries. Table 2.2 summarised the empirical studies on the Australian stock market during financial crises and non-financial crises periods.

Table 2.2 Australian Stock Market Volatility During Financial Crises

	Econometric Model	Data	Findings
1. Ellis and Lewis (2001)	• VAR approach.	Australian and New Zealand daily market-close data for stock prices and bond-futures prices, and 4 pm readings for the bilateral exchange rates from the beginning of 1994 to the ending of 1999. For comparison purposes US data was also incorporated (US S&P500 stock price index to represent stock returns and the futures contract, the 30-year Treasury bond for explaining the bond price).	• Financial markets of Australian and New Zealand were positively correlated with Asian news events. • More specifically, the Australian and New Zealand stock indices were more volatile in all news-event days compared non-news-event days during the Asian crisis. • Especially for the Australian shocks, volatility in the world crisis period was similar to the volatility in the Asian crisis period. • The mean volatility in the New Zealand market is larger in the crisis and post crisis periods compared to other periods.
2. Cheunga *et al.* (2010)	• VAR model, Granger causality test, and cointegrated VECM.	Weekly stock returns of Australia, China, Hong Kong, Japan, Russia, the UK, and the US with the difference between 3-month T-bill interest rate and the 3-month London Interbank Offered Rate from 3 January 2003 to 3 April 2009.	• The US market shocks transmitted to other global financial markets at least two times during financial crisis period. • Especially, the influence from the US market returns and volatility towards the Australian stock market returns and volatility increased substantially than that from other markets to the Australian market. • According to cointegrated VECM, the long-run relationship between the US market and other stock markets became stronger during financial crisis period. • The cointegrating rank test results indicated that an equilibrium relationship between the US stock market and the Australian stock market before and during the crisis suggesting when the US market increasing (decreasing) the Australian stock market will also increasing (decreasing) towards the level of US stock index.

2.4. The Interaction Between the Australian Stock Market Return and GDP Growth

Empirical studies have identified that the economic fluctuations within a country influence stock market returns and volatility. Using the US data Schwert (1989b, 1990b) and others identified stock market volatility increases during economic recession. However, the influence from stock market volatility to macroeconomic volatility is higher than that from macroeconomic volatility to stock market volatility.[7] According to Ritter (2005), the relationship between stock returns and economic growth is significant for investors to manage their portfolios utilising the release of macroeconomics news to identify stock market trends.

In an Australian context, Kearney and Daly (1998) focused on the relationship between the stock market volatility and the conditional volatilities of economic growth with other macroeconomic variables.[8] According to their findings, an increased in the conditional volatility of industrial production was linked with lower stock market volatility. In addition, Brooks *et al.* (1999) argued that the good and bad news of GDP and current account balance have no impact on Australian stock returns.[9] Groenewold (2003) also could not find an influence on the Australian share prices from real output after deregulation of the Australian

[7] Schwert (1989b) used Industrial Production, Producer Price Index and Monetary Based Growth Rates as macroeconomic variables and Schwert (1990b) used Industrial Production as macroeconomic variable.

[8] This study used monthly data of inflation, interest rates, industrial production, the current account deficit, and the money supply from July 1970 to January 1994 for univariate ARCH model with Generalized Least Square (GLS) method.

[9] In this study, Brooks *et al.* (1999) considered positive (negative) revisions of both current account and GDP as good (bad) news if an unexpected component of announcement was positive (negative). They used daily data (from 3 January 1989 to 31 December 1993) of nine financial markets namely the All Ordinaries Index, 90-day bank bills, 3-year bonds, 10-year bonds, share price index futures, 90-day bank bill futures, 3-year bond futures, and 10-year bond futures.

financial market.[10] However, the findings of Groenewold (2003) indicated that the Australian share prices influence real output the during post-deregulation period. In contrast, Chaudhuri and Smiles (2004) identified a significant effect on the Australian stock returns from the growth rate of real GDP. They also found that negative effect from the two lags of real consumptions towards the stock price movement.

Besides the influence from domestic economic factors, Kim and In (2002) and Kim (2003) identified international macroeconomic influence towards the Australian stock returns and volatility.[11] Even though these two studies incorporate influence from other countries to their models, their approaches are confined to univariate GARCH models. Thus, they did not capture the varying volatility implications on covolatility across Australian and international stock markets and macroeconomic variables from corresponding countries. The current study therefore, focuses to fill this gap in the literature.

The empirical studies discussed in this section evaluating the relationship between the Australian stock market and macroeconomic variables are summarised in Table 2.3.

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[10] Groenewold (2003) used December 1983 as break-date for constructing two-sub period for pre-deregulation and post-deregulation based on the floating of Australian dollar and the opening up of Australian financial markets to foreign investors.

[11] Kim and In (2002) use the Australian, Japanese, the UK and the US stock market data and the Australian and the US macroeconomic news (Consumer Price Index, GDP, and employment data) from July 1991 to December 2000. Kim (2003) uses macroeconomic news from Japan (Trade Balance, Current account Balance, Unemployment Rate, Money Supply Growth Rate, Wholesale Price Index Inflation, and Consumer Price Inflation) and the US (Trade Balance, Gross Domestic Product Growth Rate, Retail Sales Growth Rate, Unemployment Rate, Producer Price Index Inflation, Consumer Price Inflation) for the period spanning form early 1991 to mid 1999.

Table 2.3 Interaction Between the Australian Stock Market and Macroeconomic Variables

	Econometric Model	Data	Findings
1. Kearney and Daly (1998)	• The GLS estimation procedure together with the Hendry general-to-specific modelling strategy (In this method they included the equation for the conditional volatility of stock market returns together with the equations determining the conditional volatilities of inflation, interest rates, industrial production, the current account deficit, and the money supply).	Monthly data on the Australian stock market, and business cycle variables including the interest rate on 3-month bank accepted bills, the exchange rate (AUD-USD), the rate of inflation of the wholesale price index, the current account deficit and the level of industrial production from July 1970 to January 1994.	• The increase in the conditional volatility of interest rates and inflation rates were related to higher stock market volatility • An increased in the conditional volatility of industrial production, the current account deficit, and the money supply were linked with lower stock market volatility. • They could not find any significant relationship between the conditional volatility of foreign exchange rate and the Australian stock market volatility.
2. Brooks *et al.* (1999)	• An ARIMA model.	Daily data of the AUD-USD exchange rate, the all ordinaries index, 90-day bank bills, 3-year bonds, 10-year bonds, share price index futures, 90-day bank bill futures, and 10-year bond futures from 3 January 1989 to 31 December 1993. Data for the 3-year bond futures from 15 May 1989 to 31 December 1993.	• The good and bad news of GDP and current account balance have no impact on Australian stock returns.
3. Kim and In (2002)	• Bivariate GJR–GARCH model.	Daily closing prices of Australian Stock Exchange's All Ordinaries Index and the Sydney Futures Exchange's Share Price Index with Nikkei 225 from Japan, FTSE 100 from the UK and S&P 500 from the US from 1 July 1991 to 18 December 2000. Consumer Price Index, GDP and employment scheduled announcements for Australian and the US were used as macroeconomic variables. There were 186 and 335 scheduled announcement during the sample period for Australia and the US respectively.	• The fluctuations of stock markets of Japan, the UK, and the US significantly influence the Australian futures and stock markets. • Some US and Australian macroeconomic news has a significant effect on the first and second moments of Australian financial markets • More specifically, the announcements of the US Consumer Price Index and the Australian GDP have a significant effect on the Australian futures market. • The negative shock of the futures market influences the stock market but not the other way around.

Table 2.3 Continued…

	Econometric Model	Data	Findings
4. Groenewold (2003)	• VAR / VECM models.	Quarterly Australian data of aggregate share prices, real output (GDP valued at 1999/2000 prices), the term spread (spread between the 10-year bond rate and the 3-month Treasury Note) and the default spread (spread between 5-year Commonwealth government bond and a 5-year NSW Treasury bond). The sample period was from the first quarter of 1978 to the second quarter of 2001. The break-date was the fourth quarter of 1983 for the deregulation of financial markets.	• After the Australian financial markets deregulation, the share market has influenced the real output but no evidence indicated that changes in output growth have impacted on share prices.
5. Kim (2003)	• Moving average EGARCH(1,1) model.	Daily index observations (open, high, low, and close) of the US and four advanced Asia-Pacific region (Australia, Japan, Hong Kong, and Singapore) as stock market data. Balance of payment, real GDP growth rate, retail sales growth rate, unemployment rate, producer price index inflation, and consumer price index inflation as the US scheduled announcements with trade balance, current account balance, unemployment rate, money supply growth rate, wholesale price index inflation, and consumer price index inflation as the Japanese scheduled announcements were used. Sample period was from 2 January 1991 to 31 May 1999.	• The scheduled macroeconomic announcement news from both the US and Japan significantly influenced the first and second moments of other stock markets but individual influences on different markets varied. • More specifically, the overall US news announcements had a positive effect on returns in all non-US markets, with only exception being for the balance of payment news in Hong Kong and Singapore. • Trade balance news from Japan significantly reduced the volatility in Australia, Hong Kong, and Singapore, while bad news had the opposite impact.

Table 2.3 Continued…

	Econometric Model	Data	Findings
6. Chaudhuri and Smiles (2004)	• Multivariate cointegration methodology	Quarterly data of Australian real stock price and measures of aggregate real activity (real GDP, real private consumption, real money, and the real price of oil in the Australian market) from the first quarter 1960 to the fourth quarter 1998. In addition, term spread (the difference between the long-term and short-term interest rates) was also included. Furthermore, Japanese, New Zealand, and the US stock return were included.	• A long-run relationship existed between real stock prices and real activity, measured by real price of oil, real GDP, real private consumption, and real money supply. • In contrast, the term spread, future GDP growth rates did not indicate a significant influence on stock return variations. • The US market indicated a dominant role in explaining the real stock return in Australia. • In addition, there were some influence from stock return of New Zealand towards Australian market but there was not any significant influence from the Japanese market

2.5. The Australian Stock Market and its Integration with other International Stock Markets

In addition to international macroeconomic influence, there has been a growing interest in evaluating different aspects of international stock markets interdependency in Australian context. One group of empirical studies on the Australian stock market and international stock market integration evaluates the correlation of stock market returns and volatility. For instance, McNelis (1993) found that the volatility of the UK, Singapore, and the US stock markets were highly positively correlated with the Australian stock market volatility of six countries.[12] However, Australian stock market volatility was found to have only a low correlation with the stock market volatilities of Japan and German.

Similarly, based on the rolling correlation coefficient of daily percentage changes in share prices, Kortian and O'Regan (1996) identified that the Australian stock market volatility was highly correlated with the US market over the period from 1978 to 1996. During this sample period, they also found that pairwise correlation coefficient between the Australian stock market volatility on one hand and Germany, Japan, and the UK stock market volatilities on the other hand was lower than the correlation coefficient between the Australian stock market volatility and the US market volatility. In addition, recently Valadkhani *et al.* (2008) identified that strong pair-wise correlation among the stock returns of Australia, Singapore, the UK and the US. Furthermore, they argued that these pair-wise correlation coefficients were higher among the stock markets in the same geographical region and/or at the similar stage of economic developments.

[12] For this study McNelis (1993) uses monthly data from January 1982 to March 1992 and six countries are Australia, Germany, Japan, Singapore, the UK, and the US.

The next group of studies focuses on the cointegration technique. In this regard, Drew and Chong (2002) noted long and short run linkages between the Australian stock returns and the US stock returns using the VAR and Johansen cointegration method.[13] Furthermore, they found that Granger-causality and common stochastic trends exist only between the US market and the Australian market. In contrast to the findings of Drew and Chong (2002), Narayan and Smyth (2004) and more recently Kazi (2008) argued that the Australian stock price was not cointegrated with stock price of the US and France.[14] Furthermore, Narayan and Smyth (2004), could not capture a pair-wise long-run relationship between the Australian and German stock markets while Kazi (2008) could not notice any relationship between the Australian and the Japanese stock markets. These variations of above findings could be due to methodological differences. For example, Kazi (2008) uses Johansen cointegration technique with VAR and VECM while Narayan and Smyth (2004) employed Johansen cointegration and Residual-based cointegration tests. Furthermore, these studies did not use the same data set for a unique sample period.

The last group of empirical studies investigates the volatility spillovers across international stock markets identifying the international influence towards the volatility of Australian stock market. Brailsford (1996), for example identified volatility spillovers from the New Zealand stock market to the Australian stock

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[13] Drew and Chong (2002) used weekly stock market data of Australia, France, Germany, Japan, the UK, and the US from the first week of January 1991 to the last week of June 2001.

[14] Kazi (2008) employed Johansen cointegration method for annual stock indices of Australia, Canada, France, Germany, the UK, and the US from 1945 to 2002 while Narayan and Smyth (2004) used monthly data of G7 countries. Their data period spanned from January 1960 to April 2003 for Australia–Canada, Australia–Japan, Australia– France, Australia–Germany and Australia–the UK, June 1964 to April 2003 for Australia–the US and January 1975 to April 2003 for Australia–Italy.

market and *vice versa* during the period from January 1974 to September 1991. Unlike Brailsford (1996), who used a univariate asymmetric GARCH approach, Brooks and Henry (2000) captured volatility spillovers across international stock markets using a MGARCH framework. More importantly, they argue that the Australian stock market would be more volatile when the US markets was trading downwards.[15] In the context of cross-market volatility spillovers, empirical evidence claims that the US market is the most influential market towards the volatility of the Australian market. In addition to the US stock market, the Australian stock market has highly integrated with some other markets such as Singapore, New Zealand, and the UK (for example see McNelis, 1993, Brailsford, 1996, Valadkhani *et al.*, 2008). However, no study so far focuses on these countries in multivariate context capturing any possible volatility spillovers between the Australian stock market and international stock markets.

The empirical studies discussed in this section evaluating the linkages between the Australian stock market and international stock markets are summarised in Table 2.4.

[15] For this study, Brooks and Henry (2000) used the parametric and non-parametric technique for the weekly data of the US, Japan and Australian stock markets from January 1980 to June 1998 and multivariate BEKK model to identify the existence of linear and non-linear transmission of return and volatility across these markets.

Table 2.4 Interaction Between the Australian Stock Market and International Stock Markets

	Econometric Model	Data	Findings
1. McNelis (1993)	• Schwert measures of volatility, VAR estimation, Granger causality, impulse response functions, variance-decomposition analysis, and Kalman filtering.	End-of-month stock price indexes, exchange rates, and bond yields of Australia, Germany, Japan, Singapore, UK, and the US from the beginning of 1982 to March 1992.	• In general, the Australia stock, foreign exchange, and bond markets indicated different relationship patterns with international stock, foreign exchange and bond markets. • In the context of stock market, the Australian stock market price volatility was highly correlated with the stock market price volatilities of UK, Singapore, and the US. • The lowest correlation was between the Australian stock price volatility and the volatility of Japanese stock price. • Furthermore, the volatility of the Australian stock index did not indicate significant predictive power for explaining the volatility of other five stock price indexes but the Australian stock index volatility predicted the Australian stock index itself. • In contrast, the UK, Japan, and the US were the three most significant stock markets that explained the Australian stock price volatility during the sample period.
2. Brailsford (1996)	• Asymmetric GARCH models.	Daily data of Australian, New Zealand, and the US stock markets from January 1974 to September 1991.	• The conditional volatility of the New Zealand market influences the conditional volatility of the Australian market and *vice versa*. • The overnight international news from the US stock market influenced the return and volatility of the Australian stock market.
3. Kortian and O'Regan (1996)	• Rolling correlations and rolling regressions.	Daily data of bond, share and foreign exchange markets in Australia, Germany, Japan, the UK, and the US from May 1987 to February 1996.	In the context of share market; • The Australian and the US market volatility was much stronger than in other markets following the October-1987 stock-market crash. • Over the sample period, falling correlation results indicated that the Australian share market was less sensitive to other markets' volatility. • Turning to international stock market influence towards the Australian stock market, during whole sample period, the US stock market showed a significant impact on the Australian stock market in determining the size and direction of daily changes. • In addition, the period from mid 1990 to end 1992, the Australian stock prices were mainly influenced from the Japanese stock prices while the period from late 1992 to end 1994 the changes in the UK stock prices influenced the Australian stock prices.

Table 2.4 Continued...

	Econometric Model	Data	Findings
4. Brooks and Henry (2000)	• Asymmetric BEKK model with VAR(1) structure (i.e. current period returns are based on one lag returns of each market). In addition, a dummy variable is incorporated for 1987 crash.	Weekly stock returns from Australia, the US, and Japan from 1 January 1980 to 22 June 1998.	• The Australian stock market becomes more volatile when the US markets are trending downwards. • Asymmetric BEKK model provides evidence that the estimated variance and covariance matrix is time varying and asymmetric.
5. Drew and Chong (2002)	• VAR framework using the Johansen co-integration method	Weekly real stock returns of France, Germany, Japan, the UK and the US from 4 January 1991 through 29 June 2001.	• The results from bivariate cointegration analysis evidenced that a significant long-run price linkage exist between the Australian and the US stock markets. • The results from multivariate cointegration analysis indicated that no cointegrating relationships in the system of 6 markets over the sample period. • The US market was the only market, which was found to Granger-cause the Australian market.
6. Narayan and Smyth (2004)	• Cointegration techniques (Johansen test and Gregory and Hansen test)	Monthly stock market data of Australia and the G7 countries (Canada, France, Germany, Italy, Japan, the US and the UK). Sample period was: For Australia–Canada, Australia–Japan, Australia– France, Australia–Germany and Australia–UK from January 1960 to April 2003: For Australia–US, from June 1964 to April 2003: and For Australia–Italy from January 1975 to April 2003	• Results showed that cointegration between Australia and the UK at all lags and Australia is not cointegrated with France, Germany, Italy, Japan, or the US at any lag length.

Table 2.4 Continued...

	Econometric Model	Data	Findings
7. Kazi (2008)	• Johansen cointegration technique.	Annual stock market data of Australia, Canada, French, Germany, Japan, the UK, and the US from 1945 to 2002.	• The results indicated a significant long-run relationship between the Australia stock market on one hand and the UK, Canadian and German stock markets on the other hand. • In addition, the UK market was the most significant market for Australia. • Contrast to these findings, the US, French and Japanese stock markets were not found to be significant for Australia.
8. Valadkhani *et al*. (2008)	• The principal component and maximum likelihood methods.	Monthly data of 13 countries (Australia, Germany, Hong Kong, Indonesia, Japan, Korea, Malaysia, the Philippines, Singapore, Taiwan, Thailand, the UK, and the US) from December 1987 to April 2007.	• In Australian context, results indicated that the Australian stock returns were highly correlated with the stock market returns of Singapore, the UK and the US.

2.6. Summary and Conclusion

This chapter has examined previous empirical works on the Australian stock market returns and its volatility. A review of those empirical studies reveals that not only domestic factors but also international influences are important for explaining the dynamics of Australian stock market volatility. Furthermore, there are several important implications arising in explaining the dynamics of international stock market volatility transmission towards the Australian stock market.

First, a number of studies have evaluated the asymmetric impact of stock returns in Australian context. The majority of those studies argue that there is no asymmetric effect in the Australian data. On the other hand, empirical studies on the asymmetric impact in international context has identified that negative shocks of international stock market returns could influences the Australian stock market volatility. However, those studies did not explain the negative shocks arising from which international market influence the Australian stock market volatility the most and the least. An exploration of such impact distinguishing the relative importance of positive and negative shocks from regional verses world stock markets enables us to identify how the Australian stock market movements with global stock markets. As noted earlier in this chapter, the existing literature is lacking with regard to the asymmetric impact arising from international stock markets towards the Australian stock market. Therefore, the current thesis is aimed to provide an insight into the asymmetric volatility effect to fill this gap in the literature.

The second issue is how regional and global financial crises influence the cross-market volatility spillovers across the Australian stock market and other international stock markets. In this regard, the existing literature shows that no study has compared and contrasted the varying volatility dynamics between the Australian stock market and the international stock markets by distinguishing the nature of different financial crises in terms of origins, the geographical location where it initiates and how rapidly it spreads to other countries. Thus, the current study contributes to the literature providing a comprehensive evaluation of how volatility transmission varies between the Australian stock market and the international stock markets during different financial crises periods. The final issue is how fluctuation of domestic and international GDP growth rate, influences the stock market volatility transmission. This thesis becomes the first study to contribute to the literature by examining the volatility transmission dynamics across stock markets and GDP growth rates in a multi-country context.

In order to examine the volatility spillovers across Australian stock market and international stock markets, the current thesis intends to focus on recent econometric techniques to capture: (1) the asymmetric volatility effect of one stock market towards the volatility of other stock markets and *vice versa;* (2) the fundamental differences between financial crises providing some light as how and where they originated explaining whether cross-country spillovers in volatility were similar for the different financial crises; and (3) the role of GDP growth volatility of one country on the stock market volatility of other countries. Hence, the next chapter aims to examine the literature on financial data analysis methods to identify the most appropriate econometric techniques to address the above issues.

CHAPTER THREE

REVIEWS OF MULTIVARIATE GRNERALISED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTIC MODELS

3.1. Introduction

The main purpose of this chapter is to review the econometric techniques that have been applied in studying the dynamics of volatility transmission across different international stock markets. Analysing stock market volatility is particularly demanding because of the characteristic of the data. Commonly accepted features in financial data are non-linearity and time-varying variance and covariance. Furthermore, the most common stylised statistical facts of financial data discussed in the literature are the presence of autocorrelations, the non-normal distribution of data, volatility clustering, mean revision in volatility, volatility correlation, and persistence (see for example: Bollerslev *et al.*, 1992, Bollerslev *et al.*, 1994, Patterson, 2000, Cont, 2001, Engle and Patton, 2001, Brooks, 2008).

Due to the difficulty of identifying unobservable second and higher order moments in financial data, Engle (1982) introduced a functional form to model these moments simultaneously. With the introduction of the Autoregressive Conditional Heteroskedastic (ARCH) process (Engle, 1982), and its generalization, GARCH (Bollerslev, 1986), gives a new direction for development of econometric models. As stated by Engle (1982), ARCH regression models have been used in empirical studies because: (1) it is useful for forecasting variance, which may change over time and predicted by past forecast errors; (2) it holds as a function of the expected means and variance of the rates of return; (3) it can be used as an approximation of ARCH models to more complex models with non-ARCH disturbances. Thus, these univariate ARCH and GARCH models are capable of analysing most of the non-linearity in the volatility of financial data.

In recent years, these models have been developed theoretically and used empirically in the area of financial econometrics. However, the applications of these univariate models focus on analysing the volatility of a single time series at a time. However, an important aspect of financial time series is the nature of covariance structure between different series. As suggested by Bauwens *et al*. (2003, 2006), Brooks (2008) and Silvennoinen and Teräsvirta (2008) the covariances are important for computation of hedge ratios, value at risk estimates and many other areas in financial econometrics. Furthermore, the multivariate versions of these univariate ARCH/GARCH models are capable of analysing both variances and covariances (also known as volatility and covolatility) among the multiple financial time series. According to Caporin and McAleer (2009), the univariate ARCH/GARCH models are appropriate for studying single events or multiple events where they can be aggregated into a single event. On the other hand, the multivariate framework of these models is applicable for analysing the interaction effects of volatility and covolatility among the multiple series or events.

It is therefore, important to identify the recent developments of MGARCH models. This chapter evaluates the theoretical framework of MGARCH models and their applications on volatility transmission across different financial markets.

The remaining sections of this chapter are thus, organised as follows. The Section 3.2 presents the theoretical framework of MGARCH models while Section 3.3 discusses parameter estimation, followed by diagnostic testing methods in Section 3.4. Empirical implementations of these MGARCH models for analysing the dynamics of stock market volatility transmission across international stock markets are presented in Section 3.5 and Section 3.6 presents some concluding remarks.

3.2. Theoretical Framework of MGARCH Models

The multivariate models for *N* numbers of series contain the conditional variance and covariance matrix (H_t) of dimension $N \times N$ and a vector stochastic process (y_t) of dimension $N \times 1$. Then y_t can be specified as follows:

$$y_t = \mu_t(\theta) + \varepsilon_t \tag{3.1}$$

where μ_t is the conditional mean vector; θ is the finite vector of parameters; and ε_t is the vector of innovations associated with y_t and ε_t can be written as:

$$\varepsilon_t = H_t^{1/2} z_t \tag{3.2}$$

where z_t is a $N \times 1$ random vector with the properties of $E(z_t) = 0$, $Var(z_t) = I_N$
.

