ESSAYS ON INTERNATIONAL TRANSMISSION OF SHOCKS

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(MSc in Economics)

A THESIS SUBMITTED

FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

DEPARTMENT OF ECONOMICS
NATIONAL UNIVERSITY OF SINGAPORE

2010

ACKNOWLEDGEMENTS

I am largely indebted to Prof. Tilak Abeysinghe, who has been such as a great advisor and mentor to me. His encouragements and ceaseless support have been critical in motivating me to forge ahead with this prolonged task. He has also read my dissertation carefully and provided many useful comments. I am always feeling lucky to be supervised by him.

I would also like to thank for Prof. Parimal Bag, Dr Hee Joon Hang, Prof. Albert Tsui, Prof. Anthony Chin, Dr Lee Soo Ann and Mr Chan Kok Hoe for giving me useful comments at my pre-submission presentation. Last but not least, I would like to thank Ms. Nicky and Sagi and other faculty staff in the Department of Economics, NUS, for their kind help during the course of my study.

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SUMMARY

This thesis is composed of three essays on international transmission of shocks. The first chapter examines international linkages of a set of key macroeconomic variables in a multi-variable multi-country setting. A multi-variable cointegrating structural VAR model is constructed using trade matrices developed by Abeysinghe (1999) and Abeysinghe and Forbes (2001). We include in the model a set of key macroeconomic variables, namely real GDP, CPI, equity price, interest rate and exchange rate for ASEAN countries and their major trading partners. Structural impulse responses are derived to study various international transmission effects of different economic and financial shocks. Interestingly, we find the international transmission of real shocks such as GDP shock is not as strong as what is expected in some literature. In most cases, foreign shocks will be swamped by the shock originated within that country. On the other hand, financial shocks can be transmitted to other countries rapidly and the impacts are quite substantial. The finding also confirms that the US plays a prominent role in the international propagation of shocks to ASEAN countries, while the Philippines are the most isolated country in the region.

The second chapter investigates how different types of structural oil shocks affect the GDP growth of different economies directly and indirectly. We first decompose oil-price changes into three structural shocks, namely oil-supply shocks, aggregate demand shocks and oil-specific demand shocks by modifying Kilian (2007)'s structural VAR model. We then incorporate the structural oil shocks into Abeysinghe

(2001)'s structural VARX model to examine the direct and indirect effects of various oil shocks on the GDP growth. A set of 12 economies including ASEAN-4 (Indonesia, Malaysia, the Philippines and Thailand), NIE-4 (South Korea, Hong Kong, Singapore, Taiwan), China, Japan, USA, and the rest of OECD as one country are selected for study. It is found that different structural oil shocks have strikingly different effects on the GDP growth, and the indirect effect of an oil shock through trading partners plays a very important role in the economic growth.

In the third chapter, we propose a new testing methodology for contagion under the consideration of the relationship between time-varying volatility and correlation. To capture the volatility effects on correlations, we develop a GARCH-in-DCC model based on Engle's (2002) dynamic conditional correlation (DCC) model. Empirical results show that the model is able to better capture the dynamics in conditional correlation. The LR test confirms that the GARCH-in-DCC model performs better than standard DCC model in most cases. We then modify the proposed GARCH-in-DCC model and apply it to test for contagion during the 1997 Hong Kong stock market crash. Our testing results are compared with the results from traditional test.

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Chapter 1

Measuring International Transmission of Economic and Financial Shocks: A Cointegrating SVAR Model

1.1 Introduction:

In a world characterized by increasing economic integration and international interdependence, disturbances that originated in one economy are readily transmitted to other economies. It is often said that "When America sneezes, Europe catches a cold". However, the nature of this interdependence and the transmission mechanisms through which the shocks spread are still not well known. It is striking that one strand of literature focuses only on transmission of real shocks and international business cycle linkages among major economies, whereas the other strand concentrates on international spillover in financial markets. So far, the role of cross-sector and indirect transmission is still largely neglected. For example, the transmission of real shocks does not take place only through trade, but also as importantly through the impact of real shocks on financial sectors with subsequent spillover effects on real sectors. It therefore seems important to model the transmission of shocks not merely within an individual sector, but also to account for direct and indirect cross-sector spillovers.

To understand how different types of shocks are transmitted, it is crucial to identify the origin of shocks. Without properly identifying the origin of shocks, causes and effects cannot be distinguished correctly. Rigobon and Sack (2003) show that the signs of correlation between short-run interest rate and equity markets depend on the nature of the underlying shocks. If interest rate shocks prevail, there is a negative correlation between short-term interest rate and equity market, because higher interest rates adversely affect the profitability of corporations and thus depress the equity prices. On the other hand, if shocks originate from equity markets, there is a positive correlation between interest rate and equity price, as a rise in equity prices is likely to trigger an increase in interest rates due to an endogenous reaction of monetary policy. This example suggests that the exact transmission effects depend both on the nature of shocks and the precise channels of propagation. It also raises another potential problem in econometrics called endogeneity, which makes the identification of the transmission mechanism inherently difficult.

The objective of this chapter is to measure the various transmission effects of different shocks by properly addressing the endogeneity issue through a cointegrating structural VAR model. By including a number of core macro-economic variables such as real GDP, CPI, equity price, interest rate and exchange rate in a multi-country setting, the model is able to account for cross-section interaction and second and even third round effects of the shocks. In a traditional unrestricted VAR(p) model covering N countries with K domestic variables in each country, there will be $N \times K \times P$ unknown parameters in each equation to be estimated, excluding the intercept and any exogenous variables. For example, if we consider a VAR(2) model with 8 countries and $k=5$, there will be at least 80 unknown parameters in each equation and totally 3200 unknown parameters in the system. This over parameterization problem is easily solved in this structural VAR model where we use trade matrices to implicitly impose restrictions on parameters. The idea was first developed by Abeysinghe (1999) and Abeysinghe and Forbes (2001) in which they study output multiplier effects of shocks, and was later extended by Pesaran *et al.* (2004). Our model looks close to the latter, but we make one important improvement in this paper. Unlike Pesaran *et al.* (2004)'s, we start with specifying the structural-form instead of reduced-form country specific model, and then recover the structural shocks and finally derive the complete model in structural form. Meanwhile, the structural impulse response functions are calculated for each variable such that each of the shocks can be interpreted in a meaningful way, whereas Pesaran *et al.* (2004) only presented the generalized impulse response function.

The rest of the chapter is organized in the following way. Section 1.2 briefly reviews the literature on international transmission of shocks. Section 1.3 presents the details of the model and Section 1.4 describes the estimation procedure. Section 1.5 derives structural impulse response functions and explains empirical findings of the chapter. Finally, Section 1.6 offers some concluding remarks.

1.2 A Review on the International Transmission of Shocks

In this section, we first review some theories regarding the international transmission of shocks that have been developed in the literature. Second, we summarize the empirical works that are available.

1.2.1 Theories

In general, theories concerning the transmission of shocks can be divided into two broad categories, namely, the crisis contingent and non-crisis contingent theories. The first class of literature studies the transmission of shocks that are particularly related to the existence of crises. Within these frameworks, the role of the rational and irrational behavior of investors is emphasized for transmitting the shocks from one market to another. The second class of theories studies the transmission mechanism both in the periods of crises and tranquility. These theories are based on the role of fundamental linkages such as trade and capital flows.