I_N is the identity matrix of order *N*; and $H_t^{1/2}$ is a $N \times N$ positive definite matrix such that H_t is the conditional variance and covariance matrix of y_t. Furthermore, $N \times N$ positive definite conditional variance and covariance matrix H_t can be written as follows:

$$H_t = \begin{pmatrix} h_{11t} & \cdots & h_{1Nt} \\ \vdots & \ddots & \vdots \\ h_{N1t} & \cdots & h_{NNt} \end{pmatrix} \tag{3.3}$$

The diagonal element of this matrix (i.e. h_{iit}) is the conditional variance at time t of the assets return while the off-diagonal elements (i.e. h_{ijt}) represent the conditional covariance at time t between the asset returns of i and j where $i \neq j$. There are two main parametric formulations of H_t that have been used in the literature. The first formulation is modelling variance and covariance matrix and the two main specifications of this class of formulation includes the VECH model and the BEKK model. The second category is the formulation of correlation structure. The main specification of this group of formulation includes the CCC model of Bollerslev (1990). In addition to these formulations, there are several other extensions of VECH, BEKK and CCC that have been used in the empirical studies in financial econometric analysis. Those extensions and their applications are discussed later in this chapter.

3.2.1. VECH Specification

The model specification of VECH(*p*,*q*) is assumed to take the following form:

$$vech\left(H_t\right) = C + \sum_{i=1}^{q} A_i \; vech\left(\varepsilon_{t-i}\varepsilon'_{t-i}\right) + \sum_{j=1}^{p} B_j \; vech\left(H_{t-j}\right) \tag{3.4}$$

where $\varepsilon_t \sim N(0, H_t)$; A and B are squared parameter matrices of order $N\left(N+1\right)/2$; C is a $N\left(N+1\right)/2\times 1$ parameter vector; N is the number of series considered in the model; p and q indicate the number of GARCH and ARCH lags respectively; and *vech(·)* is the operator that stacks the lower triangle of a $N \times N$ matrix as a $N\left(N+1\right)/2 \times 1$ vector.

As indicated by Bollerslev *et al.* (1988), Engle and Kroner (1993, 1995), Campbell *et al.* (1997), de Goeij and Marquering (2004), Bauwens *et al.* (2003, 2006) there are two major issues related to the empirical implementation of the VECH model. One major issue is that the number of parameters to be estimated increase with the number of data series in the sample. The second important issue is to maintain the positive definite of H_t. Thus for empirical implementation of the VECH model, several restrictions have discussed in the literature. For example, to reduce the number of parameters the DVECH model, which is initially introduced by Bollerslev *et al.* (1988) can be used. To guarantee positive definite of H_t, restrictions can be imposed on the initial values of H_t in the estimation process. As an example, one such condition suggested by Bollerslev *et al.* (1988) is to employ the maximum likelihood function to generate the parameter estimates and use the unconditional residual variance as the pre-sample conditional variance.

3.2.2. *BEKK Specification*

As an alternative to high parameterization and to ensure positive definite of H_t in the VECH model, Engle and Kroner (1993, 1995) proposed BEKK(*p*,*q*) model, which can be written as follows:

$$H_t = C'C + \sum_{i=1}^{q} A_i'\varepsilon_{t-i}\varepsilon_{t-i}'A_i + \sum_{j=1}^{p} B_j'H_{t-j}B_j \qquad (3.5)$$

where A and B are $N \times N$ matrices; C is $N \times N$ upper triangular matrix of parameters; N is the number of series considered in the model; p and q indicate the number of GARCH and ARCH lags respectively.

In order to make the estimation process relatively simple, further restrictions on the A and B matrices are considered to obtain the DBEKK, which contains less parameters and guarantees a positive definite of H_t. Engle and Kroner (1993, 1995) find that the DBEKK model can be formulated from the BEKK parameterization if and only if each of the A and B matrices in equation (3.5) are diagonal. Thus, the volatility and covolatility equations for the DBEKK(1,1) (equations 3.6 and 3.7) can be written as:

$$h_{iit} = c_{ii} + a_{ii}^2 \varepsilon_{it-1}^2 + b_{ii}^2 h_{iit-1} \tag{3.6}$$

$$h_{ijt} = c_{ij} + a_{ii} a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ii} b_{jj} h_{ijt-1} \tag{3.7}$$

where, h_{iit} is the own-volatility of series i; h_{ijt} is the covolatility between series i and series j;

$a_{ii} \times a_{ii}$ is the coefficient of lagged squared own-volatility shocks of series i;

$b_{ii} \times b_{ii}$ is the coefficient of lagged own volatility of series i;

$a_{ii} \times a_{jj}$ is the coefficient of cross-products of lagged volatility shocks between series i and series j;

$b_{ii} \times b_{jj}$ is the coefficient of lagged covolatility between series i and series j.

This implies that the volatility spillovers within one data series can be determined by the sum of squares of the diagonal elements of matrix A and square of the diagonal elements of matrix B. In other words, volatility spillovers depend on the squared sum of own-volatility shocks representing the impacts arising from past squared innovations and own-volatility spillovers representing the impact arising from past volatility. The covolatility spillovers between two data series can be estimated by the sum of cross products of diagonal elements of *A* and cross products of diagonal elements of *B*. That is the sum of cross products of past innovations and past covolatility between these two series.

3.2.3. CCC Specification

The CCC model proposed by Bollerslev (1990) formulates the correlation structure of the variance and covariance matrix. This model contains time varying conditional variance and covariance with constant conditional correlations. It also allows univariate analyses for each of the assets returns assuming the GARCH(1,1) structure for conditional variances and non-zero constant conditional correlations across series. Suppose y_{it} and ε_{it} are i^{th} elements in the vector of asset returns (y_t) and the vector of innovations (ε_t) respectively, the CCC model can be written as follows:

$$\begin{aligned} h_{iit} &= \alpha_i + \beta_{i1}\varepsilon_{it-1}^2 + \gamma_{i1}h_{iit-1} \\ \rho_{ij} &= h_{ijt} \big/ \left(h_{iit}h_{jjt}\right)^{1/2} \end{aligned} \qquad (3.8)$$

h_{ijt} is the ij^{th} element in H_t and ρ_{ij} is conditional correlation between assets return *i* and *j*, where $-1 < \rho_{ij} < 1$ and $i \neq j$.

According to survey on MGARCH models of Bauwens *et al*. (2003, 2006), the conditional correlations of CCC model are constant. Therefore, the conditional covariances are proportional to the product of the corresponding conditional standard deviations, which make estimation simple and reduce the number of unknown parameters. Furthermore, they argued that H_t is positive definite if and only if all the conditional variances and constant conditional correlations are positive. Although the unconditional variances are easily obtained, the unconditional covariances are difficult to calculate because of the nonlinearity in $\rho_{ij} = h_{ijt} / \left(h_{iit} h_{jjt}\right)^{1/2}$.

In addition to these three main MGARCH models (VECH, BEKK, and CCC) Factor GARCH (FGARCH) model, Orthogonal GARCH (OGARCH) model, Dynamic Conditional Correlation (DCC) model, and Copula-MGARCH model are a few other MGARCH models discussed in the literature. According to Kroner and Ng (1998) and Bauwens *et al.* (2003, 2006), the FGARCH model is considered as a special case of BEKK model. Furthermore, the FGARCH model is capable of applying for a large number of series while maintaining positive definite of H_t (Lin, 1992, Kroner and Ng, 1998). Moreover, Lin (1992) argued that time-varying covariance matrix of FGARCH model is a function of linear combination of random variables. While introducing few alternative estimators for the FGARCH models, Lin (1992) explained that the number of factors in the FGARCH model should not be greater than the number of variables.

The OGARCH model is based on a linear combination of univariate GARCH models (Laurent *et al.*, 2010) whereas the DCC model is a nonlinear combination of univariate model (Bauwens *et al.*, 2003, 2006). According to Bauwens *et al.* (2003, 2006) and Lanne and Saikkonen (2005), the OGARCH model is a particular type of the FGARCH mode. In this regard, the OGARCH model is also considered as a special case of the BEKK model. In addition, Lanne and Saikkonen (2005) introduced a generalised version of OGARCH model, which allows for a reduced number of conditionally heteroskedastic factors and idiosyncratic shocks. On the other hand, Christodoulakis and Satchell (2002), Engle (2002) and Tse and Tsui (2002) proposed three different DCC models, which were the generalized versions of CCC model. Christodoulakis and Satchell's (2002) DCC model was a bivariate version and used Fisher transformation to guarantee the conditional correlation matrix. Conversely, the DCC models proposed by Engle (2002) and Tse and Tsui (2002) were multivariate models and capable of modelling high dimensional data set. Turning to conditional dependency, Jondeau and Rockinger (2002) introduced another MGARCH model based on the copula function allowing marginal distributions to be conditionally dependent. Therefore, this model is known as Copula-GARCH model and it can be used to analyse conditional dependencies between time series, value at risk and portfolio allocations in non-Gaussian environment.

Even though, MGARCH models are useful for analysing different aspects of financial time series, there are some difficulties in estimation due to high parameterization. As pointed out by Bauwens *et al.* (2003, 2006) and Brooks *et al.* (2003) availability of software packages are relatively limited thus, for estimating most of these MGARCH models is one major problem in empirical application of these models.

3.3. Parameter Estimation for MGARCH models

Despite the different MGARCH specifications, parameter estimation methods are also established for these MGARCH specifications. The most common parameter estimation method is maximum likelihood method. When estimating MGARCH models maximizing the log likelihood function can be used under the assumption of conditional normality (Brooks, 2008). Let θ as a parameter matrix and for a sample of T observations, the log likelihood function discussed by Engle and Kroner (1993) then can be written as:

$$L_T(\theta) = \sum_{t=1}^{T} l_t(\theta) \tag{3.9}$$

where $l_t(\theta) = \frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t$

Although error vectors (ε_t) are assumed to be normally distributed, the noticeable characteristic of financial time series are kurtosis and skewness. According to, Engle and Kroner (1993, 1995), Harris and Sollis (2003), and Bauwens *et al.* (2003, 2006) maximum likelihood function can therefore, be used for MGARCH models with student *t*-distribution. Furthermore, to obtain optimal parameter values the most common numerical procedure is the Berndt *et al.*'s (BHHH, 1974) algorithm, which is an iterative method. With reference to Engle and Kroner (1993, 1995) and Chou *et al*. (1999) the optimal parameters using the BHHH algorithm could be obtained from the following equation.

$$\theta^{(i+1)} = \theta^{(i)} + \lambda_i \left(\left(\frac{\partial l_t}{\partial \theta} \right)' \frac{\partial l_t}{\partial \theta} \right)^{-1} \left(\frac{\partial l_t}{\partial \theta} \right)' \tag{3.10}$$

where $\theta^{(i)}$ denote the parameter estimate after i^{th} iteration; $\frac{\partial l_t}{\partial \theta}$ is evaluated at $\theta^{(i)}$; and λ is a variable step length that is chosen to maximise the likelihood function in the given direction, which is easily calculated from a least squares regression of a $T \times 1$ vector of ones on $\frac{\partial l_t}{\partial \theta}$.

In addition to maximum likelihood method, a two-step estimation method is also used in the empirical studies (Chou *et al.*, 1999, Engle, 2002). According to Engle (2002) and Bauwens *et al*. (2003, 2006), some useful features of the DCC models can be estimated using a two-step estimation. Furthermore, the log likelihood can be expressed as the sum of a mean, volatility, and correlations. Let θ is unknown parameter of $diag\left\{\sqrt{h_{it}}\right\}$ and ϕ is additional parameters of correlation matrix containing conditional correlations.[16] Then, the log likelihood function can be written as:

$$L(\theta,\phi) = L_V(\theta) + L_C(\theta,\phi) \tag{3.11}$$

where L_V is the mean and volatility component and L_C is the correlation component. Then two-step approach can be used to maximize the likelihood is to find L_V and L_C.

The first stage is:

$$\hat{\theta} = argmax\left\{L_V(\theta)\right\} \tag{3.12}$$

Then $\hat{\theta}$ in equation (3.12) can be used for the second stage.

$$\max_{\phi}\left\{L_C\left(\hat{\theta},\phi\right)\right\} \tag{3.13}$$

3.4. Diagnostic Testing for MGARCH models

Both univariate and multivariate ARCH and GARCH models are based on the assumption of autoregressive conditionally heteroskedasticity. Therefore, it is essentially to test whether the data present the evidence of ARCH effects. However, compared to univariate diagnostic testing method, there are few tests available for the multivariate case (Bauwens *et al.*, 2003, 2006).

[16] $diag\left\{\sqrt{h_{it}}\right\}$ denotes the *N x N* stochastic diagonal matrix with squared volatility elements.

Ding and Engle (2001) show that the standardized residuals, which are given by $z_t = H_t^{-1/2}\varepsilon_t$ of the correctly specified models should fulfil the following three conditions.

i. $E(z_t z_t') = I_N$, where I_N is identity matrix of order N

This condition is satisfied if the conditional mean equation is correctly specified but it has no power for detecting some important misspecifications of the conditional covariance equation.

ii. $\operatorname{cov}\left(z_{it}^2, z_{jt}^2\right) = 0$ for all $i \neq j$

This condition is able to test non-normality in conditional distribution.

iii. $\operatorname{cov}\left(z_{it}^2, z_{jt-k}^2\right) = 0$ for all $k > 0$

The purpose of this test is to detect the adequacy of the dynamic structure of H_t.

In addition, conditions ii and iii observe cross-section and time series independence of the normalized residuals.

The most common application to detect the ARCH effect is the Ljung-Box Portmanteau test statistic (Hosking, 1980). The Ljung-Box test statistic for a multivariate process of order (p, q) and stationary m-variates time series $\{y_t : t = 1, 2, ..., T\}$ is given in the following equation:

$$Q = T^2 \sum_{j=1}^{s} \left(T - j\right)^{-1} tj\left\{C_{Y_t}^{-1}\left(0\right) C_{Y_t}\left(j\right) C_{Y_t}^{-1}\left(0\right) C_{Y_t}'\left(j\right)\right\} \tag{3.14}$$

where $Y_t = vech\left(y_t y_t'\right)$; $C_{Y_t}\left(j\right)$ is the sample autocovariance matrix of order *j*; *s* is the number of lags being tested and *T* is the number of observations. The Ljung-Box test statistic, *Q* is distributed asymptotically as a Chi-squared distribution for large samples under the null hypothesis of no ARCH effect. Replacing y_t by standardized residuals can be used to detect misspecification in the conditional variance matrix (Bauwens *et al.*, 2003, 2006).

Another commonly used method is the Lagrange Multiplier test. Engle and Kroner (1993) calculated the Lagrange Multiplier test statistic for the BEKK model using the first iteration of the BHHH algorithm. In addition, Busch (2005), proposed a robust likelihood ratio statistic to test conditional variance misspecification under the assumption of symmetric disturbances. Besides, the Portmanteau test and the Lagrange Multiplier test, Tse (2002) discussed residual-based diagnostic tests for conditional heteroskedasticity models. Furthermore, this residual-based diagnostic test for MGARCH models is based on the regression between the estimated squared standardized residuals ($\hat{z}_t = \hat{h}_{iit}^{-1/2}\hat{\varepsilon}_t$) and the cross-products of the estimated standardized residuals as follows:

$$\hat{z}_{it}^2 - 1 = \hat{d}_{it}'\delta_i + \zeta_{it} \qquad \text{for } i = 1, \ldots N \tag{3.15}$$

$$\hat{z}_{it}\hat{z}_{jt} - \hat{\rho}_{ijt} = \hat{d}_{ijt}'\delta_{ij} + \zeta_{ijt} \qquad 1 \le i < j \le N \tag{3.16}$$

where $\hat{d}_{it} = \left(\hat{z}_{it-1}^2, \ldots, \hat{z}_{it-M}^2\right)'$, $\hat{d}_{ijt} = \left(\hat{z}_{it-1}\hat{z}_{jt-1}, \ldots, \hat{z}_{it-M}\hat{z}_{jt-M}\right)'$, δ_i and δ_{ij} are *m*-vector of regression parameters, and $\hat{\rho}_{ijt} = \hat{h}_{ijt} \Big/ \sqrt{\hat{h}_{iit}\hat{h}_{jjt}}$.

The test statistic for the estimated values of δ_i and δ_{ij} are $T\hat{\delta}_i\hat{L}_i\hat{\Omega}_i^{-1}\hat{L}_i\hat{\delta}_i$ and $T\hat{\delta}_{ij}\hat{L}_{ij}\hat{\Omega}_{ij}^{-1}\hat{L}_{ij}\hat{\delta}_{ij}$ respectively. [17] These test statistics are asymptotically distributed as Chi-squared distribution under the null-hypothesis of correct specification of multivariate time series where:

$$\begin{aligned} L_i &= p\lim\left(\frac{1}{T}\sum d_{it}d_{it}'\right) \\ \Omega_i &= E\left\{\left(z_{it}^2-1\right)^2\right\}L_i - Q_iGQ_i' \end{aligned} \tag{3.17}$$

where $Q_i = p\lim\left(\frac{1}{T}\sum d_{it}\frac{\partial z_{it}^2}{\partial\theta'}\right)$

However, in empirical application, one has to replace c_i, L_i and Q_i values by their counterpart estimators.

3.5. Empirical Application of MGARCH Models for Stock Markets Volatility Transmission

The above sections provided the theoretical background of three main MGARCH models viz. VECH, BEKK, and CCC models with some parameter estimations methods and diagnostic tests. These models have been applied not only stock market data but also other financial data such as exchange rates, bond market data, and inflation rates. For example, Bollerslev *et al.* (1988) and de Goeij and Marquering (2004) used the VECH model for studying the conditional covariance structure between stock and bond returns; Wang and Wang (1999) analysed foreign exchange market volatility across South East Asian countries using the

[17] Estimators are denoted by ^ symbol.

BEKK model; and Wei (2008) employed the CCC and the DCC models for analysing exchange rate volatility spillovers to the stock market.

However, the purpose of this section is to evaluate the empirical implementation of those models and their extensions for studying volatility transmission across different international stock markets. To make this section clearer and more precise, empirical implementation of these models and their extensions is divided into three sub-sections as follows: Section 3.5.1 presents empirical implementations of MGARCH models to capture the asymmetric volatility effect in stock markets. Section 3.5.2 provides evidence on the applicability of these models for capturing varying volatility influence across different international stock markets during financial and non-financial crises periods. Finally, Section 3.5.3 discusses the employability of these MGARCH models and their extensions to detect any possible influence from macroeconomic (especially GDP growth rates) variables towards stock market volatility.

3.5.1. Asymmetry Dynamics in Stock Market Volatility Transmission

In the context of volatility transmission across different international stock markets, Koutmos and Booth (1995), Brooks and Henry (2000), and others find that bad news (or negative shocks) in one stock market increase the volatility of that market itself as well as other international markets more than good news (or positive shocks) do. However, there are limited recent empirical studies capturing such potential asymmetries in a multi-country setting. At an empirical level, Koutmos and Booth (1995) extended Nelson’s (1991) univariate EGARCH model to the multivariate context. For the conditional variance process they used the exponential function allowing standardized innovations of own lags and cross-market lags to capture the asymmetry impact. Their methodology is important as it allows one to evaluate how varying volatility influence due to negative and positive innovations of different international stock markets impact on the volatility of other stock markets. However, this methodology does not take in to account how asymmetry of volatility effect across different stock markets impacts on the covolatility between two stock markets. This is particularly import as illustrated by Kroner and Ng (1998) the optimal portfolio will depend on the selection of the covariance model.

Few other studies have attempted to capture the asymmetric impact in both variance and covariances using the other MGARCH models. For example, Brooks and Henry (2000) and Li (2007) used the asymmetric version of the BEKK model while Kroner and Ng (1998) introduced the ADC model to capture asymmetry dynamics in variance and covariances of stock market data. In addition to the ADC model, Kroner and Ng (1998) used asymmetric versions of VECH, BEKK and CCC models for weekly returns from a large and small firm portfolios. Brooks and Henry (2000) included stock market data of Australia, Japan, and the US in their asymmetric BEKK model. However, they did not explain how asymmetric spillovers of stock returns vary across these stock markets indicating negative shocks from which stock market could have the greater impact on future volatility of other markets.

The asymmetric extensions of VECH and BEKK models use a similar dummy structure as that introduced by Glosten *et al*. (1993) for univariate ARCH/GARCH models. For example, as explained by Kroner and Ng's (1998), variance function in the Asymmetric DVECH (ADVECH) models uses squared of negative shocks of a stock market while covariance function in a the symmetric DVECH model uses cross-product of negative shocks between two stock markets. Although this method is easy to implement and estimate, a drawback related to this method is that the covariance will be higher when there are two negative shocks from two markets. Another issue is that it does not account for negative shocks from one market and positive shocks from the other market as the aggregate effect on covariance becomes zero. The asymmetric BEKK model on the other hand, uses a quadratic form of dummy variables to capture the varying volatility influences from negative shocks.

The empirical studies discusses in this section regarding the use of MGARCH models for capturing asymmetry dynamics in stock market volatility are summarised in Table 3.1.

Table 3.1 Empirical Implementations of MGARCH Models on the Asymmetry Dynamics in Stock Market Volatility Transmission

	Econometric Model	Data	Findings
1. Koutmos and Booth (1995)	• Variance and Covariance Structure: Multivariate EGARCH model • Mean Equation: Vector Moving Average (i.e. current period returns are based on own past innovations and past innovations of other markets up to one lag).	Daily data from opening and closing stock prices indexes of Japan, the UK, and the US stock market Sample period: 3 September 1986 to 1 December 1993	• According to the analysis using full sample data, volatility spillovers exist: (i) from New York and London to Tokyo; (ii) from Tokyo and New York to London; (iii) from London and Tokyo to New York. • This volatility transmission mechanism is asymmetric. • Based on the analysis using the sample data before the stock market crash in October 1987, volatility spillovers do not significant between New York and Tokyo in any direction. • According to results using the sample data after the stock market crash in October 1987, volatility spillovers exist across all three markets
2. Kroner and Ng (1998)	• Variance and Covariance Structure: VECH, BEKK, FARCH, CCC, GDC, and Asymmetric Dynamic Correlation models (ADC). In addition, they compare asymmetric versions of VECH, BEKK, FGARCH, and CCC models theoretically. • Mean Equation: VAR(10) structure (i.e. current period returns are based on lag returns of both small and large firms up to 10 lags). Threshold terms up to 10 lags are also included to avoid misspecification in the mean.	Weekly data from large-firm and small-firm portfolio returns using stock returns of American and New York stock exchanges (for more information about how to calculated large-firm and small-firm portfolio returns refer Conrad, Gultekin and Kaul, 1991) Sample period: July 1962 to December 1988.	• Different MGARCH models give different results. For example, estimated covariances from the BEKK and FGARCH models tend to be higher and more volatile than the covariances obtained from VECH and CCC models. • According to the results from ADC model, the covariance between large-firm returns and small-firm returns is higher due to negative shocks to the large-firm portfolio. However, the negative shocks to the small-firm portfolio do not increase the covariance between large-firm returns and small-firm returns.
3. Brooks and Henry (2000)	• Variance and Covariance Structure: Asymmetric BEKK model • Mean Equation: VAR(1) structure (i.e. current period returns are based on one lag returns of each market). In addition, a dummy variable is incorporated for 1987 crash.	Weekly stock returns from Australia, the US, and Japan Sample period: 1 January 1980 to 22 June 1998.	• The Australian stock market becomes more volatile when the US markets are trending downwards. • Asymmetric BEKK model provides evidence that the estimated variance-covariance matrix is time varying and asymmetric.

Table 3.1 Continued …….

	Econometric Model	Data	Findings
4. Li (2007)	• Variance and Covariance Structure: Asymmetric BEKK model • Mean Equation: Current period return is based on own market returns and returns of other markets up to one lag.	Daily stock returns from Shanghai, Shenzhen (these two indexes to represent Chinese stock exchange), Hong Kong and the US Sample period: 4 January 2000 to 17 August 2005.	• There are unidirectional return and volatility spillovers from Hong Kong market to Shanghai and Shenzhen. • Regional influence (influence from Hong Kong market) on Shanghai and Shenzhen markets is higher than the international influence (influence from the US). • The asymmetric response to negative shocks (bad news) of own market for all four share price indices affects the conditional variance of each index. • The cross-market asymmetric response is evident between the Shenzhen component index and the Shanghai composite index.