Crises contingent theories were developed after a series of severe crises in the 1990s. These studies attempt to explain financial crises based on investors' behavior. At least three mechanisms have been identified to be responsible for the transmission of shocks under this category. The first one is multiple equilibria. Under this framework, a crisis in one country could coordinate investors' expectation on another country, shifting them from a good to a bad equilibrium and thereby sell of another country's assets regardless of the fundamentals. Formal multiple equilibria models are developed by Massson (1998), Mullainathan (1998) and Jeanne (1997). This branch of theories can explain not only the bunching of crises, but also why speculative attacks occur in economies that appear to be fundamentally sound.

The second transmission mechanism under crisis contingent theories is endogenous liquidity. Valdes (1998) analyzes the impact of a liquidity shock on the portfolio reallocation across emerging markets. He shows that the liquidity shocks caused by a crisis could force investors to reallocate their portfolio and sell securities in other countries in order to raise cash in anticipation of greater redemption or to satisfy margin call. Therefore, a crisis in one country increases the degree of rationing and, in turn, causes the collapse of prices in other markets. Calvo (1999) also shows that liquidity issue is an important component of the contagion in the Russian crisis.

The third transmission channel under crisis contingent theories is herding. Bikhchandani, Hirshleifer and Welch (1992) model the fragility of mass behavior as a consequence of informational cascades. An information cascade happens when it is optimal for an investor, after observing the behavior of others ahead of him, to follow their behavior without considering their own information. Calvo and Mendoza (2000) and Agenor and Aizenmar (1998) also show that in the presence of asymmetry in information and fixed cost of gathering country-specific information, less informed investors may find it is an advantage to follow the investment patterns of informed investors, even when investors are rational. The herding behavior generates excess volatility in financial markets and shocks are readily propagated across all asset classes.

In conclusion, these theories have two important empirical implications. First, the effects on the transmission mechanism are short lived. Second, the theories imply that shock transmission in periods of crises is different from the periods of tranquility. Particularly, these models suggest an increase in the international propagation of shocks during crisis, which is also called contagion in most literature.

The second class of theories studies the transmission of shocks resulting from the normal interdependence among different economies. These theories suggest that shocks, whether of a global or local nature, are transmitted across countries because of their real and financial linkages. Gerlach and Smets (1995) first develop a model with respect to bilateral trade, and show a speculative attack against one currency may accelerate the "warranted" collapse of a second parity. Corsetti, Roubin and Tille (1998) use micro-foundations to extend this idea to competition in a third market. They argue that devaluation in a crises country reduces the export competitiveness of other countries that compete in the same third market, and a game of competitive devaluation can cause larger currency depreciation than are required by the initial deterioration in fundamentals. Regarding financial linkages, Shimokawa ands Steven (2003) analyze the transmission of shocks through international bank lending. They develop a portfolio selection model which explicitly includes the economic condition of the bank's home country. Cem Karayalcin (1996) studies the role of stock markets in the international transmission of supply shocks. He builds a two-country one-good model where inter-temporal optimization behavior of agents endogenously determine the rate of capital accumulation and the current account, and shows that the presence of stock market with adjustment costs provides new insights concerning the transmission channels. The main implication of these theories is that the methods by which shocks are transmitted are similar during both tranquil and crisis periods.

1.2.2 Empirical Literature

In line with the theories, empirical literature on the international transmission of shocks can be divided into two broad classes.

The first class of literature investigates the transmission mechanism as independent of crises. In other words, it investigates the fundamental linkages and interdependences across countries both in the periods of crises and tranquility. The first line of enquiry under this category is related to the investigation of business cycles transmission and the determinants of business cycle synchronization. Back in 1927, Wesley C. Mitchell found a positive correlation of business cycles across countries and detected that this correlation was growing over time. More recently, a large empirical literature has emerged to investigate the international business cycle transmission. Hickman and Filatov (1983) worked with Project LINK, an international econometric model to calculate cross-income elasticity and measure the trade effects of the fluctuations of certain OECD countries upon others. Swoboda (1983), Baxter and Stockman (1989) and Backus and Kehoe (1992) worked on correlation and principal components analysis to study the changing patterns of output co-movements over different time periods. Magill *et al.* (1981), Dellas (1986) and Gerlach (1988) worked with spectral analysis. Buridge and Harrison (1985), Kirchgassner and Wolters (1987), Hutchison and Walsh (1992) and Selover (1999) employed VAR models and impulse response/variance decomposition functions. Ahmed *et al.* (1993) used structural VAR models and cointegration tests to investigate business cycle transmission between the US and a five-nation OECD aggregate. Abeysinghe (1999) developed a structural VAR framework to measure how a shock to one country can affect output in other countries (see Abeysinghe and Forbes, 2001). It first incorporates trade linkages into the model and shows that indirect effect through third party trade plays an important role in explaining output fluctuation.

Another line of the literature under the first category is related to the investigation of financial transmission and examines the co-movement in asset markets in terms of return or volatility. Most studies have so far concentrated only on individual asset prices, mostly on equity market. For instance, the empirical work by Hamao, Masulis and Ng (1990), King, Sentana and Wadhwani (1994) and Lin, Engle and Ito (1994), based on reduced-form GARCH models, detect some spillovers from the US to the Japanese and UK equity markets, both for returns and in particular for conditional volatility. Also Becker, Finnerty and Friedman (1995) find spillovers between the US and UK stock markets and show that this is in part due to US news and information. For foreign exchange markets, the seminal work by Engle, Ito and Lin (1990) finds strong spillovers in foreign exchange markets, both in conditional first and second moments. More recently, Andersen, Bollerslev, Diebold and Vega (2003) and

Ehrmann and Fratzscher (2005b) show that in particular US macroeconomic news have a significant effect on the US dollar – euro exchange rate. For bond markets Goldberg and Leonard (2003) and Ehrmann and Fratzscher (2005a) find that not only macroeconomic news is an important driving force behind changes in bond yields, but also there are significant international bond market linkages between the United States and the euro area. The results of Ehrmann and Fratzscher (2005a) indicate that spillovers are stronger from the US to the euro-area market, but that spillovers in the opposite direction are present since the introduction of the euro in 1999.

Other studies around the issue of international financial co-movements attempt to explain the determinants of financial spillovers through real and financial linkages of the underlying economies. Heston and Rouwenhorst (1994), Griffin and Karolyi (1998) and Brooks and del Negro (2002) argue that mainly country-specific shocks, and to a lesser extent industry-specific and global shocks, can explain international equity returns. Eichengreen and Rose (1999) and Glick and Rose (1999) find that the degree of bilateral trade rather than country-specific fundamentals alone play an important role for understanding financial co-movements during crisis episodes. Focusing on mature economies, Forbes and Chinn (2003) find that the country-specific factors have become somewhat less important and bilateral trade and financial linkages significantly are nowadays more important factors for explaining international spillovers across equity and bond markets.

The second class of literature examines the transmission mechanism as dependent of the crises. The main hypothesis is to test whether or not the transmission has significantly increased during the periods of crises. This hypothesis is commonly referred as contagion in the literature [1]. In general, at least four different methodologies have been adopted in the empirical work, namely, the analysis of cross-market correlation coefficient, GARCH framework, VAR approach and probability model.