3.5.2. Stock Market Volatility Transmission During Financial Crises

For investigating the impacts of financial crises, empirical studies have used MGARCH models mainly in two different ways. One group of studies divided their sample period into sub-samples based on the financial crises impact time-line and applied MGARCH model to each sub-samples. For instance, Polasek and Ren (2001) analysed volatility transmission during the 1997 Asian crisis using daily data of Germany, Japan, and the US stock markets for a period of two years (June 1996 to June 1998) using the multivariate VAR GARCH in Mean model. They identified that different volatility transmission patterns occurred among the stock markets of the US, Germany and Japan before and after the Asian crisis. For comparing volatility transmission Polasek and Ren (2001) divided their sample period into two sup-samples taking 23 October 1997 as the breaking point. Similarly, Caporale *et al.* (2006) applied the BEKK model to analyse volatility transmission across the US, Japan, European, and South East Asian stock markets during the 1997 Asian financial crisis. For this study they used daily data of from January 1986 to October 2000 and divided into two sub-samples taking 01 July 1997 as a breaking point. Furthermore, Caporale *et al.* (2006) identified that unidirectional causality links from the markets in turmoil to the other markets following the commencement of crisis 1997-98 Asian financial crisis.

The other group of studies used dummy variables to capture the effects from financial crisis and non-financial crises periods. For example, Theodossiou *et al.* (1997) extended the CCC model by incorporating structural dummies for the 1987 financial crisis using weekly stock market returns of the US, the UK, and Japan for the period starting from May 1984 to October 1994. They found that the

US market had less volatility during the post-October 1987 crisis. However, the volatilities in the UK and Japan stock markets were the same during both pre and post-October 1987 periods.

According to the literature, MGARCH models have used to capture any possible influence from financial crises towards the stock market volatility transmission. As mentioned, one group of studies have used the original models for sub-samples separately during financial crisis and non-financial periods. The major difficulty of using these models for sub-samples is the number of observations becomes small that makes insufficient number of observations for estimation. For example, Caporale *et al.* (2006) used a total of 3855 observations from January 1986 to October 2000 and pre-crisis sample includes 3000 observations while post-crisis sample only includes remaining 855 observations. On the other hand, another group of studies used structural dummies which allow using the full sample for the analysis. As stated by Lamoureux and Lastrapes (1990), unlike smaller samples, the longer sample period increases the probability of the presence of structural shifts. Thus, the use of dummy variables to account for structural changes reduces the persistence of ARCH effect in the data series.

The empirical studies reviewed in this section, which applied MGARCH models to analyse stock market volatility transmission during financial crises are summarised in Table 3.2.

Table 3.2 Empirical Implementations of MGARCH Models for Stock Market Volatility Transmission During Financial Crises

	Econometric Model	Data	Findings
1. Theodossiou *et al.* (1997)	• Variance and Covariance Structure: Trivariant GARCH model (based on the CCC model) with structural dummies for pre and post-October 1987 crisis. (The break point is on 15 October 1987) • Mean Equation: VAR(2) process (Mean return is a function of past returns from all three markets up to two lags).	Weekly stock market data from the US, the UK, and Japan. Sample period: 4 May 1984 to 21 October 1994.	• Mean spillovers exist from the US and Japan to the UK from the first lag value. • Mean spillovers from the second lag values are insignificant in all instances. • Dummy variable in the mean equation for October 1987 crash does not significant. • Own volatility spillovers are significant only in the US and Japan. • Significant cross volatility spillovers exist from the US to the UK and from Japan to the UK.
2. Polasek and Ren (2001)	• Variance and Covariance Structure: Multivariate ARCH-M model used for full sample period and two sub-samples. (The two sub-samples are before and after Asian crisis. The break point is on 23 October 1997) • Mean Equation: VAR process.	Daily stock market data from the US (Dow Jones index), Japan (Nikkei index), and Germany (DAX index). Sample period: 21 June 1996 to 22 June 1998.	• The Dow Jones index positively influences on the returns of other two indexes and itself. • Variance of the returns in all three markets is larger after the Asian crisis compared to before the crisis. • The dynamic interactions of volatility before the Asian crisis are characterised by longer lags compared to after the crisis. The lag structure before the crises is VAR(2)-MARCH(2,2)-M(2) and after the crisis is VAR(2)-MARCH(1,1)-M(1).
3. Caporale *et al.* (2006)	• Variance and Covariance Structure: Bivariate BEKK model for full sample period and two sub-samples. (The two sub-samples are before and after Asian crisis. The break point is on 1 July 1997) • Mean Equation: The rate of current period returns is specified as a function of own lag returns up to one lag.	Daily stock market data from the US, Japan, and two other aggregate series: (i) for Europe (includes Italy, France, the UK, and Germany); (ii) for the South East Asia (includes Hong Kong, Indonesia, Malaysia, Philippines, Singapore, South Korea, Taiwan, and Thailand) Sample period: 1 January 1986 to 11 October 2000.	• Own market volatility persistence is higher during the post-crisis period than that of pre-crisis period. • Japanese market has positive influence on the conditional variances of the South East Asian market over the full sample whereas this influence is negative and smaller during pre-crisis period. • During post-crisis period, cross market volatility is unidirectional and running from the European and the US markets to the South East Asian market.

3.5.3. Volatility Transmission Across Stock Market and Macroeconomic Variables

There are a large number of studies that have been conducted on stock market and macroeconomic variables separately based on ARCH/GARCH models. However, only a few studies analysed the relationship between the stock market volatility and the volatility of macroeconomic variables simultaneously using univariate GARCH models (for example: Liljeblom and Stenius, 1997, Davis and Kutan, 2003, Saryal, 2007). These studies incorporated influence from macroeconomic variables towards stock market volatility and *vice versa*. For instance, Davis and Kutan (2003) uses multicounty data (13 countries) while Saryal (2007) uses data from Canada and Turkey for univariate GARCH models.

In the context of volatility transmission across stock markets and GDP growth rates using MGARCH models, Caporale and Spagnolo (2003) and Ahn and Lee (2006) have focused on volatility transmission mechanism across two series. For example, Caporale and Spagnolo (2003) used bivariate version of BEKK model whereas Ahn and Lee (2006) applied bivariate extension of univariate GARCH model. Furthermore, Caporale and Spagnolo (2003) identified that positive and significant volatility spillovers running from stock market to output growth in all six countries in their sample.[18] Ahn and Lee (2006) on the other hand, recognised that high volatility in stock market is followed by the increased volatility in the output sector and *vice versa*.

However, both these studies used stock market data and macroeconomics variables from one country as two series in their bivariate model. In other words,

[18] The six countries in Caporale and Spagnolo's (2003) study include Canada, Malaysia, Philippines, Thailand, the UK, and the US.

they have analysed the volatility relationship between the stock market returns and the macroeconomic variables for one country at a time. Thus, these studies do not provide evidence on how macroeconomic variable or a stock market volatility of one country can influence the volatility of macroeconomic variable and stock market of itself and other countries. Although it is important for investors to identify varying volatility implications across different international stock markets due to GDP growth fluctuations in the wake of regional or global economic crises, no study has so far used MGARCH models for analysing volatility spillovers across stock markets and GDP growth rates in multi-country context.

Table 3.3 summarises the empirical studies, which use MGARCH models evaluating the volatility transmission dynamics across stock markets and macroeconomic variables, discussed in this section.

Table 3.3 Empirical Implementations of MGARCH Models for Volatility Transmission Across Stock Markets and Macroeconomic Variables

	Econometric Model	Data	Findings
1. Caporale and Spagnolo (2003)	• Variance and Covariance Structure: Bivariate BEKK model • Mean Equation: Current period stock returns are a function of both lag stock returns and lag output growth. Similarly, the current period output growth is a function of lag stock returns and lag output growth.	Monthly data from stock market returns and output growth for three East Asian countries and three industrialised economies. Sample period: Malaysia from January 1980 to December 2000; Philippine from January 1978 to December 2000; Thailand from January 1987 to December 2000; Canada, the UK, and the US from January 1975 to December 2000.	• The stock market volatility positively influences on the volatility of output growth in all six countries. • According to the own market volatilities in all six countries, high volatility persistence exist in both stock returns and output growth.
2. Ahn and Lee (2006)	• Variance and Covariance Structure: Bivariate GARCH model (simple extension of a univariate GARCH model) • Mean Equation: VAR(1,1)	Real stock market index data and real output growth for Canada, Italy, Japan, the UK, and the US. Sample period: Italy, Japan, the UK, and the US from 1975 to 2000 and for Canada from 1977 to 2000.	• The high volatility in real output tends to be followed by increased volatility in the stock market and *vice versa*. However, the impact of stock market on output is not strong as that of output on stock market.

3.6. Summary and Conclusion

This chapter discussed the theoretical framework of three main MGARCH models namely VECH, BEKK, and CCC models and their extensions with parameter estimation methods and several diagnostic testings. It also reviewed the empirical literature on MGARCH models, which have used to evaluate asymmetry dynamics in stock market volatility transmission, financial crises and stock market volatility transmissions, and the relationship between the volatility of macroeconomic variables and the stock market.

Furthermore, this chapter has discussed some issues of using these MGARCH models in empirical applications. The high parameterization and the positive definite of variance and covariance matrix are the most common issues. However, these issues can be overcome with estimations using restrictions. One such restriction discussed in the literature is the use of initial values of residual variances for variance and covariance matrix to guarantee positive definite. Similarly, to reduce the number of parameters, the diagonal versions of the original models can be used. Therefore, despite those shortcomings, the MGARCH models are still the most useful econometric technique to analyse volatility dynamics across two or more series.

In addition, there are few studies have focused on evaluating the performances of these MGARCH models for the same problem using the same data. For instance, Kroner and Ng (1998) compared the VECH, BEKK, FGARCH and CCC models and introduced generalized model for analysing asymmetric effect in variances and covariances. Furthermore, they argued that the variance and covariance matrix is based on the choice of MGARCH model and thus influence the asset pricing, selection of optimal portfolio and risk management. Therefore, the most important issue is to identify the most appropriate MGARCH model for a particular application.

CHAPTER FOUR

ASYMMETRIC EFFECTS OF STOCK MARKET VOLATILITY TRANSMISSION*

4.1 Introduction

As stated in Chapter 1, the first piece of empirical analysis in this thesis is to examine the asymmetry of volatility effects within the stock market transmission mechanism. Evidence is provided in this chapter of how shocks originating in one stock market have an asymmetric impact on stock market volatility in other markets. This issue is especially important for international portfolio diversification decisions. According to Shamsuddin and Kim (2003), the short-run temporal relationships among national stock prices and their long-run co-movements are essential for managing international investment diversification because a low correlation among national stock market returns allows investors to minimise their portfolio risk by investing in such international stocks. Thus, if asymmetric volatility effects exist, negative shocks in highly correlated stock markets will have a particularly adverse effects on investors compared to shocks in other stock markets.

However as discussed in Chapter 2, although a number of studies have analysed the asymmetry of volatility effects on Australian stock returns (for example, Kearns and Pagan, 1993, Mian and Adam, 2001, Dowling and Muthuswamy, 2005, Frijns *et al.*, 2010), there is no consensus on the presence of

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asymmetry. In addition, these studies attempted to capture the asymmetric impact only in Australian stock returns. Thus, the existing literature lacks an exploration of how Australian stock market returns and volatility interact with other international stock markets in an international context or setting. After conducting a comprehensive review, only Brooks and Henry (2000) incorporate Australian stock returns with Japanese and US stock returns to test the asymmetry of volatility effects across these markets using the asymmetric BEKK model. Although they argued that the volatility spillovers from Japan and the US stock markets to the Australian stock market depended on both the magnitude and the sign of unanticipated shocks, they did not identify and quantify the country from which negative shocks influence the Australian market the most.

Consequently, the purpose of this chapter is to facilitate investigation of the extent to which both positive and negative shocks originating in Singapore, the UK, and the US stock markets impact on the volatility of Australian stock returns. These three stock markets are of particular interest as Valadkhani *et al.* (2008) identified that these three markets are highly correlated with the Australian stock market. Therefore, it enables us to identify asymmetry of volatility effect across highly integrated stock markets from the Asia Pacific, North American and European regions.

This chapter employs the DVECH (Bollerslev *et al.*, 1988) model to determine if the volatility influences on dynamics of the variance and covariance matrix of various stock market returns are asymmetric or not. The DVECH model is chosen for the current study based on three reasons. First, it allows the conditional variance and covariance matrix of stock market returns to vary over time. Second, many empirical studies in the literature, (For example: de Goeij and Marquering, 2004, Bauwens *et al.*, 2006), suggest this technique is capable of capturing the interaction effects within the conditional mean and variances of two or more series. Third, as proposed by de Goeij and Marquering (2004), the DVECH model used in this section can easily be augmented with dummy variables to address the asymmetric nature of volatility of stock returns. It should be noted that de Goeij and Marquering (2004) incorporated dummy variable proposed by Glosten *et al.* (1993) for univariate model to examine the asymmetric volatility effects across different stock and bond markets. In a similar way, the present study also uses dummy variable introduced by Glosten *et al.* (1993) for univariate model to examine the asymmetry of volatility effects across four different stock markets.

The remainder of this chapter is organized as follows: Section 4.2 presents the DVECH methodology, followed by a description of the data and summary statistics in Section 4.3. The empirical econometric results and policy implications of the study are set out in Section 4.4, followed by some concluding remarks in Section 4.5.

4.2 Methodology

The vector autoregressive stochastic process of asset returns has been specified by equation (4.1). Asset returns of country i (r_{iit}) are specified as a function of their own innovations (ε_{it}) and the past own return (r_{ijt-1}), for all $j = 1, \ldots, 4$ and $i = j$ as well as the lagged returns of other countries (r_{ijt-1}) for all $j = 1, \ldots, 4$ and $i \neq j$ as follows;

$$r_{iit} = \mu_{0i} + \sum_{j=1}^{4} \mu_{ij} r_{ijt-1} + \varepsilon_{it} \tag{4.1}$$

where (in alphabetical order) $i = 1$ for Australia, $i = 2$ for Singapore, $i = 3$ for the UK and $i = 4$ for the US;

μ_{0i} is the intercept for country *i*;

μ_{ij} (for all *i* = 1, .. , 4 and *j* = 1, .. , 4*)* indicates the conditional mean of stock return, which represents the influence from own past returns of country *i* (i.e. own-mean spillovers when $i = j$) and the influence from past returns of country *j* towards country *i* (i.e. cross-mean spillovers from country *j* to *i* when $i \neq j$); and

ε_{it} is own innovations (shocks) to country *i*.

The conditional variance and covariance matrix (H_t) for this study can be written as:

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} & h_{13t} & h_{14t} \\ h_{21t} & h_{22t} & h_{23t} & h_{24t} \\ h_{31t} & h_{32t} & h_{33t} & h_{34t} \\ h_{41t} & h_{42t} & h_{43t} & h_{44t} \end{pmatrix} \tag{4.2}$$

where h_{iit} is a conditional variance at time *t* of the stock return of country *i* and h_{ijt} denotes the conditional covariance between the stock returns of country *i* and country *j* (where $i \neq j$) at time *t*.

The ADVECH model can be written as follows:

$$vech(H_t) = C + A^* vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + G^* vech(\eta_{t-1}\eta'_{t-1}) + B^* vech(H_{t-1}) \tag{4.3}$$

where A^*, B^* and G^* are $\frac{1}{2}N(N+1) \times \frac{1}{2}N(N+1)$ diagonal matrix of parameter, which satisfies $A^* = diag[vech(A)]$, $B^* = diag[vech(B)]$ and $G^* = diag[vech(G)]$, where *A*, *B*, and *G* are $N \times N$ symmetrical matrices; and C is a $\frac{1}{2}N(N+1) \times 1$ vectors of parameters. The $vech(\cdot)$ operator denotes the column-stacking operator applied to upper portion of the symmetric matrix.

The diagonal elements of matrix *A* (a_{11}, a_{22}, a_{33} and a_{44}) measure the own-volatility shocks and the non-diagonal elements (a_{ij} where $i \neq j$) determine the cross-volatility shocks. The own-volatility shocks represent the impacts arising from past squared innovations on the current volatility while the cross-volatility shocks can be shown as the cross-product effects of the lagged innovations on the current covolatility. In addition, the parameters of matrix G capture the magnitude of asymmetry of volatility effect, where $\eta_{t-1} = \max[0,1]$ and is similar to the Glosten *et al.* (1993) dummy series. In other words, the term η_{t-1} takes the value of 1 for negative shocks and 0 otherwise (i.e. $\eta_{t-1} = 1$ when $\varepsilon_{t-1} < 0$ and $\eta_{t-1} = 0$ when $\varepsilon_{t-1} \geq 0$). Therefore, the significant positive values of g_{ii} indicate that negative shocks of country *i* increase the variance. Similarly, the significant positive values of g_{ij} represent the effect from negative shocks between country *i* and *j* for rising covariances. Finally, the diagonal elements of matrix *B* (b_{11}, b_{22}, b_{33} and b_{44}) determine the own-volatility spillovers that can be considered as the past volatilities on the current volatility and the non-diagonal elements (b_{ij} where $i \neq j$) capture the cross-volatility spillovers, which are the lagged covolatilities on the current covolatility.

Furthermore, as discussed in the previous chapter, this study uses the unconditional residual variance as the pre-sample conditional variance to guarantee the positive definite of conditional variance and covariance matrix (H_t) of the ADVECH. In addition, the Marquardt algorithm is use to obtain the optimal values of parameters of the ADVECH model and the Ljung-Box test statistic is used to test any remaining ARCH effects in the model.

4.3 Data and Preliminary Findings

The data used in this study are weekly average stock market price indices spanning from 6 January 1992 to 28 June 2010 (n = 965 observations) and downloaded from http://www.au.finance.yahoo.com. Other sources such as the Organisation for Economic Co-operation and Development (OECD, http://www.oecd.org) and dXtime databases have stock market indexes, however, are only available as monthly, quarterly or annual data. The present study uses weekly data based on the assumption that investors can insure against the currency risk. Furthermore, weekly data provides a number of advantages over the use of daily data. Firstly, it avoids the interferences associated with the use of synchronised data as the trading day of one country may coincide with a public holiday in another country. Secondly, it also avoids the time zone differences due to the four countries being located in various time zones with associated different opening and closing times. For the same reasons Theodossiou and Lee (1993, 1995), Theodossiou *et al.* (1997), Brooks and Henry (2000), and Ng (2000) have also used weekly data in their studies.

The stock market price data used in this study includes the All Ordinaries Index (AORD) of Australia, the Straits Times Index (STI) of Singapore, the Financial Times Stock Exchange Index (FTSE100) of the UK and the Standard and Poor's Index (S&P 500) of the US. However, it should be noted that the STI did not contain the data for two weeks covering the period from Monday, 14 January 2008 to Monday, 21 January 2008 due to the change of index methodology from the STI to the FTSE to manage its index. To ensure continuity in the time series data, this minor gap was eliminated by interpolation. The data for the week beginning from Monday, 17 September 2001 to Friday, 21 September 2001 were absent from the US data due to the terrorist attack in the US on September 11, 2001. This one-week missing value was similarly approximated by interpolating the adjacent two values.

Stock market returns are computed based on the stock market price indexes. Let p_t be the stock market price index at time t. The stock market return at time t is then calculated as $r_t = \ln\left(p_t / p_{t-1}\right)$. Table 4.1 reports the descriptive statistics for each stock market return series. The mean returns for the four stock markets are all positive, ranging from a minimum 0.0007 (Singapore and the UK) to a maximum 0.0011 (Australia). According to the sample standard deviations, the Australian stock return is the least volatile series with a standard deviation of 0.0165, while the Singapore stock return can be considered as the most volatile series with a standard deviation of 0.0266. The standard deviations for the UK and the US returns are approximately the same (0.0193). Figure 4.1 also confirms this by providing a visual perspective on the volatility of four return series over time during the period of analysis. The increased volatility is clearly seen during financial crises periods such as 1997-98 Asian financial crises and 2008-09 GFC.

Based on the estimated skewness statistics, all four return series are skewed to the left. According to Bollerslev *et al.* (1994), Brooks (2008) and many others, any high frequency financial return series indicate a typical leptokurtic distribution. As expected the value of kurtosis is greater than 3.0 for all of the return series, confirming a typical leptokurtic distribution, whereby return series are more peaked around the mean with a thicker tails compared to the normal distribution. Furthermore, the Jarque-Bera statistics and corresponding *p*-values reinforce the above findings by rejecting the null hypothesis of normality at the 1 per cent level of significance.

Table 4.1 Descriptive Statistics for Return Series

	Australia	Singapore	UK	US
Mean	0.0011	0.0007	0.0007	0.0010
Median	0.0026	0.0010	0.0023	0.0027
Maximum	0.0685	0.1278	0.1005	0.0818
Minimum	-0.1189	-0.1440	-0.0973	-0.1747
Std. Dev.	0.0165	0.0266	0.0193	0.0193
Skewness	-1.0667	-0.2709	-0.4333	-1.2963
Kurtosis	8.5963	8.0645	6.2297	12.6833
Jarque-Bera	1440.81	1042.04	449.14	4036.27
p-value	0.0000	0.0000	0.0000	0.0000
Correlation Coefficients				
Australia	1.0000			
Singapore	0.5449	1.0000		
UK	0.6631	0.5406	1.0000	
US	0.6729	0.5251	0.7813	1.0000

Sources: All Ordinaries Index (Australia), the STI (Singapore), the FTSE100 (the UK) and the S&P 500 (the US) for the period 6 January 1992- 28 June 2010, containing 965 observations and downloaded from www.au.finance.yahoo.com.

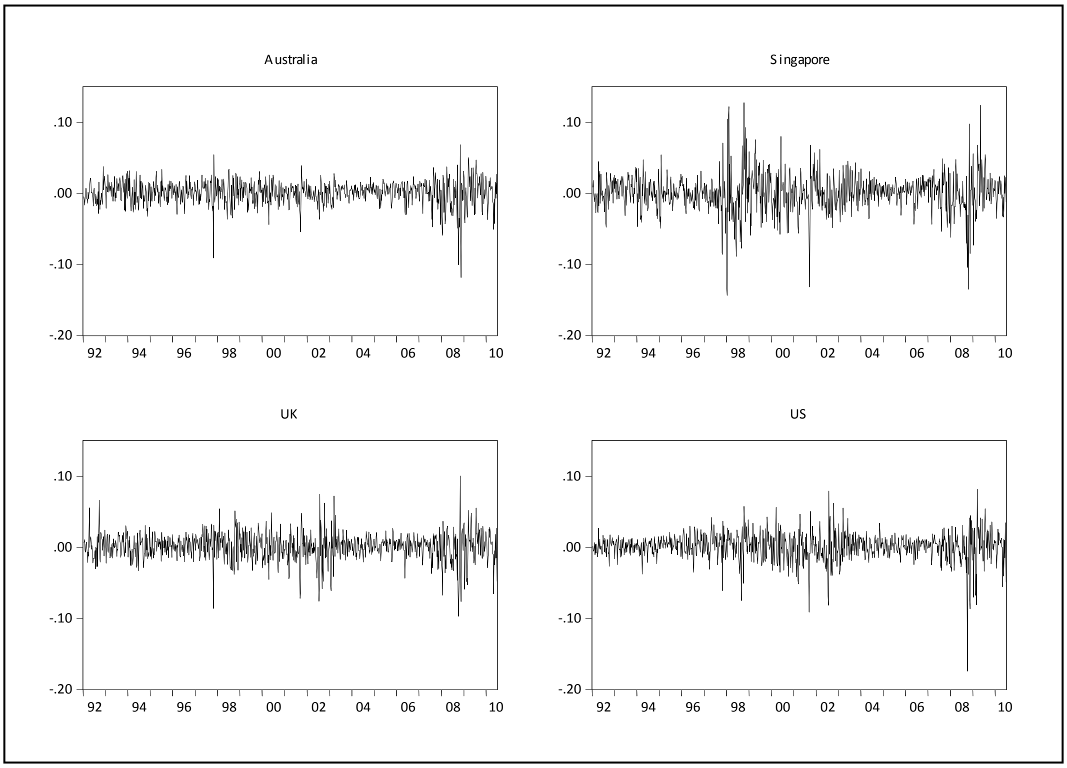

Figure 4. 1 Weekly Stock Market Returns from January 1992 to June 2010

The pairwise correlations among the four stock market returns are also presented in Table 4.1. The estimated correlation coefficients are all greater than 0.5 and statistically significant, consistent with the previous findings of McNelis (1993) and Valadkhani *et al.* (2008). The lowest correlation (0.5251) is between the stock market returns of the US and Singapore, while the highest (0.7813) is between the stock market returns of the UK and the US.

The Augmented Dickey-Fuller **(**ADF) test results presented in Table 4.2 show that the null hypothesis of the presence of a unit root in the data can be rejected at the 5 per cent level, suggesting that all of four return series (i.e. log differences) are all stationary. The calculated Ljung-Box Portmanteau test statistics in Table 4.2 provide strong evidence of serial correlation in the four series, justifying the inclusion of the lag terms in equation (4.1).

Table 4.2 ADF Test Results and Ljung-Box Q-Statistic Results for Stock Market Returns

	Australia		Singapore		UK		US	
ADF *t* statistics								
Based on min. AIC	-15.61		-11.96		-20.61		-11.47	
Based on min. SIC	-24.50		-11.96		-24.76		-25.56	
Ljung-Box test statistics for return series								
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Q(1)	51.44	0.00	62.65	0.00	45.24	0.00	33.31	0.00
Q(2)	51.49	0.00	64.04	0.00	45.48	0.00	33.33	0.00
Q(3)	55.81	0.00	80.85	0.00	46.07	0.00	34.48	0.00
Q(4)	55.83	0.00	81.71	0.00	48.74	0.00	37.12	0.00
Q(5)	56.16	0.00	83.34	0.00	49.00	0.00	38.55	0.00
Q(6)	57.20	0.00	87.07	0.00	49.13	0.00	41.31	0.00
Q(7)	59.51	0.00	87.11	0.00	50.82	0.00	43.87	0.00
Q(8)	59.52	0.00	88.16	0.00	50.98	0.00	45.79	0.00
Q(9)	62.46	0.00	88.17	0.00	50.98	0.00	45.99	0.00
Q(10)	62.62	0.00	88.19	0.00	51.81	0.00	45.99	0.00
Q(11)	62.66	0.00	89.07	0.00	52.55	0.00	50.19	0.00
Q(12)	63.20	0.00	89.10	0.00	52.60	0.00	50.20	0.00
Q(13)	63.39	0.00	89.10	0.00	53.45	0.00	50.73	0.00
Q(14)	67.71	0.00	89.25	0.00	54.32	0.00	54.36	0.00
Q(15)	71.55	0.00	89.26	0.00	54.35	0.00	58.77	0.00
Q(16)	71.74	0.00	90.08	0.00	54.62	0.00	58.95	0.00
Q(17)	72.61	0.00	91.76	0.00	55.04	0.00	59.48	0.00
Q(18)	74.45	0.00	91.75	0.00	61.79	0.00	62.08	0.00
Q(19)	74.86	0.00	91.80	0.00	62.13	0.00	62.46	0.00
Q(20)	75.18	0.00	91.86	0.00	62.14	0.00	64.47	0.00
Q(21)	76.28	0.00	92.34	0.00	62.82	0.00	67.99	0.00
Q(22)	77.04	0.00	95.79	0.00	64.85	0.00	69.83	0.00
Q(23)	78.05	0.00	95.80	0.00	64.86	0.00	69.83	0.00
Q(24)	81.67	0.00	99.04	0.00	64.94	0.00	71.39	0.00

Note: AIC = Akaike information criterion and SIC = Schwarz information criterion. Q(n) is the n^{th} lag Ljung-Box test statistics.

4.4 Empirical Results

First, to decide the number of lagged ARCH and GARCH effects on the variance and covariance matrix this empirical study tests various ADVECH(p,q) specifications, where p = 1, 2, and 3 and q = 1, 2, and 3 based on three model selection criteria, namely the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HIC). The test results from various ADVECH(p,q) specifications indicate that the

ADVECH(1,1) specification has consistently the lowest AIC (-23.17), SIC (-22.98) and HIC (-23.10) with a log-likelihood of 11192.78.

The results using equation (4.3) with the conditional mean equation (4.1) are given in Table 4.3. Based on the results presented in Table 4.3, the own-mean spillovers (μ_{ii} for all i= 1,..,4) are significant at the 1 per cent level of significance, providing evidence of an influence on current returns of each stock market arising from their first lag returns (r_{iit-1}). The own-mean spillovers vary from a minimum of 0.1444 (Australia) to a maximum of 0.2120 (the US). Significant positive cross-mean spillover effects exist from the US to Australia, to Singapore, and to the UK. However, an important finding is that there is no positive and significant impact in the opposite direction. This means that lagged stock returns of larger stock markets can influence the future returns of smaller stock markets.

The significant cross-mean spillover impact from the US to Australia (0.1376) is higher than that of Singapore (0.1143). In other words, as expected past US stock market returns have a relatively greater impact on the Australian stock market. These results are consistent with the univariate GARCH application of Brailsford (1996) for Australia, New Zealand and the US, and with the multivariate GARCH application of Brooks and Henry (2000) for Australia, Japan, and the US, indicating that the lagged returns of the US stock market heavily influence the returns of the Australian stock market but not *vice versa*. Brooks and Henry's (2000, p 509) also stated, "when the US sneezes Australia catches pneumonia", is therefore supported by the results obtained from the current study. The R_i^2 values presented in Table 4.3, calculated as

$1-\left[\mathrm{var}\left(\varepsilon_{it}\right)/\mathrm{var}\left(r_{iit}\right)\right]$, measure the predictability of variations of future stock market returns due to the conditional mean spillovers. Similar to Theodossiou and Lee (1993), these R_i^2 are less than 9 per cent, indicating very low explanatory power.

Own-volatility shocks for all four markets (a_{11}, a_{22}, a_{33} and a_{44}) are significant and vary from 0.0125 (the UK) to 0.0622 (Singapore), indicating the presence of ARCH effects. This means that past shocks arising from the Singapore market will have the strongest impact on its own future market volatility compared to shocks stemming from the other three markets. Based on the magnitudes of the estimated cross-volatility coefficients, a_{ij} ($i \neq j$), innovations in all of the four stock markets influence the volatility of other markets, but the own-volatility shocks, a_{ij} ($i = j$), are generally larger than the cross-volatility shocks. This suggests that past volatility shocks in individual markets have a greater effect on their own future volatility than past volatility shocks arising from other markets. Therefore, it appears that the lagged country-specific shocks (ARCH effects) do contribute to the stock market volatility of any given country in a recursive way. According to the results, the degree of cross-volatility shocks is pairwise, with the weakest between UK-US (0.0158) and the strongest between Australia-Singapore (0.0417).

The estimated coefficients for the asymmetric impact in the variance equations (g_{ii} for all i= 1,..,4) are positive and significant for all four stock markets. As expected, this suggests that negative shocks emanating from each stock market increase volatility to a greater extent than positive shocks. In other words, compared to a rise in price, a drop in stock price tends to increase the volatility more. In this regard, the lowest coefficient belongs to Australia (0.0189) and the highest to the UK (0.0616).

Furthermore, coefficients for asymmetric impact in the covariance equations (g_{ij} for all $i \neq j$) are all positive and statistically significant suggesting that the negative shocks in each stock market have contributed to raise covolatilities across these four markets. The lowest coefficient for asymmetric impact in the covariance equation is between Australia and Singapore (0.0240), while the highest figure occurs between the UK and the US (0.0556). In addition, the asymmetric coefficient between Australia and the US is 0.0308, while this coefficient between Australia and the UK is 0.0341 in the corresponding covariance equation. This is not counter intuitive as this finding indicates that the volatility of smaller markets (Australia and Singapore) will increase when larger markets (the UK and the US) are moving downwards. Therefore, this asymmetry in covariances represents an important implication for portfolio diversification since it is riskier to invest in two stocks if they move in the same direction. More specifically, when investors spread their funds amongst different international stocks, they can minimise risk if they know how bad news (negative shocks) from one stock market influences other stock markets.

Table 4.3 Parameter Estimation for the Mean Equation, the Variance and Covariance Matrix of the ADVECH(1,1) Model

Parameter	Australia	Singapore	UK	US
μ_{0i}	0.0019***	0.0017***	0.0016***	0.0019***
	(5.34)	*(3.14)*	*(3.99)*	*(4.66)*
μ_{i1}	0.1444***	-0.0204	-0.0196	-0.0873**
	(4.04)	*(-0.45)*	*(-0.52)*	*(-2.26)*
μ_{i2}	-0.0034	0.1948***	-0.0171	0.0179
	(-0.16)	*(6.25)*	*(-0.81)*	*(0.84)*
μ_{i3}	0.0185	0.1272**	0.1654***	0.0199
	(0.60)	*(2.58)*	*(4.21)*	*(0.50)*
μ_{i4}	0.1376***	0.1143**	0.0982**	0.2120***
	(3.97)	*(2.27)*	*(2.46)*	*(4.85)*
c_{i1}	0.00000005			
	(0.72)			
c_{i2}	0.00000006	0.00000007		
	(0.65)	*(0.48)*		
c_{i3}	0.00000008	0.00000008	0.00000010	
	(0.83)	*(0.70)*	*(0.75)*	
c_{i4}	0.00000035	0.00000038	0.00000048	0.00000218***
	(1.24)	*(0.89)*	*(1.25)*	*(3.09)*
a_{i1}	0.0280***			
	(5.36)			
a_{i2}	0.0417***	0.0622***		
	(6.46)	*(6.19)*		
a_{i3}	0.0187***	0.0279***	0.0125**	
	(3.79)	*(4.06)*	*(2.57)*	
a_{i4}	0.0236***	0.0352***	0.0158**	0.0199***
	(4.55)	*(4.97)*	*(3.05)*	*(3.28)*
g_{i1}	0.0189***			
	(3.34)			
g_{i2}	0.0240***	0.0305**		
	(3.35)	*(2.82)*		
g_{i3}	0.0341***	0.0433***	0.0616***	
	(4.64)	*(4.35)*	*(6.07)*	
g_{i4}	0.0308***	0.0391***	0.0556***	0.0501***
	(4.31)	*(4.09)*	*(5.82)*	*(4.81)*
b_{i1}	0.9658***			
	(240.40)			
b_{i2}	0.9473***	0.9299***		
	(187.99)	*(118.28)*		
b_{i3}	0.9609***	0.9433***	0.9568***	
	(284.17)	*(197.54)*	*(225.11)*	
b_{i4}	0.9553***	0.9377***	0.9512***	0.9455***
	(219.03)	*(173.49)*	*(207.40)*	*(146.29)*
$a_{ii} + b_{ii}$	0.9938	0.9921	0.9693	0.9654
R_i^2	0.0844	0.0889	0.0506	0.0307

Notes: (a) i = 1 for Australia, i = 2 for Singapore, i = 3 for the UK and i = 4 for the US. (b) *** indicates that statistically significant at 1 per cent level, ** indicates that statistically significant at 5 per cent level and * indicates that statistically significant at 10 per cent level. (c) R_i^2 is the percentage change of variation in the returns of market *i* explained by the conditional mean equation. (d) *t*-ratios are given in parenthesis.

On the other hand, the correlation coefficients presented in Table 4.1 indicated that similar to the asymmetric coefficient the highest correlation coefficient is between the UK and the US while the Australian stock market is having approximately the same correlation coefficient with the UK and the US (0.66 and 0.67) and these correlation coefficients are higher than the correlation coefficient between stock returns of Australia and Singapore (0.54). These findings support the argument that negative shocks in highly correlated stock markets can involve higher investment risk more than positive or negative shocks in any other stock markets.

The estimated coefficients for the variance and covariance matrix (equation 4.3) have also been presented in Table 4.3. Similar to Theodossiou and Lee (1993) and Worthington and Higgs (2004), the estimated results in this study indicate statistically significant and positive b_{ij} ($i \neq j$) coefficients for the one-lag conditional variance, thereby suggesting the presence of high volatility persistence. The lowest value for the own-volatility spillovers effect belongs to Singapore (0.9299) and the highest one belongs to the Australian market (0.9658). This implies that past volatility in the Australian market will have the strongest impact on its own future volatility compared to the other three markets. The significant nonzero b_{ij} coefficients (where $i \neq j$ for all i and j) provide further evidence for the presence of high and positive volatility spillovers across these well-integrated markets. The estimated lagged cross volatility persistence between Australia on the one hand, and Singapore, the UK, and the US on the other, are 0.9473, 0.9609, and 0.9553, respectively, supporting the evidence of volatility persistence emanating from all of the other three markets to Australia. Cross-volatility persistence for Singapore, stemming from the UK and the US, are 0.9433 and 0.9377, respectively. Consequently, the UK and the US appear to be the most influential markets for Australia and Singapore. The sum of the lagged ARCH and GARCH coefficients ($a_{ii} + b_{ii}$) for Australia, Singapore, the UK and the US are 0.9938, 0.9921, 0.9693 and 0.9654, respectively. These values are very close to unity, supporting the assumption of covariance stationarity and the volatility persistence in the data.

Table 4.4 presents the normality test and the unit root test results on the standardized residuals of the model. According to the ADF test results, all four standardized residual series are stationary. Due to the nature of financial data the resulting residuals are not normally distributed, however, based on the skewness and kurtosis statistics the standardized residuals are closer to a normal distribution than the return series. Table 4.5 provides the estimated Portmanteau Box-Pierce/Ljung-Box Q-statistics and the adjusted Q-statistics for the system residuals using the Conditional Correlation (Doornik-Hansen) Orthogonization method. Both the Q-statistics and the adjusted Q-statistics show that the null hypothesis of no autocorrelations cannot be rejected at the 5 per cent level for various lags of up to 24, with the only exception being from the third lag to the sixth lag. Thus, one can conclude that there is no significant amount of serial correlation left in the system residuals as the bulk of the serial correlation observed in Table 4.2 (original return series) has now disappeared in the resulting system residuals in Table 4.5. This provides further support for the VECH model as it absorbs a great deal of inertia and the ARCH and GARCH effects present in the original return series.

Table 4.4 Diagnostic Tests on the Standardized Residuals

	Australia	Singapore	UK	US
Statistics on standardized residuals				
Skewness	-0.2720	-0.4391	-0.0629	-1.3573
Kurtosis	4.0692	4.8799	4.4925	17.0105
Jarque-Bera	57.7481	172.7469	90.0155	8171.970
ADF *t* statistics				
Based on min. AIC	-22.96	-16.95	-19.85	-30.57
Based on min. SIC	-30.66	-30.20	-30.35	-30.57

Note: AIC = Akaike information criterion and SIC = Schwarz information criterion.

Table 4.5 The Results of System Residual Portmanteau Tests for Autocorrelations Using the Conditional Correlation (Doornik-Hansen) Orthogonalization Method

Autocorrelation coefficients	Q-Stat	p-value	Adj. Q-Stat	p-value	d.f
Q(1)	12.88	0.68	12.89	0.68	16
Q(2)	41.25	0.13	41.32	0.13	32
Q(3)	66.44	0.04	66.59	0.04	48
Q(4)	86.28	0.03	86.51	0.03	64
Q(5)	103.62	0.04	103.94	0.04	80
Q(6)	120.50	0.05	120.93	0.04	96
Q(7)	130.93	0.11	131.44	0.10	112
Q(8)	146.13	0.13	146.76	0.12	128
Q(9)	159.97	0.17	160.73	0.16	144
Q(10)	175.31	0.19	176.23	0.18	160
Q(11)	188.31	0.25	189.39	0.23	176
Q(12)	203.50	0.27	204.76	0.25	192
Q(13)	226.92	0.18	228.51	0.16	208
Q(14)	239.40	0.23	241.17	0.21	224
Q(15)	253.64	0.26	255.63	0.23	240
Q(16)	271.01	0.25	273.30	0.22	256
Q(17)	285.70	0.27	288.25	0.24	272
Q(18)	302.20	0.27	305.07	0.24	288
Q(19)	320.28	0.25	323.51	0.21	304
Q(20)	332.73	0.30	336.23	0.26	320
Q(21)	343.36	0.38	347.10	0.33	336
Q(22)	356.77	0.42	360.82	0.36	352
Q(23)	380.01	0.32	384.62	0.26	368
Q(24)	396.95	0.31	402.00	0.25	384

Note: Q(n) is the n^{th} lag Ljung-Box test statistics.

4.5 Summary and Conclusion

This chapter used the ADVECH model and weekly stock market data from January 1992 to June 2010 to investigate the dynamics of stock market returns and volatility across stock markets of Australia, Singapore, the UK and the US and capture the possible the asymmetric nature of variance and covariances across these stock markets. The estimated ADVECH(1,1) model passed the standard diagnostic tests and a restriction was imposed on the parameters of the model using the unconditional residual variance as the pre-sample conditional variance. The resulting estimated coefficients from such a restriction are all positive definite as indicated in the conditional variance and covariance matrix.

The results from ADVECH(1,1) model indicated that the positive return spillover effects are only unidirectional and run from both the US and the UK (the bigger markets) to Australia and Singapore (the smaller markets). Based on the magnitude of innovations, the shocks arising from the US market can indiscriminately impact on all of the other markets in the sample. According to Sabri (2002), the world's leading stock market would have an influence on the volatility of other markets. Therefore, the results from this study also support Sabri's argument that being the world largest stock market the US can influence the other markets.

Finally, unlike previous empirical studies, the current study takes into account potential asymmetries that may exist in own-volatility spillovers as well as cross-volatility spillovers and find evidence for such asymmetries. The findings from the asymmetry volatility spillovers analysis are twofold. First, it reveals that negative shocks emanating in each stock market increases their own volatility to a greater extent than positive shocks. It also evident that the asymmetric impact in the covariance equations are all positive and statistically significant suggesting that the negative shocks in each stock market have contributed to raise covariance across these four markets. A noteworthy aspect of this asymmetric impact in the variances and covariances is for smaller stock markets (Australia and Singapore) the asymmetry coefficient for covariances are generally higher than that for variances. This finding indicated that the volatility of smaller markets will increase following negative shocks from larger markets. This would suggest that in such markets, changes in volatility are likely to emanate from negative shocks due to domestic conditions but their covolatility persistence is intertwined with negative shocks from global financial markets.

Second, the asymmetric coefficient in covariance is higher between the stock markets with high correlation coefficient. This suggests that the negative shocks in highly correlated stock markets can involve higher investment risk more than positive or negative shocks on any other stock markets. Thus, similar to Kroner and Ng (1998), the present study also concludes that it is riskier for investors to invest in stocks from only these four markets because a high degree of time-varying covolatility amongst these for markets can involve higher investment risks.

CHAPTER FIVE

FINANCIAL CRISES AND STOCK MARKET VOLATILITY TRANSMISSION**

5.1 Introduction

The findings from the previous chapter confirm that the asymmetry of volatility effects arising from international stock markets can influence the Australian stock market. Furthermore, the empirical studies reviewed in Chapter 2 found evidence that international influences on the Australian stock market relate not only to asymmetric volatility effects but also from other factors such as financial crises. For example, Ellis and Lewis (2001) identified the US stock market influence on increasing price and volatility of the Australian stock market during the 1997-98 Asian financial crisis. Similarly, Cheunga *et al.* (2010) found evidence of the US influence towards the Australian stock market during the recent 2008-09 GFC period. This chapter aims to investigate the nature of the dynamics of volatility transmission across different international stock markets during financial crisis

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** This chapter is based on the following papers:

(a) Valadkhani, A and Karunanayake, I 2011, 'An empirical analysis of financial crises using the MGARCH model', *Cambridge Conference on Business and Economics Conference*, 27-28 June, Murray Edwards College, Cambridge University, UK.

(b) Karunanayake, I, Valadkhani, A and O'Brien, M 2010, 'Financial crises and international stock market volatility transmission', *Australian Economic Papers*, Vol.49, No.3, pp 209-21.

(c) Karunanayake, I, Valadkhani, A and O'Brien, M 2010, 'Effects of financial crises on international stock market volatility transmission', *Economics Joint Scientific Conference*, 09-10 February 2010, Korea Economic Association, Korea.

(d) Karunanayake, I, Valadkhani, A and O'Brien, M 2009, 'Financial crises and stock market volatility transmission: evidence from Australia, Singapore, the UK, and the US', *Financial Crises: Causes, Characteristics, and Effects International Conference*, 23-25 November 2009, Edith Cowan University, Australia.

and non-crisis periods. Specifically, the factors affecting the cross-country spillovers in the volatility of stock returns during the 1997-98 Asian crisis and the 2008-09 GFC.

It is important to compare and contrast the nature of the two crises in terms of cause and geographic origin. Inadequately supervised banking systems, asset price bubbles, increase of credit growth, over-expansion of the capital stock and rigid exchange rate regimes were recognized by the BIS as key issues for the countries affected with the 1997-98 Asian crisis. Similarly, the solvency of large parts of the global banking system, widespread increases in asset prices, easy credit conditions, and unusually low real interest rates were possible causes associated with the recent GFC (BIS, 2009). The 1997-98 Asian crisis engulfed the global market with the collapse of Thai-baht but on the other hand the recent GFC originated from the collapse of the US subprime mortgage market. Therefore, these two crises were different in terms of geographic origin. This study attempts to capture any the fundamental differences between the two crises by using dummy variables in a MGARCH model

The literature has shown that there are variations in the impact-timeline from market to market for these crises. For instance, the Asian financial crisis started in mid-1997 spreading within Asia until mid-1998 and subsequently engulfing Russia and other countries (BIS, 1999). Ellis and Lewis (2001) contend that financial market volatility in Australia and New Zealand was more pronounced in late 1998 than mid-1997, when the main events of Asian financial crisis occurred. In comparison, Richardson (1998) and Garg *et al.* (1999) assert that the Asian financial crisis had become a worldwide phenomenon on the 27th of

October 1997 when the Dow Jones Industrial Average plunged 554.26 points. This decline was recorded as the largest fall ever at the time in terms of points and the second largest decline in terms of percentages.

Due to the disparity of impact-timeline, the current study has experimented with the exact timing of the dummies to test the timing of any possible effect on the four stock markets. Ultimately, this study used the period starting from the first week of July 1997 to the last week of September 1998 to capture the Asian financial crisis. As for the more recent global financial meltdown, this chapter considers the third week of September 2008 as the starting point of the crisis. The rationale is that this financial crisis became sharply out of control following the Lehman Brothers collapse on 15 September 2008 (Frank and Hesse, 2009). According to the Business Cycle Dating Committee of National Bureau of Economic Research (NBER, 2010), the recent GFC ended and a recovery began in June 2009. Therefore, the present study uses the last week of June 2009 as the ending date of the GFC.

The rest of this chapter is organized as follows; Section 5.2 presents the empirical methodology, which is built upon the DVECH model. The data and preliminary findings are set out in Section 5.3 followed by the empirical econometric results in Section 5.4. The last section provides some concluding remarks.

5.2 Methodology

The major intention of the current chapter is to examine the interdependence of return and covolatility across four highly integrated international stock markets due to two financial crises. Thus, this study uses the DVECH model augmented with two dummy variables to study the volatility transmission across different stock markets during financial crises periods and non-financial crises periods. Similar dummy structure have also been used in some other studies (Longin and Solnik, 1995, Theodossiou *et al.*, 1997, Ellis and Lewis, 2001, Polasek and Ren, 2001). In addition, to maintain positive definite of conditional variance and covariance matrix (H_t) as suggested by Bollerslev *et al.* (1988), the current study imposes conditions on the initial values and use the maximum likelihood function to generate these parameter estimates. Similar to the previous empirical study in Chapter 4, the present study uses the Marquardt algorithm to obtain the optimal values of parameters and Ljung-Box test statistic to test any remaining ARCH effects in the model. Similar to the previous study in Chapter 4, the conditional variance and covariance matrix (H_t) for this study can also be written as:

$$H_t = \begin{pmatrix} h_{11t} & h_{12t} & h_{13t} & h_{14t} \\ h_{21t} & h_{22t} & h_{23t} & h_{24t} \\ h_{31t} & h_{32t} & h_{33t} & h_{34t} \\ h_{41t} & h_{42t} & h_{43t} & h_{44t} \end{pmatrix} \tag{5.1}$$

where h_{iit} is a conditional variance at time *t* of the stock return of country *i* and h_{ijt} denotes the conditional covariance between the stock returns of country *i* and country *j* (where $i \neq j$) at time *t*.