Tests based on cross-market correlation coefficient are straightforward and early studies on the contagion mainly focused on this approach. These tests measure the correlation in returns between two markets during pre-crisis period and crisis period, and then test for a significant increase in this coefficient. If the correlation coefficient increases significantly, it indicates that transmission mechanism between the two markets increased after a shock and contagion happened. In the first major paper on this subject, King and Wadhwani (1990) test for an increase in cross-market correlations between the US, UK and Japan and find that correlations increase significantly after the US stock market crash. There are many other similar tests conducted and almost all of them come to the same conclusion: contagion occurred during the period under investigation. However, Boyer, Gibson and Loretan (1999), Loretan and English (2000) and Forbes and Rigobon (2002) point out the test of parameter stability based on correlation coefficient are biased upward because crises

[1] See Stijn Claessens, Rudiger Dornbusch, Yung Chul Park (2000), Kristin Forbes and Roberto Rigobon (2002)

periods are typically characterized by an increase in volatility. When the heteroskedasticity is taken into consideration, most of the findings in the earlier literature are reversed. Correlation analysis also suffers from the endogeneity bias as it assumes that contagion spread from one country to another with the source country being exegonous. To deal with this issue, Rigobon (2003) proposes a limited-information procedure which uses the heteroscedastic feature of high frequency financial data to construct an instrumental variable. In this context, a test for contagion is transformed to test for the validity of the constructed instrument.

The second approach to test for contagion is to use a GARCH framework to estimate the variance-covariance transmission across countries. Chou et al. (1994) and Hamao et al. (1990) use this procedure and find evidence of significant spillover effects across markets after the 1987 US stock market crash. Edward (1998) estimates an augmented GARCH model and shows that there were significant spillovers from Mexico bond markets to Argentina bond markets after the Mexican peso crises. But his test does not indicate the transmission of volatility changed during the crises. Fang and Miller (2002) use a bivariate GARCH model to examine the effects of country depreciation on equity market returns in East Asia and find evidence of contagion.

The third approach of contagion tests is based on a VAR approach developed by Favero and Giavazzi (2002). It uses a VAR to control for the interdependence between asset returns, and use the heteroscedasticity and nonnormalities of the residuals from that VAR to identify unexpected shocks that may be transmitted across countries and hence considered contagion. This methodology first estimates a simple VAR and considers the distribution of the residuals. Residuals that contribute to non-normality and heteroskedasticity in the data are identified with a set of dummies associated with "unusual" residuals for each country, indicating crises observations. The test for contagion is then given as testing the significance of those dummies in explaining the returns for the alternative assets in a structural model.

The last approach used to test for contagion is the probability-based framework. By choosing an appropriate threshold value, it constructs a crisis indicator which classifies asset return into crisis and non-crisis periods. Eichengreen, Rose and Wyplosz (1996) estimate the probit models to test how a crisis in one country affects the probability of a crisis occurring in other countries. By examining the ERM countries in 1992 and 1993, they find that the probability of a country suffering a speculative attack increases when another country in the ERM is under attack. Kaminsky and Reinhart (1999) estimate the conditional probability that a crisis will occur in a given country and find that this probability increases when more crises are occurring in other countries.

A key characteristic of the literature on shock transmissions is that it has evolved along distinct paths, one focusing on normal international interdependence and others on financial contagion during crises. The present analysis follows the first strand of literature. Though contagion effects can be investigated by extending the framework built in the following, it is beyond the scope of this paper due to the size of model and limited data.

1.3 The Model

The following cointegrating Structural VAR model is developed based on the work of Abeysinghe (see Abeysinghe and Forbes, 2001) and Pesaran, Schuermann and Weiner (2004).

Suppose there are N countries (or regions) in the global economy, indexed by i=1, 2,.., N. x_{it} is a $k \times 1$ vector, which denotes country-specific variables such as real GDP, inflation, interest rate and stock price in country i at time t. Given the general nature of interdependencies that exist in the world economy, it is clearly desirable that all the country-specific variables x_{it}, i =1, ..., N, are treated endogenously. For each country, we assume that country-specific variables are related to their own lags, the global economy variables measured as weighted averages of foreign country-specific variables, exogenously common global variables such as oil prices, country-specific dummies and a time trend. For simplicity, we use one lag in our specifications for each individual economy. The structural representation of this VAR(1) model is

$$a_i x_{it} = \delta_{i0} + \delta_{i1} t + \phi_i x_{it-1} + b_i x_{it}^* + c_i x_{it-1}^* + \gamma_i G_t + \lambda_i G_{t-1} + \theta_i D_{it} + \eta_{it} \qquad (3.1)$$

where a_i is a $k \times k$ matrix capturing contemporaneous relationship between x_{it}, x_{it}^* is a

$k^* \times 1$ vector of foreign variables specific to country i, the $k \times k^*$ matrices b_i and c_i capture the contemporaneous and lagged effects of foreign variables, G_t is an $m \times 1$ vector representing the observed global factors such as oil price and other commodity prices, D_{it} are country-specific dummy variables capturing major institutional and political events. Finally, η_{it} denotes the $k \times 1$ vector of serially and mutually uncorrelated structural innovations to country i. Specifically, it follows

$$\eta_{it} \sim IID(0, \Sigma_{ii}), \Sigma_{ii} = E(\eta_{it}\eta_{it}^{'}) = diag(\sigma_{11,i}^2, ..., \sigma_{kk,i}^2) \qquad (3.2)$$

Meanwhile, we allow the structural innovations to be correlated across countries. In particular, we assume that

$$\begin{aligned} \Sigma_{ij} &= E(\eta_{it}\eta_{js}^{'}) = diag(\sigma_{11,ij}^2, ..., \sigma_{kk,ij}^2) && \text{for t=s} \\ &=0 && \text{for } t \neq s \end{aligned}$$

We first rewrite (3.1) in the error-correction form

$$a_i \Delta x_{it} = \delta_{i0} + \delta_{i1} t + (\phi_i - a_i) x_{it-1} + (b_i + c_i) x_{it-1}^* + (\lambda_i + \gamma_i) G_{t-1} + b_i \Delta x_{it}^* + \gamma_i \Delta G_t + \theta_i D_{it} + \eta_{it} \qquad (3.3)$$

or in the form

$$a_i \Delta x_{it} = \delta_{i0} + \delta_{i1} t - \pi_i z_{it-1} + (\lambda_i + \gamma_i) G_{t-1} + b_i \Delta x_{it}^* + \gamma_i \Delta G_t + \theta_i D_{it} + \eta_{it} \qquad (3.3')$$

where $\pi_i = (-\phi_i + a_i, -b_i - c_i)$, $z_{it-1} = (x_{it-1}' \; x_{it-1}^{*}{}')'$. To avoid the problem of introducing quadratic trends in the variables when π_i is rank deficient, we impose restrictions on the trend coefficients, namely $\delta_{i1} = \pi_i \beta_i$. Under these restrictions, (3.3') becomes

$$a_i \Delta x_{it} = c_{i0} - \varphi_i v_{it-1} + b_i \Delta x_{it}^* + \gamma_i \Delta G_t + \theta_i D_{it} + \eta_{it}, \qquad (3.4)$$

where

$$c_{i0} = \delta_{i0} + \pi_i \beta_i ,$$

$$\varphi_i = (\pi_i, -\lambda_i - \gamma_i, -\pi_i \beta_i) ,$$

$$v_{it-1} = (z_{it-1}^{'}, G_{t-1}^{'}, t-1)' . \tag{3.5}$$

φ_i is a $k \times (k + k^* + m + 1)$ matrix and provide information on the long-run relationships that may exist among the variables in the model. In the case where all the variables z_{it} and G_t are I(1) and not cointegrated, then φ_i will be equal to zero and (3.4) reduces to a simple first differenced model. But as in general there may exist some inter-linkage between domestic variables and foreign variables as well as the domestic variables themselves, one would expect φ_i to be non-zero but rank deficient. The rank of φ_i identifies the number of long-run or cointegration relationships. These cointegration properties may arise from relationships like purchasing power parity (PPP) or uncovered interest parity (UIP) or other relationships that connect the domestic variables and foreign variables. If we assume