The vector autoregressive stochastic process of assets returns is given in equation (5.2), representing the mean equation. Similar to the previous study in Chapter 4, asset returns of country i (r_{iit}) are assumed to be a function of own innovations (ε_{it}) and the past own return (r_{ijt-1}), for all $j = 1, \ldots, 4$ and $i = j$ as well as the lagged returns of other countries (r_{ijt-1}) for all $j = 1, .., 4$ and $i \neq j$. Besides the above variables, to capture the potential influence on the mean equation from the Asian crisis and the more recent GFC this study additionally incorporates two dummy variables to the mean equation (5.2). Thus, the mean equation for the current study can be written as follows;

$$r_{iit} = \mu_{0i} + \delta_{97i} D_{97} + \delta_{08i} D_{08} + \sum_{j=1}^{4} \mu_{ij} r_{ijt-1} + \varepsilon_{it} \tag{5.2}$$

where $i = 1$ for Australia, $i = 2$ for Singapore, $i = 3$ for the UK, and $i = 4$ for the US; μ_{0i} is the intercept for country i; μ_{ij} (for all i = 1, .. , 4 and j = 1, .. , 4) indicates the conditional mean of stock return (i.e. own-mean spillovers) when $i = j$; and the cross-mean spillovers from country j to i when $i \neq j$; and ε_{it} is referred to as own innovations (shocks) to country i.

The D_{97} dummy variable captures the effect of the Asian crisis by taking the value 1 for the period from the first week of July 1997 to the last week of September 1998 and 0 otherwise. Similarly, the D_{08} dummy variable is included in the model to capture the more recent GFC by taking the value 1 in the period from 15 September 2008 to the last week of June 2009 and 0 otherwise as this crisis is deemed to be ongoing in the sample period of analysis. The coefficients δ_{97} and δ_{08} are the corresponding coefficients of dummy variables D_{97} and D_{08}.

Therefore, intercept of mean equation (5.2) for the Asian crisis is postulated to be $\mu_{0i} + \delta_{97i}$ and for the GFC would be $\mu_{0i} + \delta_{08i}$ for each country *i*.

Then, the corresponding DVECH model can be written as follows:

$$vech(H_t) = C + G^*_{97} D_{97} + G^*_{08} D_{08} + A^* vech(\varepsilon_{t-1}\varepsilon'_{t-1}) + B^* vech(H_{t-1}) \tag{5.3}$$

where A^*, B^*, G^*_{97} and G^*_{08} are $\frac{1}{2}N(N+1) \times \frac{1}{2}N(N+1)$ diagonal matrix of parameter, which satisfies $A^* = diag[vech(A)]$, $B^* = diag[vech(B)]$, $G^*_{97} = diag[vech(G_{97})]$ and $G^*_{08} = diag[vech(G_{08})]$ where *A, B,* G_{97} and G_{08} are $N \times N$ symmetrical matrices; and C is a $\frac{1}{2}N(N+1) \times 1$ vectors of parameters. The $vech(\cdot)$ operator denotes the column-stacking operator applied to upper portion of the symmetric matrix. As mentioned in Chapter 4, the diagonal elements of matrix *A* (a_{ii} for all *i=1..4*) measure the own-volatility shocks while non-diagonal elements (a_{ij} where $i \neq j$) determine the cross-volatility shocks. Similarly, the diagonal elements of matrix *B* (b_{ii} for all *i=1..4)* determine the own-volatility spillovers and finally the non-diagonal elements (b_{ij} where $i \neq j$) capture the cross-volatility spillovers.

The intercept of variances for the Asian and global financial crises for country *i* are $c_{ii} + g_{97ii}$ and $c_{ii} + g_{08ii}$, respectively. Correspondingly, the intercept of covariances between country *i* and *j* for the Asian crisis is $c_{ij} + g_{97ij}$ and for the global crisis is $c_{ij} + g_{08ij}$ for all $i \neq j$. In addition, the expected significant positive values of g_{97ij} and g_{08ij} for all *i* and *j* indicate that the crises are expected to have positive effects on the volatility and cross volatility.

5.3 Data and Preliminary Findings

This Chapter also uses the same sample data from the previous chapter. Table 5.1 and Table 5.2 present the descriptive statistics for return series during the 1997-08 Asian crisis and the 2008-09 GFC periods respectively. Compared to the mean returns during the overall sample period given in Table 4.1 the stock returns of Australia and Singapore indicate negative return during the Asian crisis period (see Table 5.1) while all four markets show negative return during the GFC period (see Table 5.2). Similarly, the standard deviations have increased in stock markets of Australia and Singapore during the Asian crisis period and in all four markets during the GFC period. These findings suggest that, the stock market volatility based on the standard deviations increased after stock price fall during financial crises period. Furthermore, the highlighted areas in Figure 5.1 on four graphs which represent 1997-98 Asian crisis and 2008-09 GFC periods indicates large spikes as expected during financial crises period confirming above findings. Similar evidence has also noted by Schwert (1989a) in the US data from l834 to 1987 and Schwert (2011) in the monthly returns from 1802-2010, daily returns from 1885-2010, and intraday returns from 1982-2010 in the US data around major financial crises and during recessions.

Table 5.1 Descriptive Statistics for Return Series During the Asian Financial Crisis Period

	Australia	Singapore	UK	US
Mean	-0.0010	-0.0118	0.0006	0.0019
Median	-0.0020	-0.0079	0.0039	0.0062
Maximum	0.0547	0.1222	0.0543	0.0368
Minimum	-0.0911	-0.1440	-0.0865	-0.0752
Std. Dev.	0.0211	0.0482	0.0217	0.0196
Skewness	-0.9074	0.1658	-0.9385	-1.4321
Kurtosis	6.9215	4.5251	5.7420	6.4051
Jarque-Bera	50.5679	6.5975	29.9045	53.6215
p-value	0.0000	0.0369	0.0000	0.0000

Table 5.2 Descriptive Statistics for Return Series During the GFC Period

	Australia	Singapore	UK	US
Mean	-0.0061	-0.0029	-0.0054	-0.0073
Median	-0.0029	-0.0021	0.0007	0.0005
Maximum	0.0685	0.1246	0.1005	0.0818
Minimum	-0.1189	-0.1351	-0.0973	-0.1747
Std. Dev.	0.0377	0.0518	0.0387	0.0464
Skewness	-0.7283	-0.1886	-0.0807	-1.2240
Kurtosis	4.0077	3.4137	3.3376	5.4576
Jarque-Bera	5.4903	0.5485	0.2451	21.0558
p-value	0.0642	0.7601	0.8847	0.0000

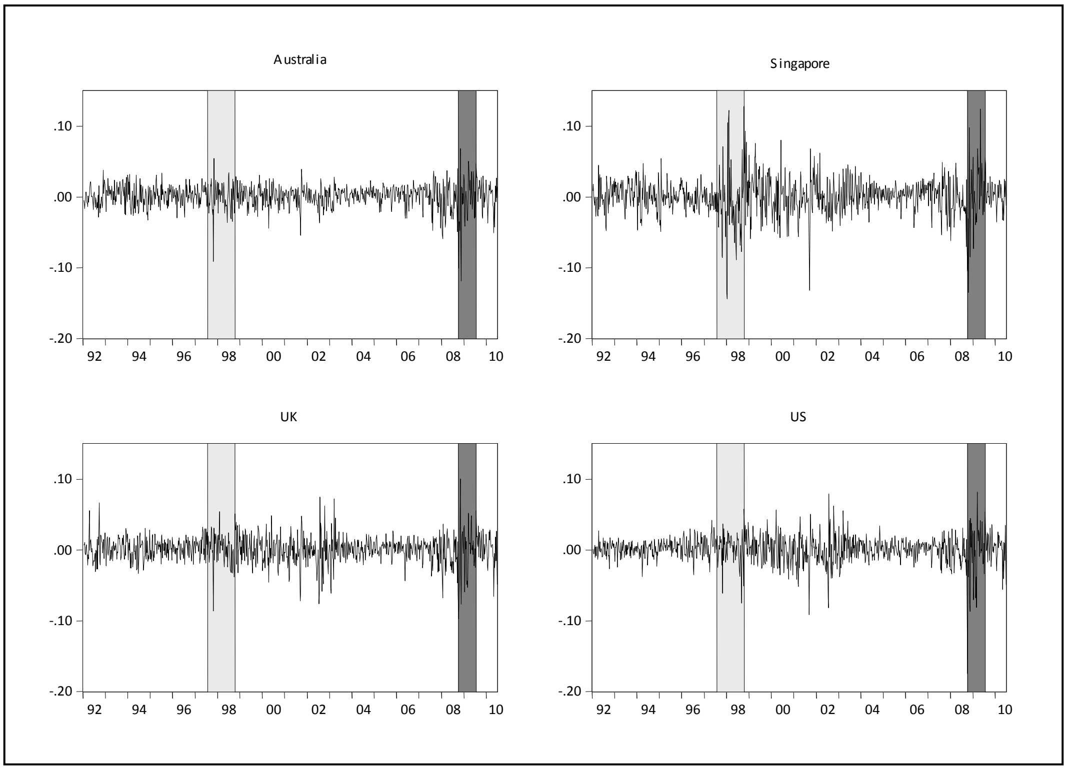

Figure 5.1 Weekly Stock Market Returns from January 1992 to June 2010 (Financial Crisis Period Highlighted)

5.4 Empirical Results

Similar to the previous study in Chapter 4, starting with various DVECH(p,q) specifications (where p = 1, 2, and 3 and q = 1, 2, and 3) this study adopted the DVECH(1,1) specification augmented with two dummy variables on the basis of three model selection criteria with the lowest AIC (-23.20), SIC (-22.86), HIC (-22.07) and a log-likelihood of 11239.06. Table 5.3 presents the estimate results from equations (5.2) and (5.3). According to the estimated coefficients, the constant terms in the mean equation are statistically significant at the 1 per cent level for all four countries. However, the coefficient of the dummy variables in the mean equation for the 1997-98 Asian crisis is statistically insignificant for all four countries with the only exception being the Singapore returns which are significant at the 10 per cent level. The 2008-09 global crisis dummy was also statistically insignificant for all four countries. Thus, one can overall conclude that these two recent global financial crises did not significantly influence the mean returns.

However, the own-mean spillovers (μ_{ii} for all i= 1,..,4) are statistically significant for all four markets, providing evidence of an influence on current returns of each stock market arising from their first lag returns (r_{iit-1}). Similar to the finding from the mean equation in the previous chapter, the own-mean spillovers is the lowest in the Australian market (0.1424) while the highest in the US market (0.2111). Although, significant positive cross-mean spillovers effects exist from the US to all three markets, there is no positive and significant impact in the opposite direction. The cross-mean spillovers impact is at its lowest for the UK (0.0938). The significant cross-mean spillovers impacting from the US to Singapore and to Australia are 0.1338 and 0.1385 respectively. In addition, the Singapore market is also positively influenced by the UK returns. However, the impact from the UK (0.1110) is much lower than that of the US. In other words, the past US stock market returns exert greater impact on the Singapore stock market than the UK market returns.

As an important finding, the coefficients of constant terms for both variance and covariance equations of each market are statistically significant. Furthermore, the estimated dummy variable coefficients for the Asian financial crisis in the variance equations are positive and significant for all four markets, suggesting that the Asian financial crisis had significant influence on the volatility of these four markets. This effect varies from 0.000019 (the US) to 0.000129 (Singapore). This indicates that the Asian crisis had the strongest impact on the Singapore market in terms of its rise in future volatility than the other three markets. However, the dummy variable coefficients for the Asian crisis in covariance equations are insignificant for all four markets except for the covariance across Australia-the US (0.000018) and Australia-the UK (0.000015). This implies that the Asian financial crisis influenced own-volatility more than cross-market volatility. In other words, although the Asian financial crisis spread outside Asia during the end of 1998, it did not significantly impact on cross-market volatility among these four countries for the entire period (starting from the first week of July 1997 to the last week of September 1998). Most certainly, such impacts contributing to rising covolatility have occurred for a much shorter period than the one proposed by the length of the sustained 1997 dummy variable.

The present study therefore, carried out a sensitivity analysis on the length of time of the dummy variable for the 199798-Asian crisis (i.e. D_{97}) using two methods. These two methods are based on stock market returns and the standard deviations to decide the length of dummy variables. The detail description of these methods and the results are given in the Appendix. Both methods indicated similar results as obtained in the initial analysis suggesting that even for shorter time periods the Asian financial crisis did not influence the cross-market volatility. Thus, the impact on cross-market volatility from the 1997-98 Asian crisis appears to be increased cross-market volatility across stock markets within the East Asian region, where the Asian crisis was originated.

The estimated coefficients for the dummy variables capturing the 2008-09 GFC in the variance equations are positive and significant for all four markets. This suggests that the recent crisis sparked in 2008 increased the volatility of stock returns of Australia, Singapore, the UK, and the US. The lowest coefficient belongs to the UK (0.00008) and the highest to Singapore (0.00019). Furthermore, the dummy variable coefficients in covariance equations are all positive and statistically significant, suggesting that the 2008-09 financial crisis has contributed to the rising covolatilities across these four markets. The lowest dummy coefficient in the covariance equation is between Australia and the UK (0.00008), while the highest figure occurs between Singapore and the US (0.00017). In addition, the dummy variable coefficient between the UK and Singapore (0.00012) in the covariance equation is higher than that of Australia. As expected, this indicates that the 2008-09 crisis had a higher impact on Singapore than Australia.

Table 5.3 Parameter Estimation for the Mean Equation the Variance and Covariance Matrix of the DVECH(1,1) Model

Parameter	Australia	Singapore	UK	US
μ_{0i}	0.001941***	0.001726***	0.001744***	0.002001***
	(4.84)	*(3.12)*	*(3.68)*	*(4.54)*
δ_{97i}	-0.002527	-0.009982*	-0.000680	0.001045
	(-0.96)	*(-1.91)*	*(-0.23)*	*(0.43)*
δ_{08i}	-0.001228	0.001812	-0.002533	-0.001907
	(-0.24)	*(0.25)*	*(-0.44)*	*(-0.24)*
μ_{i1}	0.142408***	-0.021390	-0.024476	-0.087681**
	(3.64)	*(-0.43)*	*(-0.58)*	*(-2.12)*
μ_{i2}	-0.009466	0.173467***	-0.020868	0.016786
	(-0.42)	*(5.16)*	*(-0.88)*	*(0.73)*
μ_{i3}	0.020946	0.111077**	0.151626***	0.006590
	(0.63)	*(2.14)*	*(3.37)*	*(0.16)*
μ_{i4}	0.138498***	0.133840**	0.093820**	0.211094***
	(3.64)	*(2.53)*	*(2.16)*	*(4.68)*
c_{i1}	0.000008***			
	(3.24)			
c_{i2}	0.000007***	0.000016***		
	(4.11)	*(3.29)*		
c_{i3}	0.000005***	0.000008***	0.000010***	
	(4.01)	*(4.30)*	*(3.78)*	
c_{i4}	0.000005***	0.000007***	0.000007***	0.000010***
	(4.39)	*(4.25)*	*(4.55)*	*(4.39)*
g_{97i1}	0.000024**			
	(2.11)			
g_{97i2}	0.000036	0.000129**		
	(1.49)	*(2.17)*		
g_{97i3}	0.000015*	0.000024	0.000021*	
	(1.67)	*(1.08)*	*(1.65)*	
g_{97i4}	0.000018*	0.000019	0.000013	0.000019*
	(1.91)	*(0.82)*	*(1.26)*	*(1.78)*
g_{08i1}	0.00009*			
	(1.69)			
g_{08i2}	0.00013**	0.00019*		
	(1.94)	*(1.79)*		
g_{08i3}	0.00008*	0.00012**	0.00008*	
	(1.85)	*(2.02)*	*(1.69)*	
g_{08i4}	0.00011**	0.00017**	0.00011**	0.00015**
	(2.10)	*(2.18)*	*(2.02)*	*(2.30)*
a_{i1}	0.066083***			
	(4.89)			
a_{i2}	0.054517***	0.103358***		
	(4.72)	*(5.40)*		
a_{i3}	0.051742***	0.052032***	0.061244***	
	(5.42)	*(5.03)*	*(5.99)*	
a_{i4}	0.056486***	0.058709***	0.060704***	0.07123***
	(5.87)	*(5.37)*	*(6.48)*	*(5.76)*
b_{i1}	0.882194***			
	(39.94)			
b_{i2}	0.864641***	0.847436***		
	(49.54)	*(34.40)*		
b_{i3}	0.887758***	0.870094***	0.893358***	
	(56.22)	*(54.80)*	*(53.36)*	
b_{i4}	0.878617***	0.861134***	0.884158***	0.875054***
	(57.40)	*(54.25)*	*(61.10)*	*(49.30)*

Notes: (a) i = 1 for Australia, i = 2 for Singapore, i = 3 for the UK and i = 4 for the US. (b) *** indicates that statistically significant at 1 per cent level, ** indicates that statistically significant at 5 per cent level and * indicates that statistically significant at 10 per cent level. (c) *t*-ratios are given in the parentheses.

The a_{ii} for all $i = 1..4$ parameters measure the persistency of own-volatility shocks and the estimate results are also reported in Table 5.3. Significant a_{ii} values for all four markets indicate the presence of ARCH effects in these four markets. According to the estimated own-volatility shocks, the Singapore stock market is the most influential market on own future volatility. Parameters a_{ij} ($i \neq j$ for all i and j) measure the persistency of cross-volatility shocks across four stock markets. Another consideration is that the coefficients of own-volatility shocks a_{ij} ($i = j$), are generally higher than the cross-volatility shocks. It is therefore suggested that country-specific shocks are stronger on their own future volatility than past volatility shocks arising from other markets. During the sample period, the magnitude of cross-volatility shocks is pair-wise the weakest between Australia-the UK (0.0517) and the strongest between the US-the UK (0.0429). There is evidence for the persistence of volatility shocks emanating from other two markets toward Australia. This cross volatility persistence between Australia on one hand and Singapore, and the US on the other are 0.0545, and 0.0565, respectively.

Table 5.3 also presents the estimated volatility (b_{ii}) and covolatility (b_{ij} for all $i \neq j$) coefficients of the DVECH(1,1) specification. All volatility and covolatility coefficients for four stock markets are statistically significant and positive indicating highly persistent volatility and covolatility spillovers within and across the four markets. According to the degree of estimated coefficients, the own-volatility spillovers is at its lowest in the Singapore market (0.8474) and the highest in the UK market (0.8934). In other words, the UK market will have the strongest impact on its own future volatility compared to the other three markets. In addition, the important finding is the evidence of volatility transmission from all of the other three markets towards Australia. These cross volatility effects between Australia and those of Singapore, the UK, and the US are 0.8646, 0.8878, and 0.8786, respectively. As a comparison, the cross-volatility persistence between Singapore on one hand and the UK and the US on the other, are 0.8700 and 0.8611, respectively. In this respect, it may appear that the US market influences the Australian stock market more than that of Singapore market.

The spillovers in the second moments (i.e. volatility spillovers) indicate similarities in own-volatility spillovers but differences in cross-volatility spillovers in the context of the two crises. First, the own-volatility spillovers in these four stock markets increased during both financial crises. As identified by Schwert (1989a, 1990a), over-leveraging could have an influence on increasing own-volatility spillovers in each market during these two financial crises. Of note is that the own-volatility spillovers are greater in the recent GFC compared to the Asian crisis. Apart from over-leveraging, a loss of confidence by investors in the value of sub-prime mortgages, a rise in defaults and under-provision for nonperforming loans by the banking system and the failure of banks to manage risks can also be regarded as other relevant causes of the volatility of stock markets during the recent global crisis. On the other hand, the dollarization of foreign debt could be another contributing factor for the increase in volatility of stock markets in the Asian crisis period.

Second, significant cross-volatility spillovers across all four markets do exist during the recent GFC period only. Furthermore, the transmission of this volatility shock during the recent financial crisis is the greatest from the US market to other markets. This particular finding is not counterintuitive, given the geographic dissimilarities of the origin of the two crises. The recent financial crisis emerged with the collapse of financial markets in the US, being the world's leading stock markets. As Sabri (2002) stated, the world's leading stock market would have an influence on the volatility of other markets. In addition, as Eun and Shim (1989, p.254) argued "no national stock market is nearly as influential as the US in terms of its capability of accounting for the error variance of other markets." On the other hand, the Asian crisis originated with the collapse of Thai-baht leading to a disruption in foreign exchange markets mainly within the Asian region. s Asian financial turmoil occurred in emerging Asian economies, it could not exert a significant role on cross-volatility spillovers in stock markets outside the region.

In addition to the results from the main model, i.e. equations (5.2) and (5.3), this section also reports the results from diagnostic tests discussed in Chapter 3, for the resulting standardized residual series. In particular, Table 5.4 presents the normality test statistics, the unit root test results, and the Ljung-Box test statistics for the standardised residual series of the DVECH(1,1) model. The estimated result from these tests confirms that the resulting residuals are not normally distributed; all four standardised residual series are stationary and no serial correlation mainly in the Australian and the US market. Furthermore, the estimated the Portmanteau Box-Pierce/Ljung-Box Q-statistics and the adjusted Q-statistics for the standardised system residuals using the Cholesky Orthogonalization method presented in Table 5.5 support the null hypothesis of no autocorrelations at the 5 per cent level. Finally, this may suggest that the DVECH(1,1) model absorbs most of ARCH and GARCH effects present in the original return series.

Table 5.4 Diagnostic Tests on the Standardized Residuals

	Australia		Singapore		UK		US	
Statistics on standardized residuals								
Skewness	-0.43		-0.10		0.07		-0.28	
Kurtosis	3.61		3.66		4.08		6.15	
Jarque-Bera	44.05		19.42		46.43		410.55	
ADF *t* statistics								
Based on min. AIC	-30.70		-15.81		-22.97		-19.41	
Based on min. SIC	-30.70		-29.57		-28.94		-30.80	
Ljung-Box test statistics for standardized residuals								
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Q(1)	0.08	0.78	2.07	0.15	3.27	0.07	0.02	0.89
Q(2)	0.34	0.84	7.18	0.03	9.68	0.01	0.80	0.67
Q(3)	2.91	0.41	10.67	0.01	11.60	0.01	5.17	0.16
Q(4)	4.72	0.32	12.02	0.02	11.60	0.02	5.19	0.27
Q(5)	4.72	0.45	12.21	0.03	12.40	0.03	6.38	0.27
Q(6)	5.05	0.54	12.23	0.06	12.90	0.05	6.47	0.37
Q(7)	5.46	0.60	12.30	0.09	13.75	0.06	6.60	0.47
Q(8)	5.46	0.71	12.30	0.14	13.95	0.08	6.66	0.57
Q(9)	6.73	0.67	12.39	0.19	14.31	0.11	6.77	0.66
Q(10)	6.75	0.75	12.48	0.25	14.52	0.15	7.21	0.71
Q(11)	7.34	0.77	12.48	0.33	15.88	0.15	7.48	0.76
Q(12)	9.59	0.65	12.49	0.41	15.91	0.20	8.65	0.73
Q(13)	9.59	0.73	12.79	0.46	16.19	0.24	10.10	0.69
Q(14)	11.49	0.65	12.87	0.54	16.51	0.28	10.21	0.75
Q(15)	11.76	0.70	13.19	0.59	17.41	0.30	11.62	0.71
Q(16)	12.44	0.71	14.91	0.53	18.61	0.29	12.01	0.74
Q(17)	13.58	0.70	17.79	0.40	19.52	0.30	12.75	0.75
Q(18)	13.62	0.75	17.85	0.47	19.84	0.34	14.51	0.70
Q(19)	14.88	0.73	18.24	0.51	21.43	0.31	14.72	0.74
Q(20)	15.03	0.78	18.90	0.53	21.43	0.37	15.02	0.78
Q(21)	15.09	0.82	18.93	0.59	22.05	0.40	16.25	0.76
Q(22)	15.74	0.83	19.28	0.63	22.74	0.42	16.25	0.80
Q(23)	17.54	0.78	20.78	0.59	27.02	0.26	16.25	0.84
Q(24)	18.21	0.79	20.81	0.65	30.38	0.17	17.20	0.84

Note: Q(n) is the n^{th} lag Ljung-Box test statistics.

Table 5.5 The Results of System Residual Portmanteau Tests for Autocorrelations Using the Cholesky Orthogonalization Method

Autocorrelation coefficients	Q-Stat	p-value	Adj. Q-Stat	p-value	d.f
Q(1)	16.30	0.43	16.31	0.43	16
Q(2)	42.58	0.10	42.65	0.10	32
Q(3)	66.62	0.04	66.77	0.04	48
Q(4)	82.04	0.06	82.25	0.06	64
Q(5)	97.40	0.09	97.70	0.09	80
Q(6)	114.67	0.09	115.07	0.09	96
Q(7)	122.73	0.23	123.18	0.22	112
Q(8)	135.02	0.32	135.59	0.31	128
Q(9)	147.27	0.41	147.95	0.39	144
Q(10)	162.88	0.42	163.72	0.40	160
Q(11)	176.99	0.46	177.99	0.44	176
Q(12)	193.95	0.45	195.17	0.42	192
Q(13)	218.30	0.30	219.85	0.27	208
Q(14)	228.62	0.40	230.32	0.37	224
Q(15)	240.48	0.48	242.37	0.45	240
Q(16)	260.54	0.41	262.77	0.37	256
Q(17)	273.47	0.46	275.93	0.42	272
Q(18)	287.79	0.49	290.52	0.45	288
Q(19)	302.83	0.51	305.86	0.46	304
Q(20)	314.41	0.58	317.70	0.53	320
Q(21)	326.29	0.64	329.84	0.58	336
Q(22)	338.84	0.68	342.68	0.63	352
Q(23)	362.20	0.58	366.61	0.51	368
Q(24)	378.10	0.58	382.92	0.51	384

Note: Q(n) is the n^{th} lag Ljung-Box test statistics.

5.5 Summary and Conclusion

The purpose of the empirical analysis in this chapter is to capture the effects of the 1997-98 Asian financial crisis and the 2008-09 GFC to identify the source and magnitude of mean and volatility spillovers across highly integrated stock markets. Thus, the current study used the DVECH(1,1) model augmented with two dummy variables for weekly stock market data (January 1992 – June 2010) of Australia, Singapore, the UK and the US. The findings from this empirical study could not indicate positive significant influence on the mean returns in all four markets resulting from these two financial crises. However, the results show a significant influence arising from the Asian financial crisis on volatility in all four markets. The factors like over-leveraging affecting both crises could have similarities in terms of own-volatility spillovers. In addition, other factors such as a loss of confidence by investors in the value of sub-prime mortgages during the recent GFC and the dollarization of foreign debt during the Asian crisis could have an influence on increasing own-volatility spillovers in each market.

More specifically the Asian financial crisis influenced the own-volatility more than that of the cross-market volatility. During the entire 1997-98 crisis (i.e. from the first week of July 1997 to the last week of September 1998) significant influences on covolatility were not observed. One may argue that the covolatility across these four markets presumably did rise for a much shorter (country specific) period than the one proposed by the length of the sustained 1997 dummy variable utilised in this thesis. However, the results from the sensitivity analysis indicated that the above argument is void. A plausible explanation would be the Asian financial crisis could increase the cross-market volatility across stock markets within the East Asian region where the crisis was originated. In contrast, the findings provide ample evidence that the 2008-09 financial crisis has contributed to the increased stock return volatilities across all these four markets suggesting that the recent GFC originated in the US sparked across the stock markets outside the North American region. On the other hand, the US stock market being the world largest stock market and the collapse of financial markets in the US would have an influence on the volatility of other markets. Thus, it appears that in addition to geographic location, the differences in terms of cross-market volatility spillovers could be being the world largest stock market, the US stock market would have predominately influenced the other market.

CHAPTER SIX

GDP GROWTH VOLATILITY AND STOCK MARKET VOLATILITY TRANSMISSION

6.1 Introduction

Building on the factors affecting the cross-country spillovers in stock market returns and their volatilities, the final issue is whether GDP growth can influence volatility spillovers across different international stock markets and *vice versa*. As noted by Antonios (2010), there has been a growing interest in recent years on stock market indexes and the effect of stock markets on economic development. According to Fama (1990), Liua and Sinclairb (2008), Oskooe (2010) and many others, economic growth through real economic activities influences the profitability and activity of firms thereby affecting expected earnings, dividends of shares and stock prices fluctuations. Antonios (2010) suggests risk diversification through stock market integration can improve the resource allocation and influence the banking operations hence impact on the economic growth.

According to Ritter (2005) long-run equity returns are based on dividend yields and the growth of per share dividends. Therefore, Ritter (2005) argues that future economic growth is irrelevant for predicting future equity returns although economic growth is good for stock returns, and forecast of economic growth is important for international asset allocation decisions. This is because economic growth comes from (1) the technological change that increase the productivity rising per capita income of consumers; and (2) either reinvesting earnings into the existing firms or into the new firms. Therefore, the benefit from the technological change goes to consumers and labours. On the other hand, much of economic growth has come from investing into new firms, which does not result in a higher growth rate of dividends per share for existing firms (Ritter, 2005).

Furthermore, Schwert (1989b, 1990a) related stock return volatility to the level of economic activity through financial and operating leverage. When stock prices fall relative to bond prices or when firms increase financial leverage by issuing debt to buy back their stocks, the volatility of firms' stock return increases. With the unexpected demand fall, the profits of firms with large fixed costs falls more than the profits of firms that avoid large capital investment or long-term supply contracts. Thus, firms operating leverage (firms with large fixed costs) can increase their stock return volatility.

In the context of volatility analysis, recent studies indicate that the nature of the relationship between stock market and the output growth are mixed. As noted in Chapter 1, one group of studies argues that this relationship is unidirectional from GDP volatility to stock market volatility (for example, Caporale and Spagnolo, 2003, Diebold and Yilmaz, 2008); while the other group claims that it is bidirectional (Ahn and Lee, 2006, Leon and Filis, 2008). Of note, these studies are methodologically different from each other. In the first group, Caporale and Spagnolo (2003) employed a bivariate version of the BEKK model while Diebold and Yilmaz (2008) used the standard deviation of stock return and GDP growth and residuals from an AR(3) model as of Schwert (1989b) to measure the volatility. In the second group, Ahn and Lee (2006) applied a bivariate extension of the univariate GARCH model whereas Leon and Filis

(2008) adopted VAR analysis. A major issue for all these studies was that they focussed on one country at a time, although they use data from multiple countries to their sample. In other word, these studies do not provide cross-country analysis on the interaction effect of volatility across stock market returns and GDP growth rates.

Therefore, contributing to this debate this study provides some insight into a noteworthy aspect of volatility transmission across stock markets and GDP growth to identify and quantify possible influence from GDP growth rate and volatility of one county on the volatility and covolatility across stock markets. To evaluate the volatility and covolatility dynamics across different international stock markets and GDP growth rates this chapter employs a sophisticated MGARCH model for eight series. Unlike, above approaches the MGARCH model used in this study simultaneously takes into account the first and the second order moments of eight series in the sample. The present study then, becomes the first study to conduct a simultaneous analysis of the nature of volatility transmission across stock market and GDP growth rates in a multi-country context.

The remainder of this chapter is organized in the following way. Section 6.2 presents the empirical methodology, followed by the data and preliminary findings in Section 6.3. The empirical econometric results are described in Section 6.4 with some concluding remarks in the last section.

6.2 Methodology

This section of the current thesis uses the diagonal version of Engle and Kroner's (1995) BEKK model to study the volatility spillovers within and across stock market returns and GDP growth rates and the vector autoregressive stochastic process for the mean equations to examine the nature of stock returns and GDP growth rate interdependencies. The DBEKK model is used for this study, first, because it reduce the number of parameters while guaranteeing positive definite of variance and covariance matrix. Second, MGARCH models have widely been used for analysing second order moments across financial markets in the past. In the context of present study to examine the interaction effects of the volatility and covolatility of stock market and GDP growth across various countries, the present study tests the applicability of the DBEKK model to capture first and second order moments not only stock market data but also GDP growth series.

First, the vector autoregressive stochastic process of stock returns and GDP growth rates is given in equation (6.1), which represents the mean equation for this study.

$$r_{it} = \mu_{0i} + \sum_{k=1}^{8}\sum_{j=1}^{4} \mu_{kj} r_{kt-j} + \theta_i W_i + \varepsilon_{it} \qquad (6.1)$$

where (in alphabetical order) *i=1* for Australian stock returns, *i=2* for Canadian stock returns, *i=3* for the UK stock returns, *i=4* for the US stock returns, *i=5* for Australian GDP growth, *i=6* for Canadian GDP growth, *i=7* for the UK GDP growth, and *i=8* for the US GDP growth;

μ_{0i} is the intercept for series *i*;

μ_{kj} indicates the conditional mean of stock returns/GDP growth such that when $k = i$ for all $k = 1, .. , 8$ and $j = 1, .. , 4$) represents the influence from own past returns/growth rates of series k up to four lags (i.e. own-mean spillovers) and when $k \neq i$ for all $k = 1, .. , 8$ and $j = 1, .. , 4$) represents the influence from past returns/growth rates of series k towards series i up to four lags (i.e. cross-mean spillovers);

W_i is a dummy variable to capture the abnormal observations mainly due to economic and financial crises in series i during the sample period;

θ_i denotes the estimated coefficients of the dummy variables; and

ε_{it} represents the own innovations.

Second, the BEKK model can be written as follows:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{6.2}$$

where A and B are $N \times N$ parameter matrices and C is an upper triangular $N \times N$ matrix. N is the number of series considered in the model. In order to make estimation relatively simple further restrictions on the A and B matrices are considered to obtain a diagonal version of the BEKK model, which contains less parameters and guarantees a positive definite conditional variance and covariance matrix (H_t). Engle and Kroner (1995) find that the DBEKK model can be formulated from the BEKK parameterization if and only if each of the A and B matrices in equation (2) are diagonal. Therefore, we use a similar diagonal version of the BEKK model for volatility (equation 6.3) and co-volatility (equation 6.4);

$$h_{iit} = c_{ii} + a_{ii}^2 \varepsilon_{it-1}^2 + b_{ii}^2 h_{iit-1} \tag{6.3}$$

$$h_{ijt} = c_{ij} + a_{ii} a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ii} b_{jj} h_{ijt-1} \tag{6.4}$$

where, h_{iit} is the own-volatility of series i; h_{ijt} is the covolatility between series i and series j;

$a_{ii} \times a_{ii}$ is the coefficient of lagged own-volatility shocks of series i;

$b_{ii} \times b_{ii}$ is the coefficient of lagged own-volatility of series i;

$a_{ii} \times a_{jj}$ is the coefficient of cross products of lagged volatility shocks between series i and j; and

$b_{ii} \times b_{jj}$ is the coefficient of lagged covolatility between series i and j.

This implies that the volatility spillovers within one series can be determined by the sum of squares of the diagonal elements of matrix *A* and square of the diagonal elements of matrix *B*. In other words, volatility spillovers depend on the squared sum of own-volatility shocks representing the impacts arising from past squared innovations (shocks) and own-volatility spillovers representing the impact arising from past volatility. The covolatility spillovers between two series can be estimated by the sum of cross products of diagonal elements of *A* and cross products of diagonal elements of *B*. That is the sum of cross products of past innovations and past covolatility between two series.

6.3 Data and Preliminary Findings

Unlike Chapter 4 and 5, the present empirical study uses quarterly stock market price indexes and GDP data of four countries namely Australia, Canada, the UK, and the US. Although, previous empirical studies used weekly data, the present empirical study has to use quarterly data as this is the frequency of GDP measurement. In addition, based on the stock market price index, the stock returns (r_t) at time *t* is calculated as $r_t = \ln\left(p_t / p_{t-1}\right)$ where p_t be the stock market price index at time *t*. Therefore, to make the consistency the GDP growth rate is also calculated in an analogous fashion.

Furthermore, these data are obtained from data series of OECD main economic indicators in dXtime database for the period spanning from 1959Q3 to 2010Q4 (n = 206 observations). Data series of OECD main economic indicators in dXtime database does not contain stock market indexes and GDP data for Singapore because Singapore is not a member country of OECD. Although, daily, weekly and monthly stocks return indexes for all four countries used in empirical analysis in previous two chapters are available from http://www.au.finance.yahoo.com, it does not contain GDP data. Annual GDP data for Australia, Singapore, the UK, and the US are available from http://www.ggdc.net/Maddison/ but it does not have stock market data. Therefore, with availability of data the current empirical study selects Australia, Canada, the UK, and the US. Furthermore, Valadkhani *et al*. (2011) found that GDP growth of above four Anglo-Saxon countries was highly correlated. In addition, these four countries will allow an analysis of the interplay of major stock markets and GDP growth rates from North America, Europe, and the Asia Pacific regions.

Panel *A* of Table 6.1 presents the descriptive statistics for each stock market return series while Panel *B* reports them for GDP growth series. During the overall sample period, mean stock returns of all four series are positive and rang from 0.0149 (the US) to 0.0176 (the UK). GDP growth rates of all four countries are also positive and range from 0.0057 (the UK) to 0.0090 (Australia). The sample standard deviations of stock markets suggest that the US stock returns (SD = 0.0648) can be considered as the least volatile series, while the Australian stock return (SD = 0.0835) is the most volatile series. Similarly, the sample standard deviations of GDP growth rates indicate that the least volatility in the US GDP growth rates (SD = 0.0087) and the highest volatility in the Australian GDP growth rate (SD = 0.0117). Visual perspective on the volatility of four stock market return series are given in Figure 6.1 and the volatility of four GDP growth series are given in Figure 6.2. It is clear that large spikes in Figure 6.1 during 1987 and 2008-09 indicating high volatility during stock market crash in October 1987 and recent GFC periods. In comparison, Figure 6.2 indicates large spikes during 1980s recession and during recent GFC.

Based on the skewness, all stock market return series indicate negative skewness. In comparison, only Canada and the US GDP growth series are negatively skewed. The magnitude of this skewness is higher in stock returns than GDP growth rates. Thus, one can assume that, financial and economic crises during the sample period could have greater negative influence on stock markets more than GDP growth rates. However, these catastrophes will empirically test in Section 6.4. In addition, the value of kurtosis is greater than 3.0 for all of the stock return and GDP growth series, with Canadian GDP growth the only exception. This indicates the typical leptokurtic distribution. Additionally, this non-normal properties of the data are confirmed by the Jarque-Bera test statistics and corresponding *p*-values. Finally, the ADF unit root test is employed for all of the stock market return and GDP growth rate series. The ADF test results given in Table 6.1 Panel *A* and *B*, suggest that that all eight series are stationary.

Table 6.1 Descriptive Statistics

Panel A: **Stock Market Return Series**

	Australia	Canada	UK	US
Mean	0.0157	0.0153	0.0176	0.0149
Median	0.0265	0.0235	0.0221	0.0187
Maximum	0.1962	0.1856	0.3567	0.1841
Minimum	-0.4888	-0.3337	-0.2666	-0.3622
Std. Dev.	0.0835	0.0734	0.0812	0.0648
Skewness	-1.5555	-1.0228	-0.2124	-1.3443
Kurtosis	10.0202	6.0990	5.9167	8.7778
Jarque-Bera	503.6213	117.7807	74.2065	346.8775
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
ADF t statistics				
Based on min. AIC	-11.98	-11.31	-9.73	-9.44
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Based on min. SIC	-11.97	-11.31	-10.93	-10.11
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*

Sources: (a) Quarterly stock market indexes of Australia, Canada, the UK, and the US for the period from 1959Q3 to 2010Q4 (n = 206 observations) are obtained from dXtime database. (b) *p*-values are given in parenthesis.

Panel B: **GDP Growth Series**

	Australia	Canada	UK	US
Mean	0.0090	0.0082	0.0057	0.0077
Median	0.0078	0.0079	0.0061	0.0077
Maximum	0.0563	0.0331	0.0520	0.0385
Minimum	-0.0281	-0.0195	-0.0248	-0.0216
Std. Dev.	0.0117	0.0090	0.0098	0.0087
Skewness	0.5172	-0.0082	0.3625	-0.2795
Kurtosis	4.6817	3.4640	6.8858	4.2461
Jarque-Bera	33.2947	1.8409	133.4615	15.9307
	(0.0000)	*(0.3983)*	*(0.0000)*	*(0.0003)*
ADF t statistics				
Based on min. AIC	-4.45	-3.26	-6.20	-6.84
	(0.0003)	*(0.0181)*	*(0.0000)*	*(0.0000)*
Based on min. SIC	-15.80	-10.49	-6.20	-6.84
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*

Sources: (a) Quarterly GDP data of Australia, Canada, the UK, and the US for the period from 1959Q3 to 2010Q4 (n = 206 observations) are obtained from dXtime database. (b) *p*-values are given in parenthesis.

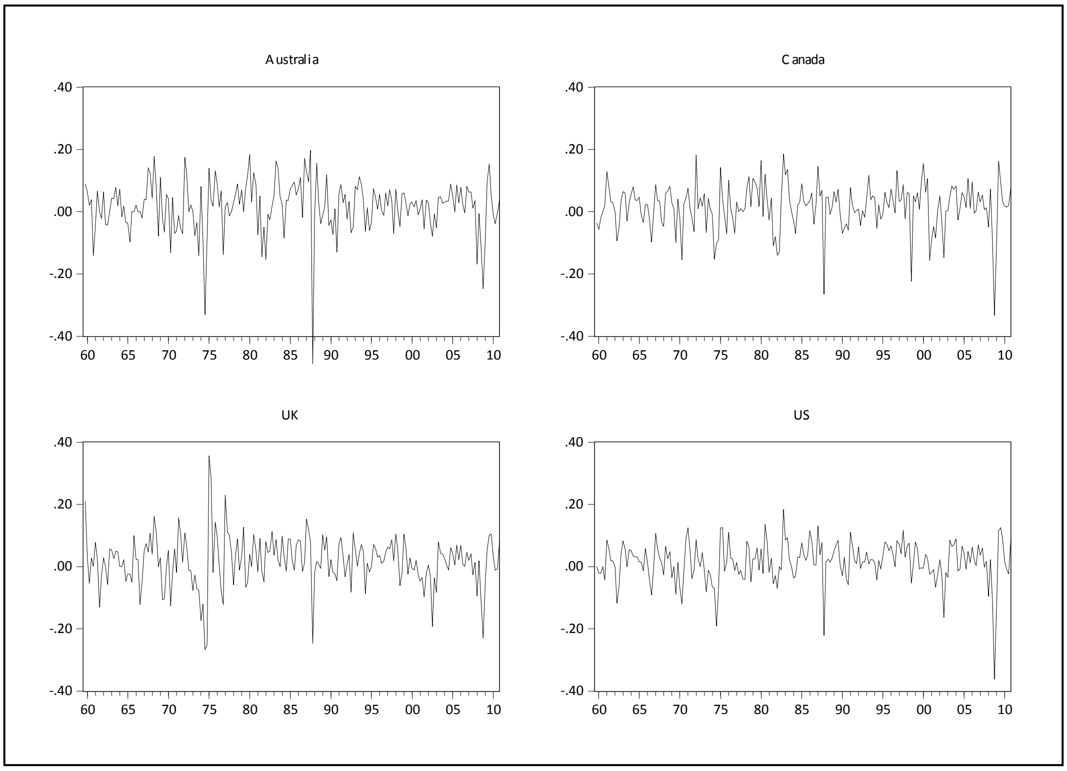

Figure 6. 1 Quarterly Stock Returns from 1959Q3 to 2010Q4

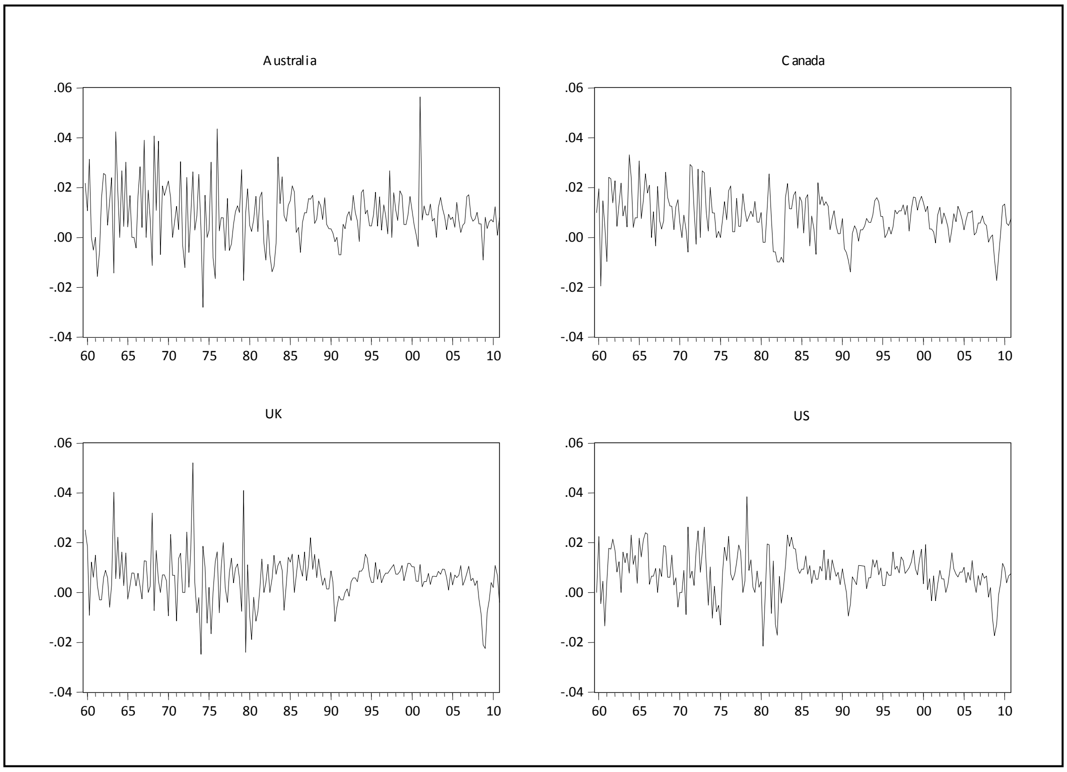

Figure 6. 2 Quarterly GDP Growth Rates from 1959Q3 to 2010Q4

6.4 Empirical Results

The analysis in this section focuses on three main aspects: (1) the mean spillovers across stock returns and GDP growth rates; (2) overall influence from major financial and economic crises during the sample period on each of the stock return series and the GDP growth series; and (3) the nature of volatility spillovers across stock markets and GDP growth rates of different countries. There are eight series in the sample and four lags for each series and for each mean equation, this makes the number of parameters to be estimated 33 for a single equation and 264 parameters (8*33) for all eight equations. Therefore, the present empirical study first, incorporates the influence from highly correlated lags of all series to the mean equation of individual series. Then, the general-to-specific methodology is used to omit insignificant variables of each series in equation (6.1). To analyse volatility and covolatility dynamics, the DBEKK(1,1) specification is adopted for this study as discussed in equations (6.2).

Table 6.2 reports the estimated results from the mean equation. The six main findings on mean spillovers across eight series are as follows: First, the own-mean spillovers of all eight series are statistically significant at 5 per cent level or below, providing strong evidence for the influence of own lagged effects on the current period stock returns and GDP growth rates. Second, country specific cross-mean spillovers from GDP growth to stock market returns exist only from the US growth to its stock market. Third, country specific cross-mean spillovers from stock market returns to GDP growth exist in both Australia and the US stock markets to corresponding GDP growth rates. Fourth, cross-country mean spillovers across stock markets present only from the US stock market to the

Australian stock market. Fifth, in contrast, cross-country mean spillovers across GDP growth rates exhibit from the US GDP growth to all three countries with the strongest impact for the Canadian economy (0.321). Sixth and the most important finding is cross-country mean spillovers from stock market to GDP growth or GDP growth to stock market does not significant across any country.