$$\text{Rank}(\varphi_i) = r_i < k, \tag{3.6}$$

we can write

$$\varphi_i = \alpha_i \beta_i^{'} , \tag{3.7}$$

where α_i is a k×r matrix with rank r and β_i is a $(k+k^*+m+1)$×r matrix describing the long-run relationships with rank r. Substituting (3.7) into (3.4) we obtain the reduced-form vector error-correction model for country i,

$$\Delta x_{it} = a_i^{-1} c_{i0} - a_i^{-1} \alpha_i \beta_i^{'} v_{it-1} + a_i^{-1} b_i \Delta x_{it}^{*} + a_i^{-1} \gamma_i \Delta G_t + a_i^{-1} \theta_i D_{it} + \varepsilon_{it} , \tag{3.8}$$

where $\varepsilon_{it} = a_i^{-1} \eta_{it}$ is k ×1 vector of reduced-form errors.

As we note, x_{it}^* is the weighted average of foreign country-specific variables, we can express it as

$$x_{it}^* = \sum_{j=1}^{N} w_{ij} x_{jt} , \quad \text{with } w_{ii} = 0 \tag{3.9}$$

where $w_{ij,}$ j=1,….N, could be used to capture the importance of country j for country i. For example, if $x_{it}=(y_{it}, \pi_{it}, r_{it,} s_{it})'$, which denotes real GDP, inflation rate, interest rate and stock price of country i, then foreign economic variables, x_{it}^*, are constructed as

$$x_{it}^*=(y_{it}^*, \pi_{it}^*, r_{it}^*, s_{it}^*)'$$

$$y_{it}^* = \sum_{j=1}^{N} w_{ij}^{\ y} y_{jt} , \qquad \pi_{it}^* = \sum_{j=1}^{N} w_{ij}^{\ \pi} \pi_{jt}$$

$$r_{it}^* = \sum_{j=1}^{N} w_{ij}^{\ r} r_{jt} , \qquad s_{it}^* = \sum_{j=1}^{N} w_{ij}^{\ s} s_{jt} \tag{3.10}$$

The weights w_{ij}^y, w_{ij}^{π}, w_{ij}^r and w_{ij}^s for country i could be based on export shares (namely the share of country j in the total export of country i) in the case of y_{it}^* and π_{it}^*, and based on capital flows in the case of stock price and interest rate, s_{it}^* and r_{it}^*. The weights could also be allowed to be time-varying so long as they are predetermined. This could be particularly important in the case of rapidly expanding emerging economies with their fast changing trade and financial relationship with the rest of world.

The N country-specific models in (3.8), together with the relations linking the foreign variables of the country-specific models to the variables in the rest of the global model in (3.10), provide a complete system. First, we rewrite (3.8) as

$$\begin{pmatrix} I_k & -a_i^{-1}b_i \end{pmatrix}\begin{pmatrix} \Delta x_{it} \\ \Delta x_{it}^{*} \end{pmatrix} = a_i^{-1}c_{i0} - a_i^{-1}\alpha_i\beta_i' v_{it-1} + a_i^{-1}\gamma_i\Delta G_t + a_i^{-1}\theta_i D_{it} + \varepsilon_{it}\,, \quad (3.11)$$

or further as

$$\begin{pmatrix} I_k & -a_i^{-1}b_i \end{pmatrix} W_i\Delta x_t = a_i^{-1}c_{i0} - a_i^{-1}\alpha_i\beta_i' v_{it-1} + a_i^{-1}\gamma_i\Delta G_t + a_i^{-1}\theta_i D_{it} + \varepsilon_{it}\,, \quad (3.11')$$

where W_i is a (k+k) ×(N×k) matrix, defined by the country specific weights, w_{ij}, and $x_t=(x_{1t}', x_{2t}',\ldots\ldots x_{Nt}')'$, is a (N×K)×1 vector which collects all endogenous variables in the model. Second, we stack all the individual country-specific models together and obtain the complete cointegrating VAR model in reduced form:

$$G_0\Delta x_t = c_0 - \alpha\beta' \begin{pmatrix} x_t \\ G_t \\ t-1 \end{pmatrix} + \gamma\Delta G_t + \theta D_t + \varepsilon_t\,, \quad (3.12)$$

where

$$G_0 = \begin{pmatrix} (I_k & -a_1^{-1}b_1)W_1 \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ (I_k & -a_N^{-1}b_N)W_N \end{pmatrix},\ c_0 = \begin{pmatrix} a_1^{-1}c_{10} \\ \ldots\ldots \\ a_N^{-1}c_{N0} \end{pmatrix},\ \alpha = \begin{pmatrix} a_1^{-1}\alpha_1 & & 0 \\ & \ddots & \\ 0 & & a_N^{-1}\alpha_N \end{pmatrix},\ \beta' = \begin{pmatrix} \beta_1'\tilde{w}_1 \\ \ldots\ldots \\ \beta_N'\tilde{w}_N \end{pmatrix},$$

$$\tilde{w}_i = \begin{pmatrix} w_i & 0 & 0 \\ 0 & I_m & 0 \\ 0 & 0 & 1 \end{pmatrix},\ \gamma = \begin{pmatrix} a_1^{-1}\gamma_1 \\ \ldots\ldots \\ a_N^{-1}\gamma_N \end{pmatrix},\ \theta = \begin{pmatrix} a_1^{-1}\theta_1 & & 0 \\ & \ddots & \\ 0 & & a_N^{-1}\theta_N \end{pmatrix},\ D_t = \begin{pmatrix} D_{1t} \\ \ldots\ldots \\ D_{Nt} \end{pmatrix}.$$

Finally, ε_t is the (N×K) ×1 vector of reduced-form errors of the complete model, where $\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \ldots \\ \varepsilon_{Nt} \end{pmatrix} = \begin{pmatrix} a_1^{-1}\eta_{1t} \\ \ldots\ldots \\ a_N^{-1}\eta_{Nt} \end{pmatrix} = A^{-1}\eta_t$, and $A^{-1} = \begin{pmatrix} a_1^{-1} & & 0 \\ & \ddots & \\ 0 & & a_N^{-1} \end{pmatrix}$.

After the country specific model in equation (3.8) is estimated country by country, reduced-form residuals $\hat{\varepsilon}_t$ can be collected and block diagonal matrix A can be further estimated. By pre-multiplying matrix A to equation (3.12), we will have the final structural VAR model.