Table 6.2 Parameter Estimation for Mean Equations

$$r_{it} = \mu_{0i} + \sum_{k=1}^{8}\sum_{j=1}^{4} \mu_{kj} r_{kt-j} + \theta_i W_i + \varepsilon_{it}$$

$$r_{1t} = \underset{(4.32)}{0.019}^{***} + \underset{(1.55)}{0.081} r_{1t-3}{}^{*} + \underset{(1.78)}{0.114} r_{4t-2}{}^{*} - \underset{(-9.13)}{0.224} W_1{}^{***}$$

$$r_{2t} = \underset{(4.11)}{0.018}^{***} + \underset{(2.84)}{0.136} r_{2t-1}{}^{**} - \underset{(-3.20)}{0.191} W_2{}^{***}$$

$$r_{3t} = \underset{(4.08)}{0.017}^{***} + \underset{(4.35)}{0.190} r_{3t-1}{}^{***} - \underset{(-4.08)}{0.149} W_3{}^{***}$$

$$r_{4t} = \underset{(5.06)}{0.020}^{***} + \underset{(4.61)}{0.246} r_{4t-1}{}^{***} - \underset{(-2.39)}{0.687} r_{8t-1}{}^{**} - \underset{(-10.35)}{0.170} W_4{}^{***}$$

$$r_{5t} = \underset{(9.63)}{0.009}^{***} + \underset{(-1.74)}{0.010} r_{1t-4}{}^{*} - \underset{(-2.33)}{0.130} r_{5t-4}{}^{**} + \underset{(-1.89)}{0.144} r_{8t-3}{}^{*} - \underset{(-9.73)}{0.031} W_5{}^{***}$$

$$r_{6t} = \underset{(6.62)}{0.004}^{***} + \underset{(3.19)}{0.156} r_{6t-1}{}^{***} + \underset{(6.19)}{0.321} r_{8t-1}{}^{***} - \underset{(-2.04)}{0.005} W_6{}^{**}$$

$$r_{7t} = \underset{(5.26)}{0.004}^{***} + \underset{(1.82)}{0.099} r_{7t-2}{}^{*} + \underset{(1.93)}{0.141} r_{8t-1}{}^{**} - \underset{(-6.98)}{0.024} W_7{}^{***}$$

$$r_{8t} = \underset{(8.37)}{0.005}^{***} + \underset{(4.52)}{0.034} r_{4t-1}{}^{***} + \underset{(5.07)}{0.240} r_{8t-2}{}^{***} - \underset{(-7.50)}{0.020} W_8{}^{***}$$

Note: (a) r_1 for Australian stock returns, r_2 for Canadian stock returns, r_3 for the UK stock returns, r_4 for the US stock returns, r_5 for Australian GDP growth, r_6 for Canadian GDP growth, r_7 for the UK GDP growth, and r_8 for the US GDP growth. (b) *t*-ratios are given in parenthesis. (c)*** indicates statistical significance at 1 per cent level, ** indicates statistical significance at the 5 per cent level and * indicates statistical significance at the 10 per cent level.

On the whole, these findings can be interpreted to suggest that events in the US economy and its stock market can predominantly influence the Australian economy as well as the Australian stock market. In addition, the above findings indicate that the US economic growth and the stock market have a strong relationship with each other. This could be a reason that although the US did not enter into major recessions, it has experienced a slowdown in economic growth following most of the financial and stock market crashes in the past. The above results also provide evidence on regional economic integration within the North American region. However, it appears that this regional influence is from the US to smaller economies.

Table 6.3 reports the estimated ARCH and GARCH coefficients of the variance and covariance equations of the DBEKK(1,1) model. First, estimate the diagonal elements of *A* and *B* matrixes and due to the quadratic form of the parameters, the Wald test is then performed to obtain the ARCH and GARCH effects on each of the variance and covariance equations (6.3) and (6.4).

The estimated results reveal that statistically significant squared own-volatility shocks exist for all eight series except for the Australian and Canadian GDP growth series. These past-squared volatility shocks are generally higher in stock markets than in GDP growth series suggesting that unanticipated own shocks are more persistent in stock markets than in economic growth. The estimated covolatility shocks (cross-product of innovations) across stock markets are all positive and significant. This result indicates that similar to past-squared shocks in individual stock markets, lagged cross-product of innovations between each of the two stock markets can increase the corresponding future covolatility. Furthermore, the covolatility shocks between stock markets and GDP growth rates are also positive and significant. However, it is noted that the covolatility shocks between the Canadian GDP growth and other stock markets are insignificant. Similarly, the covolatility across GDP growth rates is also positive and significant except for the covolatility shocks between the Canadian GDP growth and GDP growth rates of other countries. These positive and significant covolatility shocks across series suggests that unanticipated shocks in any country can adversely impact on the global stability by increasing the volatility spillovers across stock markets as well as economic growth. Of major importance is this adverse influence is stronger from stock market to other stock markets, then to economic growth.

Unlike the squared own-volatility shocks (ARCH effect), the past own-volatility spillovers (GARCH effect) in the conditional variance equations for all eight series are positive and statistically significant at the 1 per cent level. These own-volatility spillovers effects in both the stock markets and the GDP growth are the strongest for Canada (0.99 for both series) showing the strongest impact on their own future volatility compared to the other series. In this perspective, one can argue that the Canadian stock market and GDP growth is the most volatile series. The estimated nonzero coefficients for covolatility spillovers across all these eight series are also positive and significant at 1 per cent level, providing further evidence for high volatility spillovers persistence across all these eight series. The country specific covolatility between stock market and GDP growth indicate that Canada (0.99) has the strongest impact on its future covolatility while Australia (0.97) has the lowest impact on its future covolatility.

Table 6.3 Wald Test Results for Parameters of the Variance and Covariance Equations

$$h_{iit} = c_{ii} + a_{ii}^2 \varepsilon_{it-1}^2 + b_{ii}^2 h_{iit-1}$$

$$h_{ijt} = c_{ij} + a_{ii} a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ii} b_{jj} h_{ijt-1}$$

$$h_{11t} = a_{11} a_{11} \varepsilon_{1t-1}^2 + b_{11} b_{11} h_{11t-1} = \underset{(12.10)}{0.047}\, \varepsilon_{1t-1}^{2\;***} + \underset{(7539.85)}{0.949}\, h_{11}^{***}$$

$$h_{12_4 t} = a_{11} a_{22} \varepsilon_{1t-1} \varepsilon_{2t-1} + b_{11} b_{22} h_{12t-1} = \underset{(9.35)}{0.022}\, \varepsilon_{1t-1} \varepsilon_{2t-1}^{***} + \underset{(22785.25)}{0.968}\, h_{11}^{***}$$

$$h_{22t} = a_{22} a_{22} \varepsilon_{2t-1}^2 + b_{22} b_{22} h_{22t-1} = \underset{(3.61)}{0.010}\, \varepsilon_{2t-1}^{2\;*} + \underset{(41216.62)}{0.989}\, h_{22}^{***}$$

$$h_{13t} = a_{11} a_{33} \varepsilon_{1t-1} \varepsilon_{3t-1} + b_{11} b_{33} h_{13t-1} = \underset{(9.35)}{0.022}\, \varepsilon_{1t-1} \varepsilon_{3t-1}^{***} + \underset{(18354.54)}{0.959}\, h_{13}^{***}$$

$$h_{23t} = a_{22} a_{33} \varepsilon_{2t-1} \varepsilon_{3t-1} + b_{22} b_{33} h_{23t-1} = \underset{(8.31)}{0.015}\, \varepsilon_{2t-1} \varepsilon_{3t-1}^{***} + \underset{(38999.60)}{0.979}\, h_{23}^{***}$$

$$h_{33t} = a_{33} a_{33} \varepsilon_{3t-1}^2 + b_{33} b_{33} h_{33t-1} = \underset{(10.27)}{0.023}\, \varepsilon_{3t-1}^{2\;***} + \underset{(17378.12)}{0.970}\, h_{33}^{***}$$

$$h_{14t} = a_{11} a_{44} \varepsilon_{1t-1} \varepsilon_{4t-1} + b_{11} b_{44} h_{14t-1} = \underset{(12.45)}{0.031}\, \varepsilon_{1t-1} \varepsilon_{4t-1}^{***} + \underset{(17150.45)}{0.962}\, h_{14}^{***}$$

$$h_{24t} = a_{22} a_{44} \varepsilon_{2t-1} \varepsilon_{4t-1} + b_{22} b_{44} h_{24t-1} = \underset{(5.05)}{0.014}\, \varepsilon_{2t-1} \varepsilon_{4t-1}^{**} + \underset{(26627.24)}{0.982}\, h_{24}^{***}$$

$$h_{34t} = a_{33} a_{44} \varepsilon_{3t-1} \varepsilon_{4t-1} + b_{33} b_{44} h_{34t-1} = \underset{(10.86)}{0.022}\, \varepsilon_{3t-1} \varepsilon_{4t-1}^{***} + \underset{(25034.26)}{0.973}\, h_{34}^{***}$$

$$h_{44t} = a_{44} a_{44} \varepsilon_{4t-1}^2 + b_{44} b_{44} h_{44t-1} = \underset{(5.79)}{0.021}\, \varepsilon_{4t-1}^{2\;**} + \underset{(15784.29)}{0.976}\, h_{44}^{***}$$

$$h_{15t} = a_{11} a_{55} \varepsilon_{1t-1} \varepsilon_{5t-1} + b_{11} b_{55} h_{15t-1} = \underset{(6.04)}{0.018}\, \varepsilon_{1t-1} \varepsilon_{5t-1}^{**} + \underset{(24713.27)}{0.966}\, h_{15}^{***}$$

$$h_{25t} = a_{22} a_{55} \varepsilon_{2t-1} \varepsilon_{5t-1} + b_{22} b_{55} h_{25t-1} = \underset{(3.85)}{0.008}\, \varepsilon_{2t-1} \varepsilon_{5t-1}^{**} + \underset{(43587.80)}{0.986}\, h_{25}^{***}$$

$$h_{35t} = a_{33} a_{55} \varepsilon_{3t-1} \varepsilon_{5t-1} + b_{33} b_{55} h_{35t-1} = \underset{(5.30)}{0.013}\, \varepsilon_{3t-1} \varepsilon_{5t-1}^{**} + \underset{(33242.54)}{0.977}\, h_{35}^{***}$$

$$h_{45t} = a_{44} a_{55} \varepsilon_{4t-1} \varepsilon_{5t-1} + b_{44} b_{55} h_{45t-1} = \underset{(4.44)}{0.012}\, \varepsilon_{4t-1} \varepsilon_{5t-1}^{**} + \underset{(29711.92)}{0.980}\, h_{45}^{***}$$

$$h_{55t} = a_{55} a_{55} \varepsilon_{5t-1}^2 + b_{55} b_{55} h_{55t-1} = \underset{(1.66)}{0.007}\, \varepsilon_{5t-1}^2 + \underset{(18425.96)}{0.984}\, h_{55}^{***}$$

$$h_{16t} = a_{11} a_{66} \varepsilon_{1t-1} \varepsilon_{6t-1} + b_{11} b_{66} h_{16t-1} = \underset{(1.08)}{0.007}\, \varepsilon_{1t-1} \varepsilon_{6t-1} + \underset{(26201.44)}{0.970}\, h_{16}^{***}$$

$$h_{26t} = a_{22} a_{66} \varepsilon_{2t-1} \varepsilon_{6t-1} + b_{22} b_{66} h_{26t-1} = \underset{(1.00)}{0.003}\, \varepsilon_{2t-1} \varepsilon_{6t-1} + \underset{(102443.70)}{0.990}\, h_{26}^{***}$$

$$h_{36t} = a_{33} a_{66} \varepsilon_{3t-1} \varepsilon_{6t-1} + b_{33} b_{66} h_{36t-1} = \underset{(1.08)}{0.005}\, \varepsilon_{3t-1} \varepsilon_{6t-1} + \underset{(54466.08)}{0.981}\, h_{36}^{***}$$

$$h_{46t} = a_{44} a_{66} \varepsilon_{4t-1} \varepsilon_{6t-1} + b_{44} b_{66} h_{46t-1} = \underset{(1.05)}{0.005}\, \varepsilon_{4t-1} \varepsilon_{6t-1} + \underset{(50819.22)}{0.984}\, h_{46}^{***}$$

$$h_{56t} = a_{55} a_{66} \varepsilon_{5t-1} \varepsilon_{6t-1} + b_{55} b_{66} h_{56t-1} = \underset{(0.90)}{0.003}\, \varepsilon_{5t-1} \varepsilon_{6t-1} + \underset{(56148.97)}{0.988}\, h_{56}^{***}$$

$$h_{66t} = a_{66} a_{66} \varepsilon_{6t-1}^2 + b_{66} b_{66} h_{66t-1} = \underset{(0.29)}{0.001}\, \varepsilon_{6t-1}^2 + \underset{(107628.50)}{0.992}\, h_{66}^{***}$$

Table 6.3. Continued.....

$$h_{17t} = a_{11}a_{77}\varepsilon_{1t-1}\varepsilon_{7t-1} + b_{11}b_{77}h_{17t-1} = \underset{(7.85)}{0.015}\,\varepsilon_{1t-1}\varepsilon_{7t-1}^{**} + \underset{(26049.67)}{0.967}\,h_{17}^{***}$$

$$h_{27t} = a_{22}a_{77}\varepsilon_{2t-1}\varepsilon_{7t-1} + b_{22}b_{77}h_{27t-1} = \underset{(5.17)}{0.007}\,\varepsilon_{2t-1}\varepsilon_{7t-1}^{**} + \underset{(86911.66)}{0.987}\,h_{27}^{***}$$

$$h_{37t} = a_{33}a_{77}\varepsilon_{3t-1}\varepsilon_{7t-1} + b_{33}b_{77}h_{37t-1} = \underset{(7.25)}{0.011}\,\varepsilon_{3t-1}\varepsilon_{7t-1}^{**} + \underset{(49501.05)}{0.978}\,h_{37}^{***}$$

$$h_{47t} = a_{44}a_{77}\varepsilon_{4t-1}\varepsilon_{7t-1} + b_{44}b_{77}h_{47t-1} = \underset{(5.87)}{0.010}\,\varepsilon_{4t-1}\varepsilon_{7t-1}^{**} + \underset{(46129.64)}{0.981}\,h_{47}^{***}$$

$$h_{57t} = a_{55}a_{77}\varepsilon_{5t-1}\varepsilon_{7t-1} + b_{55}b_{77}h_{57t-1} = \underset{(3.54)}{0.006}\,\varepsilon_{5t-1}\varepsilon_{7t-1}^{*} + \underset{(53831.29)}{0.985}\,h_{57}^{***}$$

$$h_{67t} = a_{66}a_{77}\varepsilon_{6t-1}\varepsilon_{7t-1} + b_{66}b_{77}h_{67t-1} = \underset{(0.96)}{0.002}\,\varepsilon_{6t-1}\varepsilon_{7t-1} + \underset{(134425.90)}{0.989}\,h_{67}^{***}$$

$$h_{77t} = a_{77}a_{77}\varepsilon_{7t-1}^{2} + b_{77}b_{77}h_{77t-1} = \underset{(2.61)}{0.005}\,\varepsilon_{7t-1}^{2\,*} + \underset{(61078.05)}{0.986}\,h_{77}^{***}$$

$$h_{18t} = a_{11}a_{88}\varepsilon_{1t-1}\varepsilon_{8t-1} + b_{11}b_{88}h_{18t-1} = \underset{(7.55)}{0.002}\,\varepsilon_{1t-1}\varepsilon_{8t-1}^{**} + \underset{(17373.74)}{0.964}\,h_{18}^{***}$$

$$h_{28t} = a_{22}a_{88}\varepsilon_{2t-1}\varepsilon_{8t-1} + b_{22}b_{88}h_{28t-1} = \underset{(5.65)}{0.011}\,\varepsilon_{2t-1}\varepsilon_{8t-1}^{**} + \underset{(38474.40)}{0.985}\,h_{28}^{***}$$

$$h_{38t} = a_{33}a_{88}\varepsilon_{3t-1}\varepsilon_{8t-1} + b_{33}b_{88}h_{38t-1} = \underset{(7.62)}{0.017}\,\varepsilon_{3t-1}\varepsilon_{8t-1}^{**} + \underset{(27909.48)}{0.976}\,h_{38}^{***}$$

$$h_{48t} = a_{44}a_{88}\varepsilon_{4t-1}\varepsilon_{8t-1} + b_{44}b_{88}h_{48t-1} = \underset{(6.58)}{0.016}\,\varepsilon_{4t-1}\varepsilon_{8t-1}^{**} + \underset{(26557.84)}{0.979}\,h_{48}^{***}$$

$$h_{58t} = a_{55}a_{88}\varepsilon_{5t-1}\varepsilon_{8t-1} + b_{55}b_{88}h_{58t-1} = \underset{(3.92)}{0.009}\,\varepsilon_{5t-1}\varepsilon_{8t-1}^{**} + \underset{(30996.06)}{0.983}\,h_{58}^{***}$$

$$h_{68t} = a_{66}a_{88}\varepsilon_{6t-1}\varepsilon_{8t-1} + b_{66}b_{88}h_{68t-1} = \underset{(0.85)}{0.004}\,\varepsilon_{6t-1}\varepsilon_{8t-1} + \underset{(37448.85)}{0.987}\,h_{68}^{***}$$

$$h_{78t} = a_{77}a_{88}\varepsilon_{7t-1}\varepsilon_{8t-1} + b_{66}b_{88}h_{68t-1} = \underset{(4.30)}{0.008}\,\varepsilon_{7t-1}\varepsilon_{8t-1}^{**} + \underset{(38614.03)}{0.984}\,h_{78}^{***}$$

$$h_{88t} = a_{88}a_{88}\varepsilon_{8t-1}^{2} + b_{88}b_{88}h_{88t-1} = \underset{(2.77)}{0.013}\,\varepsilon_{8t-1}^{2\,*} + \underset{(13908.21)}{0.981}\,h_{88}^{***}$$

Note: (a) Chi-square values are given in parenthesis. (b)*** indicates statistical significance at the 1 per cent level, ** indicates statistical significance at the 5 per cent level and * indicates statistical significance at the 10 per cent level.

According to the second order moment estimates, lagged covolatility between stock market and the GDP growth have a strong relationship with each other. Some plausible explanations for this relationship are: (1) as Kose *et al.* (2003) explained, if consumers with a substantial amount of stock market investment in from different countries could induce a decline in demand for consumption and investment goods when stock markets are turning down thereby influence the output fluctuations; (2) Schwert (1989b, 1990a) claimed that financial leveraging can increase the volatility of leveraged stocks during economic recession and operating leverage can stimulate the value of firms more sensitive to economic conditions of a country. Therefore, as Karolyi (2001) argued if there are considerable number of stocks that are cross-listed across major stock markets can influence the economy as well as stock markets of other countries; and (3) according to Schwert (1990a), technological advancement can increase the information flow across different countries providing investors to access and response quickly to those new information.

Finally, to validate the findings using the DBEKK(1,1) model, we have performed diagnostic tests on standardised residuals of each series and the results are presented in Table 6.4. The estimated results from the Ljung-Box Q-statistics for the standardised residuals of eight series generated from the DBEKK(1,1) model support the null hypothesis of no autocorrelations at any conventional level. According to the ADF test results, all four standardized residual series are stationary.

Table 6.4 Diagnostic Tests on the Standardized Residuals
Panel A: **Standardized Residuals of Stock Market Return Series**

	Australia		Canada		UK		US	
ADF *t* statistics								
Based on min. AIC	-8.28		-12.39		-12.98		-7.96	
Based on min. SIC	-12.39		-12.39		-12.98		-7.96	
Ljung-Box test statistics for standardized residuals								
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Q(1)	3.82	0.05	3.44	0.06	1.22	0.27	0.24	0.62
Q(2)	7.44	0.02	3.49	0.17	2.26	0.32	11.29	0.00
Q(3)	7.55	0.06	6.94	0.07	2.26	0.52	11.57	0.01
Q(4)	8.22	0.08	7.77	0.10	2.27	0.69	12.01	0.02
Q(5)	11.38	0.04	8.70	0.12	4.32	0.51	12.15	0.03
Q(6)	11.68	0.07	8.73	0.19	4.42	0.62	12.91	0.05
Q(7)	15.93	0.03	8.76	0.27	4.52	0.72	12.92	0.07
Q(8)	15.94	0.04	10.02	0.26	4.68	0.79	13.19	0.11
Q(9)	16.29	0.06	10.05	0.35	6.79	0.66	14.75	0.10
Q(10)	17.78	0.06	10.50	0.40	6.80	0.75	15.77	0.11
Q(11)	18.38	0.07	13.44	0.27	7.51	0.76	15.96	0.14
Q(12)	18.38	0.11	13.44	0.34	7.85	0.80	16.20	0.18
Q(13)	23.75	0.03	14.61	0.33	8.75	0.79	19.19	0.12
Q(14)	23.89	0.05	14.63	0.40	9.01	0.83	19.45	0.15
Q(15)	24.15	0.06	14.75	0.47	10.84	0.76	19.47	0.19
Q(16)	24.24	0.08	17.75	0.34	11.08	0.80	20.87	0.18
Q(17)	24.25	0.11	19.01	0.33	11.29	0.84	20.94	0.23
Q(18)	24.43	0.14	19.01	0.39	11.29	0.88	21.14	0.27
Q(19)	24.59	0.17	23.26	0.23	13.79	0.80	22.64	0.25
Q(20)	27.30	0.13	23.33	0.27	17.02	0.65	23.38	0.27
Q(21)	29.32	0.11	24.49	0.27	17.02	0.71	24.69	0.26
Q(22)	29.51	0.13	24.82	0.31	18.24	0.69	28.45	0.16
Q(23)	29.67	0.16	26.15	0.29	18.24	0.74	29.22	0.17
Q(24)	29.70	0.20	26.32	0.34	18.32	0.79	29.61	0.20

Note: Q(n) is the n^{th} lag Ljung-Box test statistics.

***Panel B:* Standardized Residuals of GDP Growth Series**

	Australia		Canada		UK		US	
ADF *t* statistics								
Based on min. AIC	-15.35		-14.70		-7.37		-13.77	
Based on min. SIC	-15.35		-14.70		-13.54		-13.77	
Ljung-Box test statistics for standardized residuals								
	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value	Statistic	*p*-value
Q(1)	1.45	0.23	0.38	0.54	0.14	0.71	0.18	0.67
Q(2)	1.80	0.41	0.43	0.81	1.69	0.43	0.35	0.84
Q(3)	2.48	0.48	0.92	0.82	4.90	0.18	0.90	0.83
Q(4)	4.47	0.35	1.65	0.80	5.05	0.28	1.36	0.85
Q(5)	7.88	0.16	2.44	0.79	5.34	0.38	1.66	0.89
Q(6)	8.24	0.22	3.03	0.81	6.33	0.39	1.74	0.94
Q(7)	8.62	0.28	3.60	0.82	8.87	0.26	4.66	0.70
Q(8)	12.60	0.13	5.09	0.75	11.72	0.16	5.10	0.75
Q(9)	14.40	0.11	6.72	0.67	14.30	0.11	5.65	0.78
Q(10)	15.16	0.13	11.36	0.33	15.23	0.12	5.76	0.84
Q(11)	15.21	0.17	11.62	0.39	16.47	0.13	5.96	0.88
Q(12)	15.49	0.22	11.64	0.48	16.55	0.17	8.20	0.77
Q(13)	16.12	0.24	14.90	0.31	16.56	0.22	10.10	0.69
Q(14)	16.23	0.30	15.85	0.32	16.66	0.28	10.42	0.73
Q(15)	16.77	0.33	16.63	0.34	16.79	0.33	10.43	0.79
Q(16)	16.79	0.40	21.25	0.17	16.83	0.40	10.60	0.83
Q(17)	19.24	0.32	21.43	0.21	16.84	0.47	10.68	0.87
Q(18)	25.65	0.11	21.57	0.25	18.50	0.42	10.82	0.90
Q(19)	26.30	0.12	21.86	0.29	18.63	0.48	10.88	0.93
Q(20)	26.62	0.15	22.70	0.30	18.71	0.54	12.72	0.89
Q(21)	28.86	0.12	24.51	0.27	18.78	0.60	13.74	0.88
Q(22)	29.50	0.13	27.41	0.20	19.01	0.65	14.04	0.90
Q(23)	29.55	0.16	27.68	0.23	19.19	0.69	14.74	0.90
Q(24)	29.66	0.20	27.74	0.27	22.15	0.57	16.10	0.88

Note: Q(n) is the nth lag Ljung-Box test statistics.

6.5 Summary and Conclusion

This chapter has used quarterly data of both stock market returns and GDP growth rates of Australia, Canada, the UK and the US for the period from 1959:Q3 to 2010:Q4 to examine volatility dynamics across stock returns and GDP growth rates of these four countries. The present study therefore, employed DBEKK(1,1) specification and the estimated model passes the standard diagnostic tests.