It is worth illustrating the techniques in equation (3.11) by a simple example. Consider a model with three countries and two variables in each country, say real GDP and inflation rate. Using trade shares W^{T}_{ij} to construct the foreign variables for country 1, we have

$$\begin{pmatrix} x_{1t} \\ x_{1t}^{*} \end{pmatrix} = \begin{pmatrix} y_{1t} \\ \pi_{1t} \\ y_{1t}^{*} \\ \pi_{1t}^{*} \end{pmatrix} = \begin{pmatrix} y_{1t} \\ \pi_{1t} \\ w_{12}^{T} y_{2t} + w_{13}^{T} y_{3t} \\ w_{12}^{T} \pi_{2t} + w_{13}^{T} \pi_{3t} \end{pmatrix},$$

and then linking matrix for country 1 is

$$W_1 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & w_{12}^{T} & 0 & w_{13}^{T} & 0 \\ 0 & 0 & 0 & w_{12}^{T} & 0 & w_{13}^{T} \end{pmatrix}, \text{ with } x_t = \begin{pmatrix} y_{1t} \\ \pi_{1t} \\ y_{2t} \\ \pi_{2t} \\ y_{3t} \\ \pi_{3t} \end{pmatrix}.$$

Similarly, $W_2 = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ w_{21}^{T} & 0 & 0 & 0 & w_{23}^{T} & 0 \\ 0 & w_{21}^{T} & 0 & 0 & 0 & w_{23}^{T} \end{pmatrix}$, $W_3 = \begin{pmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ w_{31}^{T} & 0 & w_{32}^{T} & 0 & 0 & 0 \\ 0 & w_{31}^{T} & 0 & w_{32}^{T} & 0 & 0 \end{pmatrix}$

There are several advantages of this structural VAR model. First, note that in the above example, $G_0 = \begin{pmatrix} (I_2 \quad -a_1^{-1} b_1) W_1 \\ \dots\dots\dots\dots \\ (I_2 \quad -a_3^{-1} b_3) W_3 \end{pmatrix}$, is a 6×6 matrix, but there are only 12 unknown parameters. After we obtain the complete reduced-form VECM as in equation (3.12), the block diagonal matrix $\begin{pmatrix} a_1 & & 0 \\ & \ddots & \\ 0 & & a_N \end{pmatrix}$ has to be estimated and pre-multiplied to equation (3.12) in order to derive the underlining structural form VECM. This step would add another 6 parameters to be estimated after we make normalization for each equation. In total, we only need to estimate 18 parameters for matrix AG_0 in this over-identified model. As the number of countries increases, this structural VAR becomes more parsimonious as the unknown coefficients are more tightly controlled. Specifically, we only need to estimate NK×(2K-1) number of coefficients in NK×NK matrix AG_0. Second, the model is also flexible in taking account of the various cross-country transmission mechanisms. It can capture not only the direct impact but also the indirect effects through the interaction of different assets markets, which unlike many studies that only study the international transmission or spillover effect for one particular assets market; for example, if we consider the spillover effects of a positive shock in country i's stock market on other countries' stock markets. In the short run, country j would have the immediate positive spillovers from country i. But since country i will respond to the rise in stock market by increasing interest rate, which in turn will push up country j's interest rate by some time lag, and therefore would have a negative impact on country j's stock market. This model can easily capture all of these features.

1.4 Estimation

The structural cointegrating VAR applied in this chapter covers 5 ASEAN countries, Indonesia, Malaysia, Philippines, Singapore, Thailand and their major trading partners, Euro Area (EA), Japan and the US. The model is estimated over the period of 1980Q1-2004Q4. For each country, we include five domestic variables, namely real GDP (y_{it}), consumer price index (p_{it}), equity price (q_{it}), short-term interest rate (r_{it}) and exchange rate (x_{it}), where $y_{it,}$ $p_{it,}$ $q_{it,}$ x_{it} are defined in log. Since US dollar will be used as the numariare and its value in terms of other currencies is determined outside the US, exchange rate is excluded from the US model. For the Euro area, the domestic variables y_{it}, p_{it}, q_{it} r_{it} x_{it} are constructed by cross-section weighted averages over Germany, France, Italy, Spain, Netherlands and Belgium. Regarding the weights, we use purchasing power parity (ppp) weighted GDP figures.

1.4.1 Trade Matrix

The starting point for the empirical analysis is to construct foreign country-specific variables. For the weights, we decided to rely on trade matrices. The reasons are twofold. First, trade flows are a useful indicator of economic interdependence between countries, and indicate where to look for business cycle transmission. Forbes and Chinn (2004) in studying the determinants of global financial market linkages show that direct trade appears to be one of the most important determinants of cross-country linkages. Second, data on capital flows across countries such as FDI, international portfolio investment are not of high quality and tend to be rather volatile. In Table 1.1 we present trade flow matrices calculated for the period over 2000-2002. The top portion of the table displays the exports as a percentage of total exports. The second portion displays imports as a percentage of total imports. The countries along the left side of each table are the exporting countries, and the countries along the top of each table are the importing countries. The bottom portion displays trade as a percentage of total trade, where each row sums to 1.

Table 1.1: Trade Matrix (Average over 2000-2002)

Export Share									
Exporters\Importers	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	U.S.	**TOTAL**
EA		0.016	0.140	0.026	0.011	0.048	0.024	0.736	**1.000**
Indonesia	0.165		0.349	0.052	0.020	0.162	0.030	0.222	**1.000**
Japan	0.203	0.029		0.052	0.039	0.071	0.055	0.552	**1.000**
Malaysia	0.138	0.026	0.186		0.023	0.263	0.056	0.308	**1.000**
Philippines	0.178	0.006	0.217	0.060		0.097	0.044	0.397	**1.000**
Singapore	0.146	0.080	0.120	0.285	0.040		0.071	0.259	**1.000**
Thailand	0.168	0.035	0.240	0.066	0.028	0.134		0.330	**1.000**
U.S.	0.492	0.013	0.290	0.051	0.039	0.086	0.029		**1.000**

Import Share								
Exporters\Importers	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	U.S.
EA		0.136	0.195	0.086	0.082	0.124	0.129	0.408
Indonesia	0.035		0.101	0.036	0.031	0.086	0.034	0.025
Japan	0.257	0.310		0.215	0.354	0.224	0.371	0.378
Malaysia	0.048	0.074	0.087		0.057	0.225	0.103	0.057
Philippines	0.026	0.007	0.043	0.028		0.035	0.034	0.031
Singapore	0.063	0.291	0.071	0.403	0.124		0.162	0.060
Thailand	0.038	0.067	0.074	0.050	0.046	0.076		0.041
U.S.	0.533	0.115	0.428	0.181	0.307	0.231	0.167	
TOTAL	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Trade Share									
Countries	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	U.S.	**TOTAL**
EA		0.025	0.198	0.036	0.018	0.056	0.031	0.636	**1.000**
Indonesia	0.154		0.335	0.060	0.015	0.209	0.043	0.183	**1.000**
Japan	0.200	0.055		0.065	0.040	0.071	0.062	0.506	**1.000**
Malaysia	0.114	0.030	0.200		0.026	0.329	0.053	0.248	**1.000**
Philippines	0.131	0.018	0.284	0.059		0.110	0.045	0.353	**1.000**
Singapore	0.135	0.083	0.170	0.256	0.037		0.073	0.245	**1.000**
Thailand	0.150	0.034	0.299	0.083	0.031	0.147		0.256	**1.000**

U.S.	0.439	0.021	0.345	0.055	0.034	0.070	0.036	**1.000**

These matrices play a key role in linking up the individual country models and reveal the degree to which one country depends on the remaining countries. Within ASEAN, the largest relative trade flow takes place between Malaysia and Singapore. From the bottom portion of the table, we find that Malaysia and Singapore are the biggest trading partners for each other, with bilateral trade accounting for 32.9% and 25.6% of total trade respectively. Outside of ASEAN, the trade between ASEAN nations and Japan and the US are also quite notable. Japan is the biggest trading partner for Indonesia and Thailand, which accounts for 33.5% and 30% of total trade of these two countries, while the US is the biggest trading partner for Philippines which accounts for 35.3% of Philippines' total trade.

Since most trade linkage is demand driven, and, as in the trade repercussion model Dornbursh (1980) argued that business cycle transmissions are generally hypothesized to flow from the importing nation to the exporting nation, we use export share of total export as the weights for constructing foreign real GDP (y^*_{it}), instead of trade share of total trade. It is also natural to assume that inflation is generally transmitted from exporting country to importing country, therefore we use imports as a percentage of total imports as the weights for constructing foreign price level (p^*_{it}). For the rest foreign country-specific variables q^*_{it}, r^*_{it} and e^*_{it}, we use trade as a percentage of total trade as the weights.

1.4.2 Unit Root Test

The second step is to perform a unit root test to examine the integration properties of each individual series. Table 1.2 reports augmented Dicky-Fuller (ADF) statistics for the levels and first differences of the domestic variables, country specific foreign variables and oil price. For the variables such as real GDP, CPI, equity price and oil price, we include a constant and linear trend in the level regressions and only a constant in the case of first differences. For the interest rate and exchange rate, since linear trend is not visually detected when we plot the series, only a constant term is included in the case of both the levels and the differences.[2] The lag length employed in ADF test is selected by the Akaike Information Criterion(AIC). The results of these unit root tests are generally consistent with the findings in the existing literature. Almost all the variables are found to be I(1) except for the interest rate in the Philippines, Indonesia and Japan, which are found to be I(0).

Table 1.2. Augmented Dicky-Fuller Unit Root Tests

	Log`(GDP)		
	Levels	First differences	Order
Thailand	-0.862	-7.537	I(1)
Singapore	-1.311	-7.168	I(1)
Philippines	-1.279	-9.665	I(1)
Indonesia	-1.661	-6.472	I(1)
Malaysia	-1.373	-9.656	I(1)
Japan	-0.566	-8.422	I(1)
U.S.	-2.763	-5.325	I(1)
EA	-1.247	-7.985	I(1)
Thailand*	-1.286	-6.081	I(1)
Singapore*	-1.597	-4.801	I(1)
Philippines*	-1.185	-6.393	I(1)
Indonesia*	-0.984	-5.901	I(1)

[2] Including irrelevant regressors in the regression will reduce the power of the test to reject the null of a unit root.

Malaysia*	-1.234	-5.928	I(1)
Japan*	-1.922	-6.918	I(1)
US*	-0.599	-6.315	I(1)
EA*	-2.224	-6.987	I(1)

Log (CPI)			
	Levels	First differences	Order
Thailand	-0.995	-7.942	I(1)
Singapore	-2.538	-4.431	I(1)
Philippines	-1.602	-4.198	I(1)
Indonesia	-2.412	-5.496	I(1)
Malaysia	-2.169	-6.926	I(1)
Japan	-0.801	-3.167	I(1)
U.S.	-1.851	-6.214	I(1)
EA	-2.394	-3.497	I(1)
Thailand*	-1.853	-3.573	I(1)
Singapore*	-2.301	-4.841	I(1)
Philippines*	-1.817	-3.895	I(1)
Indonesia*	-1.854	-3.521	I(1)
Malaysia*	-1.853	-4.960	I(1)
Japan*	-2.743	-4.959	I(1)
US*	-1.400	-3.317	I(1)
EA*	-1.920	-6.114	I(1)

Log (equity price)			
	Levels	First differences	Order
Thailand	-2.232	-6.404	I(1)
Singapore	-3.317	-10.219	I(1)
Philippines	-1.035	-8.545	I(1)
Indonesia	-1.842	-9.248	I(1)
Malaysia	-2.799	-7.531	I(1)
Japan	-1.828	-6.656	I(1)
U.S.	-1.704	-7.422	I(1)
EA	-2.085	-6.843	I(1)
Thailand*	-1.376	-11.040	I(1)
Singapore*	-2.012	-7.449	I(1)
Philippines*	-2.119	-6.579	I(1)
Indonesia*	-2.219	-6.566	I(1)
Malaysia*	-2.309	-7.084	I(1)
Japan*	-1.924	-7.488	I(1)
US*	-1.968	-6.467	I(1)
EA*	-1.915	-6.827	I(1)

Table 1.2. Augmented Dicky-Fuller Unit Root Tests (Continued)

	Levels	First differences	Order
Interest Rate			
	Levels	First differences	Order
Thailand	-2.023	-9.459	I(1)
Singapore	-2.091	-9.674	I(1)
Philippines	-3.533	-11.777	I(0)
Indonesia	-3.735	-5.239	I(0)
Malaysia	-2.307	-7.784	I(1)
Japan	-3.511	-8.541	I(0)
U.S.	-1.673	-8.921	I(1)
EA	-1.124	-6.538	I(1)
Thailand*	-1.518	-8.210	I(1)
Singapore*	-1.533	-7.805	I(1)
Philippines*	-1.546	-8.452	I(1)
Indonesia*	-1.706	-8.241	I(1)
Malaysia*	-1.604	-8.582	I(1)
Japan*	-1.413	-8.392	I(1)
US*	-1.508	-7.613	I(1)
EA*	-1.573	-8.825	I(1)
Log (exchange rate)			
	Levels	First differences	Order
Thailand	-1.004	-6.666	I(1)
Singapore	-1.180	-8.982	I(1)
Philippines	-1.614	-5.728	I(1)
Indonesia	-0.810	-5.927	I(1)
Malaysia	-1.207	-6.486	I(1)
Japan	-1.468	-4.324	I(1)
EA	-2.395	-7.054	I(1)
Thailand*	-1.325	-7.917	I(1)
Singapore*	-1.490	-7.097	I(1)
Philippines*	-1.241	-7.883	I(1)
Indonesia*	-1.135	-7.939	I(1)
Malaysia*	-1.245	-8.183	I(1)
Japan*	-2.099	-7.267	I(1)
US*	-1.846	-7.674	I(1)
EA*	-1.670	-7.622	I(1)
Log (oil price)			
	Levels	First differences	Order
	-1.655	-8.145	I(1)

Note: Critical values at the 5% significance level with trend is -3.46, with intercept but no trend is –2.89

1.4.3. Estimation of Country-specific Vector Error-correction Model

The next step is to estimate country-specific Vector ECM model as set out in equation (3.8). First, we specify the variables to be included in each individual country model as follows. For all countries except the US, we include real GDP (y_{it}), CPI (p_{it}), equity price (q_{it}), interest rate (r_{it}) and exchange rate (x_{it}) as endogenous variables, and foreign real GDP (y^*_{it}), foreign CPI (p^*_{it}), foreign equity price (q^*_{it}), foreign interest rate (r^*_{it}) and oil price as weakly exogenous variables[3]. In the US model, we include y_{it}, p_{it}, q_{it}, r_{it} as endogenous variables. And given the size of the US economy and its importance for global economic interactions, no foreign country-specific variable is included as weakly exogenous variables except x^*_{it} and oil price.

Once the variables to be included in each country are determined, we proceed to select the order of the individual country co-integrating VARX (p_i, q_i) model. Here p_i denotes the lag of domestic variables and q_i denotes the lag of weakly exogenous foreign variables. Given the huge number of parameters to be estimated and limited data, we would set p_i and q_i equal to 2 for all countries. Of course, autocorrelation test will be performed to ascertain our order selection.