According to the estimated results, the significant own-mean spillovers effects exist in all eight series indicating lagged influence from past stock returns and GDP growth to current period returns and growth rates. More importantly, the

Australian stock returns are directly impacted from lagged US stock returns while the US stock returns are impacted from both lagged US stock returns and GDP growth rates. In addition, the Australian GDP growth is directly impacted from lagged Australian stock returns, growth rates, and lagged US growth rates. Therefore, these findings can be suggested that the slowdown in the US economy initially impacted more strongly upon the US stock market and the Australian economic growth subsequently upon the Australian stock market. However, downturn in the US financial sector directly impacted on the Australian stock market.

Based on the magnitudes of covolatility spillovers across stock markets are generally higher than the covolatility spillovers across GDP growth series. This indicates that stock markets are more volatile than GDP growth rates. In addition, there is a high degree of volatility persistence in individual series as well as between stock returns and GDP growth series across these four countries. However, positive and significant covolatility shocks across these series suggest that decrease in stock returns or economic growth in these countries could have adverse influence on the global economic stability by increasing volatility of stock markets and GDP growth.

In terms of own-volatility and covolatility spillovers within and across all eight series are positive and statistically significant providing an evidence on the relationship among covolatility across stock market and the GDP growth series from different countries. The present study, therefore, suggest three possible explanations for this relationship. First, agreeing with Kose *et al.* (2003), the present study also suggest if consumers with a large amount of stock market investment from different countries could influence the output growth through the demand for consumption and investment goods when stock markets are trading downward. Second, Schwert (1989b, 1990a) suggested financial leveraging can increase the volatility of leveraged stocks during economic recession stimulate the value of firms more sensitive to economic conditions of a country. Therefore, supporting the Karolyi's (2001) argument the current study also propose that if a considerable number of cross-listed stocks across major stock markets can influence the economy as well as stock market in different countries. Finally, as Schwert (1990a) explain, technological advancement can provide investors easy and fast access to new information from stock markets and economies of other countries thereby, investors can response to their portfolio diversified across different countries quickly.

To sum up, the identification of covolatility relationship across stock market and the GDP growth series from different countries would be important for both investors as well as macroeconomist. For investors, it is highly unlikely to benefit from investing their fund across only these four stock markets because the findings from this empirical analysis confirmed that there exists a high-degree of time-varying covolatility across these four markets. Levine (1996) explained that increasing the ability to trade securities can increase the long-term economic growth. Therefore, macroeconomist and policy makers can take policy actions to reduce obstacles such as tax, legal, and regulatory barriers to stock market development for facilitating investment and promoting capital allocation efficiently.

CHAPTER SEVEN

SUMMARY AND CONCLUSION

7.1 Introduction

The current thesis has conducted an empirical investigation on the stock market volatility of Australia and several integrated international stock markets namely Canada, Singapore, the UK, and the US. An exhaustive review of literature has identified that although asymmetry of volatility effects, financial crises, and GDP growth are significant factors affecting volatility transmission across international stock markets, no study has fully investigated these issues in Australian context. Therefore, this study has employed various MGARCH models to evaluate the impact from each of these three factors on the time-varying volatility and its spillovers across Australian stock markets and other integrated stock markets.

First, the present thesis captured the extent to which negative shocks in each stock markets influence the volatility itself and the volatility of other markets using the asymmetric DVECH model and weekly stock market data. Second, this study evaluated varying volatility implications within and across different stock markets during the 1997-98 Asian financial crisis and the 2008-09 GFC periods employing the DVECH model augmented with two dummy variables. Finally, the current thesis investigated any possible volatility transmission of stock returns and GDP growth rates across different countries employing the DBEKK model for quarterly data.

This chapter, therefore, summarizes the findings from previous chapters under the three main themes listed above. In particular, this final chapter is organized in the following way. Section 7.2 summarises the study and the main findings from the previous chapters followed by policy implications based on the empirical findings in Section 7.3. Section 7.4 are highlighted the specific contributions made in this study. Section 7.5 outlines some limitations of this study along with several suggestions for future research.

7.2 Summary of Major Findings

Starting with an overview of this thesis in Chapter 1, a review of literature on the Australian stock market and its volatility was presented in Chapter 2. More specifically, the purpose of Chapter 2 was to examine the early work on the Australian stock market and its volatility in the wake of international stock market integration. As to asymmetric of volatility effects, financial crises, and GDP growth rates, no evidence was found in the past regarding the extent negative shocks arising from other international stock markets influence the volatility of the Australian stock market, evaluating the varying volatility and covolatility implications between the Australian stock market and international stock markets during the 1997-98 Asian and the recent 2008-09 GFC crises, and finally examining any possible volatility interaction across stock market returns and GDP growth rates.

Chapter 3, therefore, focused on the recent development of econometric techniques to investigate the variance and covariance matrix of multiple financial time series. Due to the nature of financial time series and for the purpose of analysing the first and the second order moment properties of multiple time series, Chapter 3 evaluated theoretical framework of various MGARCH models. The three main MGARCH models have been employed in the literature are the VECH, the BEKK, and the CCC models. It has also reviewed the empirical implementation of these models with parameter estimation methods and diagnostic tests for analysing asymmetry dynamics in stock market volatility transmission, stock market volatility transmissions during financial crises periods, and the relationship between the volatility of macroeconomic variables and the stock market. Although, these models have some empirical implementation issues such as high parameterization and the positive definite of variance and covariance matrix, they are still admissible with some restrictions to analyse volatility dynamics within and across two or more series.

Chapter 4 adopted the DVECH(1,1) model with dummy series introduced by Glosten *et al.* (1993) for univariate models to capture asymmetry of volatility effects that may exist in the weekly stock market data of Australia, Singapore, the UK, and the US. The estimated results indicated that negative shocks in each market play a more important role in increasing both volatility and covolatilities than positive shocks. The lowest coefficient for asymmetric impact in the covariance equation is between Australia and Singapore, while the highest figure occurs between the UK and the US. In similarity, the lowest correlation coefficient is between Australia and Singapore whereas it is the highest between the UK and the US. This suggests that negative shocks in highly correlated stock markets can increase time-varying covolatility thereby involve higher investment risk more than positive or negative shocks in any other stock markets.

Chapter 5 examined the varying volatility implications across Australian, Singapore, the UK, and the US stock markets during 1997-98 Asian financial crisis and 2008-09 GFC periods using the DVECH(1,1) model augmented with two dummy variables. The empirical results evidenced that both the Asian financial crisis and the GFC influenced own-volatility indicating similarities of both crises. In contrast, significant cross-volatility spillovers across all four stock markets exist during the recent GFC period only. In addition, this cross market volatility shock during the recent GFC is the greatest from the US market to other markets indicating that the geographical location is not the only reason for this dissimilarity. It is also suggested that being the largest stock market in the world could have the strongest influence on other stock markets.

Lastly, Chapter 6 explored the effect of economic growth on stock market volatility transmission mechanism. This chapter used quarterly data of stock market and GDP growth rates from four Anglo-Saxon countries for the DBEKK(1,1) model. In terms of first order moment, for all eight series own lagged effects are more important than cross-series lagged effect on increasing mean spillovers within each series. In Australian context, cross-country mean spillovers across stock markets and GDP growth rates exhibit only from the US. However, no significant evidence found on the cross-country mean spillovers from stock market to GDP growth or GDP growth to stock market across any country. In terms of own-volatility shocks, except for the Australian and Canadian GDP growth, all other six series indicated statistically significant squared lagged effect from own-volatility shocks towards future volatility. The estimated covolatility shocks across stock markets, covolatility shocks between stock markets and GDP growth rates and the covolatility shocks across GDP growth rates are all positive and significant being the only exception for the Canadian GDP growth rates. In contrast, both own-volatility spillovers and covolatility spillovers (GARCH effect) are positive and statistically significant within and across all series evaluated. These positive and significant ARCH and GARCH effect across series suggests that unanticipated shocks in any country can adversely impact on the global financial and economic stability by increasing the covolatility spillovers across stock markets as well as GDP growth. Of major importance is this adverse influence is stronger from stock market to other stock markets, then to economic growth.

7.3 Policy Implications

There are a number of important policy implications arising from the empirical results of the present thesis. Those key policy implications from Chapters 4, 5 and 6 are as follows. The empirical findings in Chapter 4 revealed that: (1) the negative shocks in each of the individual stock market can increase time-varying volatility more than positive shocks; and (2) the negative shocks in highly correlated stock markets can increase time-varying covolatility more than positive or negative shocks on any other stock markets. Therefore, as Kroner and Ng (1998) and Shamsuddin and Kim (2003) suggested, based on a statistical judgment, an investor will be highly unlikely to benefit from diversifying their financial portfolio by acquiring stocks only from these individual markets and diversifying their investments across stock markets of Australia, Singapore, the

UK, and the US only. The reason is a high degree of time-varying covolatility amongst these highly correlated markets can involve higher investment risks.

The results from Chapter 5 provided an insight into similarities and dissimilarities of both the 1997-98 Asian crisis and the 2008-09 GFC on influencing stock market returns, volatility and covolatility within and across different stock markets. In terms of the first order moments, both the 1997-98 Asian crisis and the 2008-09 GFC did not significantly influence the mean returns with the only exception being the Singapore returns during 1997-98 Asian crisis period. According to the second moments, both crises indicated similarities in own-volatility spillovers but differences in cross-volatility spillovers. In terms of own-volatility spillovers both crises influenced the own-volatility spillovers in all four markets. On the other hand, the significant cross-volatility spillovers existed across all four markets during the recent GFC period only. This cross-volatility spillover is the strongest from the US market to other markets. Although it seems that over-leveraging is possible common factor for own-volatility spillovers in all four markets during both crises, the geographical locations were not the only reason for this dissimilarity. In addition to the geographical locations, being the world's leading stock market (Sabri, 2002) and the recent GFC emerged with the collapse of financial markets in the US would have the greatest influence on the volatility of other markets. In contrast, the Asian crisis originated with the collapse of Thai-baht indicated a significant role on cross-volatility spillovers in stock markets within the Asian region. Then, the results from Chapter 5 revealed that although there were similarities in both crises due to dissimilarities the influence from these two financial crises could make significant differences on volatility transmission. These findings will be benefitted for better understanding of systematic financial-sector risk in the wake of information flow during global and regional financial turmoils.

In Chapter 6, the current thesis evaluated the effects from economic growth on international stock market volatility. In terms of cross-country mean return spillovers, no strong evidence found on the relationship between stock market returns and GDP growth rates. However, cross-country mean return spillovers across stock markets indicated that the Australian stock market returns directly impact from lagged US stock market returns. In similar, cross-country mean return spillovers across GDP growth rates indicated that the Australian GDP growth directly impact from lagged US GDP growth rates. Therefore, it can be suggested that a downturn in the US stock market directly impacted on the Australian stock market while a slowdown in the US economy adversely influence the Australian economic growth. The results from Chapter 6 also evidenced that the US economy initially influenced the US stock market and them impacted on the Australian stock market.

The estimated results from the second order moments, the covolatility between stock markets and the GDP growth were statistically significant. A substantial amount of international stock market investment across different countries; financial and operating leverage with a considerable number of stocks that are cross-listed across major stock markets; and the information flow across countries with the technological advancement could be some reasons for this relationship. Therefore, policy makers and macroeconomists may take appropriate policy actions to reduce the risks from stock market to increase economic growth while reducing barriers for stock market investment. This is because increasing the ability to trade securities can increase the long-term economic growth (Levine, 1996).

On the whole, the findings from the present thesis would be important for investors, policy makers as well as macroeconomist. or investors, it is highly unlikely to benefit investing their fund across highly correlated stock markets only because a high-degree of time-varying covolatility across highly correlated stock markets increases the investment risks. Based on our results, policy makers can pursue right policies to promote investment and economic growth efficiently by conducting reforms in the areas of taxation, legal and regulatory barriers.

7.4 Contributions of the Thesis

This thesis has made three significant contributions on the interplay between stock market returns and their volatility in a multi-country setting. First, this study examined the asymmetric volatility effect in the variance and covariance matrix of stock market returns of Australia, Singapore, the UK, and the US. After conducting a comprehensive review, no study has identified and quantified the asymmetry of volatility effect from international stock markets towards the Australian stock market. The results from the present study confirmed that the negative shocks can increase the time-varying volatility and the negative shocks in highly correlated stock markets can increase time-varying covolatility more than positive shocks.

Second, this study has explored varying volatility implication from the 1997-98 Asian crisis and the 2008-09 GFC providing shed important light into how similarities and dissimilarities of these financial crises on the interaction across stock market returns and volatilities of Australia, Singapore, the UK, and the US. The present study, therefore adopted the DVECH model augmented with two dummy variables. The current study thus becomes the first study by using MGARCH model to identify and quantify whether varying volatility implications from international stock markets to the Australian stock market, during different financial crises periods are same or not.

Finally, contributing the debate on the nature of the relationship between stock market and the output growth across different countries, the current thesis employed a sophisticated MGARCH model for stock markets and GDP growth rates of Australia, Canada, the UK, and the US. Therefore, in a multi-country setting, this study is the first study to conduct a simultaneous analysis capturing the first and the second order moments within and across stock market and the GDP growth rates of various countries.

7.5 Limitations of the Study and Suggestions for Future Studies

Several limitations of the present study suggest some avenues for further research to deepen the understanding of volatility transmission across international stock markets. The empirical analysis in Chapters 4 used average weekly stock market indexes of Australia, Singapore, the UK and the US to evaluate the asymmetry of volatility effects within and across these stock markets. These data were obtained from http://www.au.finance.yahoo.com and they were not in a single currency. Thus, the analysis in Chapter 4 was based on the assumption that investors can insure against the currency risk. Therefore, it did not capture how asymmetry influence of stock returns was correlated with the exchange rates. Further study is therefore, required to identify whether the results would differ if returns were in a common currency.

In Chapter 5, the current thesis captured varying volatility implication during the 1997-98 Asian financial crisis and the recent GFC periods using the DVECH model augmented with two dummy variables. These dummy variables were defined as *1* for the period starting from the first week of July 1997 to the last week of September 1998 to capture the Asian financial crisis *0* for other periods. In similar, the dummy variable for the more recent GFC used *1* from the third week of September 2008 until the last week of June 2009 and *0* otherwise. Therefore, these two dummy variables represent common impact time-line for all four stock markets (Australia, Singapore, the UK, and the US). This makes the present analysis impossible to capture the extent of country specific influence from each stock market towards the variance and covariance across other stock markets during these financial crises periods. Further research is required to provide shed some light into this issue.

Chapter 6 of this thesis devoted to capture the relationship between volatility and covolatility across stock markets and GDP growth of Australia, Canada, the UK, and the US using DBEKK model. Furthermore, the empirical analysis in Chapter 6 captured overall effects from several financial and economic crises on stock market returns and GDP growth rates. The overall influence from these crises was appeared to be the strongest on stock market returns than economic growth rate. It is therefore, important to carry out further analysis capturing whether the results from individual crises would be the same or not.

Furthermore, the current study did not incorporate the influence from these financial and economic crises on the volatility and covolatility within and across these series. Further research is also required to on this issue.

Finally, providing some insight on the relationship between the covolatility of stock market and the GDP growth across Australia, Canada, the UK, and the US the last empirical analysis of this thesis has suggested three plausible explanations. They are: (1) A substantial amount of international stock market investment across different countries; (2) financial and operating leverage with a considerable number of stocks that are cross-listed across major stock markets; and (3) the information flow across countries with the technological advancement. In addition to these possible explanations, one can argue that other financial and macroeconomic factors such as exchange rates between two countries, inflation rate of one country could play an important role on the relationship between the stock markets and GDP growth across different countries. Therefore, further research by identifying the extent of influence from these factors can facilitate policy makers to take efficient policy actions during global financial and economic turmoils.

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Appendix

To decide the length of D_{97} dummy variable the present thesis uses two methods based on: (1) the highest stock market returns; and (2) the lowest standard deviation. The details of these two methods are as follows.

Sensitivity Analysis Method 1

Similar to Kearns and Pagan (1993) and Schwert (2011), based on stock market returns during 1997-98 Asian financial crisis period defined in Chapter 5 (i.e. starting from the first week of July 1997 to the last week of September 1998), first, this study list the largest weekly returns for each country. The results indicated that the first highest return during this period is in the first week of November 1997 for both Australia and the US. For Singapore this was the fourth largest while for the UK this indicated as the third largest. Since the present thesis mainly focus on the Australian stock market, in the first sensitivity analysis use last week of October 1997 as the ending period of the 1997-98 Asian crisis. Therefore, the length of D_{97} dummy variable in the first sensitivity analysis the present analysis uses from the first week of July 1997 to the last week of October 1997 and all the other variables remains as the previous analysis. The results based on this method are given in Table A1.1.

Table A1.1 Sensitivity Analysis Based on the Highest Return

Parameter	Australia	Singapore	UK	US
μ_{0i}	0.001968***	0.001664**	0.001736***	0.002074***
	(4.95)	*(3.01)*	*(3.68)*	*(4.74)*
δ_{97i}	-0.006767	-0.009917	-0.000383	-0.000894
	(-0.96)	*(-0.88)*	*(-0.05)*	*(-0.14)*
δ_{08i}	-0.000844	0.002343	-0.002112	-0.001458
	(-0.16)	*(0.31)*	*(-0.36)*	*(-0.17)*
μ_{i1}	0.138341***	-0.020180	-0.025878	-0.088645**
	(3.54)	*(-0.41)*	*(-0.62)*	*(-2.14)*
μ_{i2}	-0.011343	0.174590***	-0.024294	0.010978
	(-0.54)	*(5.29)*	*(-1.11)*	*(0.50)*
μ_{i3}	0.030811	0.116873**	0.160120***	0.015809
	(0.93)	*(2.24)*	*(3.56)*	*(0.38)*
μ_{i4}	0.136664***	0.130772**	0.092077**	0.213872***
	(3.66)	*(2.46)*	*(2.12)*	*(4.74)*
c_{i1}	0.000009***			
	(3.32)			
c_{i2}	0.000008***	0.000015***		
	(4.22)	*(3.37)*		
c_{i3}	0.000006***	0.000009***	0.000011***	
	(4.16)	*(4.48)*	*(3.88)*	
c_{i4}	0.000006***	0.000008***	0.000009***	0.000011***
	(4.58)	*(4.44)*	*(4.68)*	*(4.42)*
g_{97i1}	0.000049			
	(1.25)			
g_{97i2}	0.000061	0.000133		
	(0.98)	*(0.95)*		
g_{97i3}	0.000030	0.000030	0.000032	
	(1.27)	*(0.49)*	*(0.76)*	
g_{97i4}	0.000032	0.000025	0.000017	0.000027
	(1.39)	*(0.35)*	*(0.57)*	*(0.64)*
g_{08i1}	0.000092*			
	(1.70)			
g_{08i2}	0.000131**	0.000187*		
	(1.93)	*(1.75)*		
g_{08i3}	0.000090*	0.000129**	0.000089*	
	(1.86)	*(2.01)*	*(1.71)*	
g_{08i4}	0.000125**	0.000179**	0.000124**	0.000171**
	(2.13)	*(2.18)*	*(2.05)*	*(2.36)*
a_{i1}	0.069791***			
	(4.79)			
a_{i2}	0.056480***	0.109078***		
	(4.73)	*(5.56)*		
a_{i3}	0.054871***	0.054853***	0.067957***	
	(5.33)	*(5.13)*	*(6.02)*	
a_{i4}	0.059809***	0.061419***	0.065703***	0.077517***
	(5.80)	*(5.46)*	*(6.47)*	*(5.80)*
b_{i1}	0.878300***			
	(38.62)			
b_{i2}	0.863490***	0.848930***		
	(49.49)	*(36.20)*		
b_{i3}	0.880873***	0.866020***	0.883454***	
	(53.18)	*(55.12)*	*(49.13)*	
b_{i4}	0.871492***	0.856797***	0.874046***	0.864738***
	(54.48)	*(53.68)*	*(55.98)*	*(44.70)*

Notes: (a) i = 1 for Australia, i = 2 for Singapore, i = 3 for the UK and i = 4 for the US. (b) *** indicates that statistically significant at 1 per cent level, ** indicates that statistically significant at 5 per cent level and * indicates that statistically significant at 10 per cent level. (c) *t*-ratios are given in parentheses.

Sensitivity Analysis Method 2

As Schwert (1989b, 2011) measured monthly standard deviations using daily data, the present study calculated the monthly standard deviations using weekly stock market returns during 1997-98 Asian financial crisis period and listed the smallest standard deviations to the largest for each country. The results indicated that the smallest standard deviation was in May 1998 for the UK and the US. This was the second smallest value for Australia. Therefore, the length of D_{97} dummy variable in the second sensitivity analysis uses from the first week of July 1997 to the last week of April 1998 and all the other variables remains as the previous analysis. The results based on this method are presented in Table A1.2.

Table A1.2 Sensitivity Analysis Based on the Lowest Standard Deviation

Parameter	Australia	Singapore	UK	US
μ_{0i}	0.001876***	0.001492**	0.001412**	0.001691***
	(4.73)	*(2.71)*	*(2.99)*	*(3.87)*
δ_{97i}	-0.007843*	-0.009812*	-0.000127	0.002947
	(-1.71)	*(-1.64)*	*(-0.03)*	*(0.47)*
δ_{08i}	-0.002705	0.001317	-0.004609	-0.006229
	(-0.46)	*(0.19)*	*(-0.77)*	*(-0.79)*
μ_{i1}	0.135668***	-0.012955	-0.014028	-0.085059**
	(3.48)	*(-0.26)*	*(-0.33)*	*(-2.02)*
μ_{i2}	-0.009603	0.175300***	-0.043702*	-0.000797
	(-0.44)	*(5.23)*	*(-1.90)*	*(-0.03)*
μ_{i3}	0.045741	0.111005**	0.176338***	0.019372
	(1.38)	*(2.13)*	*(3.94)*	*(0.46)*
μ_{i4}	0.132179***	0.137008**	0.077929*	0.211214***
	(3.54)	*(2.58)*	*(1.80)*	*(4.60)*
c_{i1}	0.000009***			
	(3.36)			
c_{i2}	0.000008***	0.000015***		
	(4.14)	*(3.35)*		
c_{i3}	0.000007***	0.000009***	0.000012***	
	(4.23)	*(4.48)*	*(3.86)*	
c_{i4}	0.000007***	0.000009***	0.000009***	0.000012***
	(4.59)	*(4.52)*	*(4.70)*	*(4.49)*
g_{97i1}	0.000043*			
	(1.62)			
g_{97i2}	0.000049	0.000078		
	(1.05)	*(1.00)*		
g_{97i3}	0.000026*	0.000018	0.000029	
	(1.81)	*(0.57)*	*(1.48)*	
g_{97i4}	0.000052	0.000059	0.000015	0.000099
	(1.42)	*(0.76)*	*(0.44)*	*(0.30)*
g_{08i1}	0.000136*			
	(1.89)			
g_{08i2}	0.000161**	0.000191*		
	(1.95)	*(1.65)*		
g_{08i3}	0.000123**	0.000147**	0.000112*	
	(2.00)	*(1.98)*	*(1.78)*	
g_{08i4}	0.000165**	0.000195**	0.000150**	0.000199**
	(2.19)	*(2.09)*	*(2.06)*	*(2.28)*
a_{i1}	0.064828***			
	(4.80)			
a_{i2}	0.054624***	0.113056***		
	(4.68)	*(5.68)*		
a_{i3}	0.050783***	0.055660***	0.068899***	
	(5.20)	*(5.06)*	*(6.00)*	
a_{i4}	0.060028***	0.062189***	0.069687***	0.088228***
	(5.59)	*(5.14)*	*(6.38)*	*(5.71)*
b_{i1}	0.880657***			
	(40.34)			
b_{i2}	0.863235***	0.846157***		
	(50.80)	*(36.39)*		
b_{i3}	0.881020***	0.863591***	0.881383***	
	(54.67)	*(55.13)*	*(47.96)*	
b_{i4}	0.866341***	0.849202***	0.866698***	0.852258***
	(53.31)	*(53.46)*	*(54.21)*	*(42.79)*

Notes: (a) i = 1 for Australia, i = 2 for Singapore, i = 3 for the UK and i = 4 for the US. (b) *** indicates that statistically significant at 1 per cent level, ** indicates that statistically significant at 5 per cent level and * indicates that statistically significant at 10 per cent level. (c) *t*-ratios are given in parentheses.