After the order is selected, cointegration test is then conducted for each individual country. Since we have weakly exogenous I(1) regressors in the error correction term, our test is different from the traditional Johansen cointegration test. Therefore, we will

[3] We treat the foreign-specific variables as weakly exogenously on the grounds that most economies (with the exception of the U.S.) are small relative to the size of the world economy.

adopt Johansen's trace and maximal eigenvalue statistics as set out in Pesaran, Shin & Smith's (2004) paper which accounts for weakly exogenous I(1) regressors in the cointegration term.[4] Table 1.3a and 1.3b report the trace and maximal eigenvalue statistics for each of the eight countries. In the test, we use unrestricted constants and restricted trend coefficients for each individual country error correction model. From the table, we find that in general, more cointegration relationships would be inferred if we rely on trace statistics instead of maximal eigenvalue statistics. Since it is known in the literature that both statistics tend to over reject the null hypothesis in small samples, and some econometric professionals also argue that in a high dimensional system, cointegration may have been concluded to be present in the data whether this were true or not, we therefore base our analysis on the statistics which would yield a smaller number of cointegration relationships at the 5% significance level. Accordingly, we find three cointegration relationships for Japan and the Philippines, two cointegration relationships for EA, Indonesia, Malaysia, Thailand and the US, and one for Singapore.

Next, we proceed to estimate the cointegrating vectors β_i. In this study, only exact identifying restrictions on β_i are imposed. Although further over-identifying restrictions can also be imposed, this will require a detailed long-run structural analysis for each of the eight countries covered in the model. Since the main interest of the paper is to conduct structural impulse response analysis, the specification and

[4] Cointegration test is performed using software Microfit 4.1 which incorporates statistics with I(1) exogenous regegressors in the error correction term.

testing on long run relations among variables are beyond the scope of this study.[5]

Table 1.3a: Cointegration Rank Statistics for Countries except the U.S.

Null	Alternative	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	95% Critical Value	90% Critical Value
Maximum Eigenvalue Statistics										
r = 0	r = 1	91.68	59.01	87.70	61.03	81.42	75.41	72.46	49.76	46.74
R<= 1	r = 2	62.53	46.32	46.40	51.91	46.97	32.97	55.77	43.75	41.01
R<= 2	r = 3	21.17	35.43	37.88	29.90	43.29	29.50	32.95	37.44	34.66
R<= 3	r = 4	17.95	22.98	30.20	17.12	16.46	25.58	26.61	30.55	27.86
R<= 4	r = 5	14.32	17.19	14.98	14.68	14.63	16.30	16.29	23.17	20.73
Trace Statistics										
r = 0	r>= 1	207.66	180.93	217.16	174.64	202.76	179.76	204.08	130.6	125.1
R<= 1	r>= 2	115.97	121.92	129.46	113.61	121.34	104.35	131.62	99.11	93.98
R<= 2	r>= 3	53.44	75.60	83.06	61.70	74.37	71.38	75.85	69.84	65.9
R<= 3	r>= 4	32.27	40.17	45.18	31.80	31.08	41.88	42.90	45.1	41.57
R<= 4	r = 5	14.32	17.19	14.98	14.68	14.63	16.30	16.29	23.17	20.73

Table 1.3b: Cointegration Rank Statistics for the U.S.

Null	Alternative	U.S	95% Critical Value	90% Critical Value
Maximum Eigenvalue Statistics				
r = 0	r = 1	45.18	34.70	32.12
R<= 1	r = 2	37.08	28.72	26.10
R<= 2	r = 3	19.21	22.16	19.79
R<= 3	r = 4	4.80	15.44	13.31
Trace Statistics				
r = 0	r>= 1	106.28	72.10	68.04
R<= 1	r>= 2	61.10	49.36	46.00
R<= 2	r>= 3	24.02	30.77	27.96
R<= 3	r = 4	4.80	15.44	13.31

Note: r=number of cointegrating vectors

After the individual country model is estimated, we proceed to residual serial

[5] In doing this we run the risk of a loss of efficiency in the estimation, but we rule out inconsistency due a possible incorrect specification of the long-run structure of our statistical model (see Sims et al., 1990).

correlation test to conform our lag selection for p_i and q_i. We report the result in Table 1.4. It shows that only price level (p_{it}) in EA and Singapore and interest rate (r_{it}) in EA have some evidence of serial correlation in residuals at the 5% significance level, while for all other variables, there is no evidence of serial correlation.

Table 1.4: F Statistics and P value (in parentheses) of Residual Serial Correlation Test for Country-specific Cointegrating VAR model

Countries		ε_y	ε_p	ε_q	ε_r	ε_x
EA	F(4, 76)	1.92(.115)	9.25(.000)*	1.28(.284)	3.81(.007)*	.185(.945)
Indonesia	F(4, 63)	2.83(.032)	2.27(.072)	.441(.779)	.097(.983)	2.07(.095)
Japan	F(4, 75)	1.84(.130)	1.94(.113)	1.33(.265)	.425(.790)	2.52(.048)
Malaysia	F(4, 76)	1.03(.397)	1.65(.169)	.971(.429)	1.10(.362)	.468(.759)
Philippines	F(4, 75)	.296(.880)	1.12(.355)	.811(.522)	.819(.517)	.937(.447)
Singapore	F(4, 76)	.798(.530)	4.30(.003)*	.951(.440)	2.47(.052)	.487(.745)
Thailand	F(4, 76)	1.51(.207)	1.56(.194)	.436(.782)	.987(.420)	2.32(.065)
US	F(4, 79)	1.03(.395)	3.18(.018)	.935(.448)	2.19(.077)	N/A

1.4.4. The Complete Structural VAR Model

So far, the complete model in reduced form can be constructed by combining and rearranging the coefficients estimated in the country specific models. As a result, we have thirty-nine endogenous variables and thus thirty-nine equations in the entire model. In order to derive the structural model, the next step is to estimate matrix A as described in section 3. Recall that

$$A\varepsilon_t = \eta_t, \text{ where } A = \begin{pmatrix} a_1 & & 0 \\ & \ddots & \\ 0 & & a_8 \end{pmatrix}_{39\times 39}.$$

Using the residuals $\hat{\varepsilon}_{it}$ obtained from country specific equations, we apply two-stage least square method to estimate the block diagonal matrix A and recover the structural innovations η_t. Finally, the full structural VAR model is obtained by pre-multiplying matrix A to the equation (3.12).

After the structural innovations are estimated, we proceed to residual cross-section correlation test. Table 1.5 reports both the within-country and cross-country correlations of structural residuals. To test the null hypothesis of diagnality of all within-country and cross-country correlation matrices, we compute the Breusch–Pagan Lagrange multiplier test statistic $\lambda = T\sum_{i=2}^{k}\sum_{j=1}^{i-1} r_{ij}^2$, recursively by arranging the correlations (r_{ij}) in ascending order for each correlation matrix and comparing them to the chi-square critical values. Although the test rejects the joint diagonality of all correlation matrices, it doesn't reject the diagonality assumption of cross-country correlations. The recursive test indicates that only eight correlations in the within-country correlation matrices (bold in Table 1.5) are significantly different from zero.

Matrix AG_0 as set out in Section 1.3 represents the contemporaneous relationship among all the variables in the model. These values can be interpreted as the immediate direct effects of the various shocks and do not incorporate any possible indirect effects via other variables. Focusing on Singapore, we present the following set of equations as a simple demonstration.

Table 1.5 Cross-section Correlations of Structural Residuals

	η_y	η_p	η_q	η_r	η_x	η_y	η_p	η_q	η_r	η_x
Within-country Correlations										
	EA					Indonesia				
η_y	1					1				
η_p	-0.12	1				-0.02	1			
η_q	0.02	-0.12	1			0.16	-0.01	1		
η_r	-0.21	-0.17	-0.07	1		-0.04	0.14	0.25	1	
η_x	0.17	-0.1	-0.13	-0.13	1	0.14	**-0.29**	0.03	**-0.33**	1
	Japan					Malaysia				
η_y	1					1				
η_p	0.05	1				**-0.27**	1			
η_q	-0.07	0.04	1			0.13	-0.05	1		
η_r	-0.23	-0.18	-0.04	1		0.07	0.03	**0.36**	1	
η_x	0.01	0.06	0.24	-0.09	1	0.15	-0.3	0.11	0.18	1
	Philippines					Singapore				
η_y	1					1				
η_p	0.18	1				-0.21	1			
η_q	0.17	0	1			-0.13	0.07	1		
η_r	0.02	-0.13	0.07	1		-0.26	0.14	0.12	1	
η_x	0.2	0.12	**0.27**	-0.19	1	0.1	**-0.38**	-0.03	-0.15	1
	Thailand					US				
η_y	1					1				
η_p	0.07	1				0.03	1			
η_q	-0.19	0.16	1			-0.1	0.12	1		
η_r	0.16	0.05	**0.29**	1		-0.1	0.03	0.09	1	
η_x	0.16	-0.25	-0.13	**-0.33**	1					
Cross-country Correlations										
	Between EA and Indonesia					Between EA and Japan				
η_y	-0.11	0.12	-0.21	-0.11	0.04	0.11	0.07	-0.03	0.08	-0.11
η_p	-0.07	0.19	0.11	-0.01	-0.03	0.08	-0.15	0.01	-0.06	-0.04
η_q	-0.13	0.02	0.14	0.07	-0.22	0.16	0.12	-0.19	-0.21	0.07
η_r	0.16	0.08	-0.02	-0.07	-0.05	0.13	-0.22	-0.16	-0.15	0
η_x	0	-0.09	-0.05	-0.07	0.1	0.04	-0.09	-0.06	-0.03	0.35
	Between EA and Malaysia					Between EA and Philippines				
η_y	0.06	-0.02	0.08	-0.04	-0.05	0.02	0.05	0.09	0.03	-0.06
η_p	-0.08	0.02	0.02	0.16	0.05	0.03	-0.04	0.01	-0.07	0.18
η_q	0.1	-0.23	-0.02	-0.2	0.21	-0.1	0.09	0.01	-0.04	-0.09
η_r	0.08	-0.18	0.1	-0.11	0.15	-0.1	0.05	0.11	0.03	-0.11
η_x	0.14	-0.17	-0.04	-0.06	0.32	0.12	-0.12	-0.02	-0.16	0.23

Table 1.5 Cross-section Correlations of Structural Residuals (Continued)

	Between EA and Singapore					Between EA and Thailand				
η_y	0.09	0.08	-0.14	-0.23	0.13	0.04	0.15	-0.06	0.06	-0.1
η_p	0.04	-0.26	-0.1	-0.01	0.01	-0.1	0.03	-0.14	0.17	-0.14
η_q	0.2	-0.23	-0.07	0.07	0.06	-0.05	-0.16	-0.27	0.13	0
η_r	-0.02	-0.21	0.15	-0.14	0.07	0.03	0.02	-0.17	0.11	-0.02
η_x	0.03	0.07	0.01	0.14	0.47	-0.06	0.11	0.06	0	0.22
	Between EA and US					Between Indonesia and Japan				
η_y	-0.15	-0.02	0.08	0.21	-0.02	-0.14	0.08	-0.01	0.02	-0.07
η_p	-0.04	0.25	-0.06	0.01	-0.24	-0.19	-0.1	-0.11	0.02	0.02
η_q	-0.07	0.06	0.08	-0.07	-0.13	0.03	-0.2	-0.21	-0.1	0.19
η_r	-0.03	-0.04	0.04	-0.08	-0.14	-0.05	-0.05	-0.12	-0.2	0.04
η_x						0.19	-0.23	-0.12	-0.1	0.27
	Between Indonesia and Malaysia					Between Indonesia and Philippines				
η_y	-0.04	-0.14	-0.01	0.01	0.15	-0.1	-0.06	-0.13	0.02	-0.09
η_p	-0.03	0.27	0.04	0.09	-0.14	-0.12	0	-0.02	0.07	-0.12
η_q	0.05	-0.01	0.1	-0.04	0.06	0	0	0.05	0.27	-0.09
η_r	-0.02	0.02	-0.08	-0.06	0.04	-0.11	-0.01	0.1	0.21	-0.06
η_x	0.13	-0.13	-0.02	0.02	0.26	-0.04	-0.17	0.02	0.1	0.22
	Between Indonesia and Singapore					Between Indonesia and Thailand				
η_y	0.03	-0.03	-0.03	0	0.13	0.09	-0.04	-0.16	-0.08	0.03
η_p	0.06	-0.06	0.04	0.27	-0.1	-0.2	0	-0.04	0.04	-0.02
η_q	0.17	0.23	-0.09	-0.05	-0.16	-0.06	-0.17	0.19	0.14	0.11
η_r	0.16	-0.07	-0.01	-0.28	-0.03	-0.09	-0.13	-0.05	0.13	0.05
η_x	-0.03	-0.08	-0.18	-0.1	0.25	0.2	-0.05	0.03	-0.06	0.26
	Between Indonesia and US					Between Japan and Malaysia				
η_y	-0.04	-0.13	0.31	-0.06	0.13	-0.1	0	-0.05	0.04	0
η_p	-0.01	0.08	0.02	0.02	-0.08	-0.07	-0.27	-0.06	0.05	-0.16
η_q	-0.08	-0.16	-0.06	0.06	0.04	-0.09	-0.09	-0.18	0.15	0.1
η_r	0.06	0.05	-0.03	-0.01	-0.07	-0.16	-0.08	0.06	-0.08	-0.1
η_x						-0.02	-0.02	0.12	-0.1	0.32
	Between Japan and Philippines					Between Japan and Singapore				
η_y	0	0.09	-0.02	0.04	-0.02	-0.04	0.11	0.14	-0.13	0.09
η_p	-0.11	0.04	-0.1	0.1	0.17	0.07	0.12	-0.19	0.16	0
η_q	-0.12	0.05	0.02	-0.11	-0.07	-0.05	-0.09	-0.13	0.14	-0.06
η_r	-0.05	0.01	-0.11	-0.1	-0.15	-0.11	-0.07	-0.09	0.15	0.16
η_x	-0.09	0.11	0.26	0.01	0.09	-0.02	-0.02	0.31	-0.19	0.35
	Between Japan and Thailand					Between Japan and US				
η_y	-0.03	0.22	-0.04	-0.16	-0.24	-0.04	-0.14	-0.02	-0.08	0.08
η_p	0.2	0.3	-0.09	-0.06	-0.11	0.03	0.03	-0.1	0.12	-0.18
η_q	0.11	0.07	-0.05	0.12	0.16	-0.04	0.05	0	0.05	-0.06
η_r	0.05	0.13	0	0.17	-0.16	-0.01	0.03	-0.2	0.08	-0.18
η_x	-0.08	0.02	0.2	-0.15	0.3					

Table 1.5 Cross-section Correlations of Structural Residuals (Continued)

	Between Malaysia and Philippines					Between Malaysia and Singapore				
η_y	0.08	-0.19	0.24	0.19	0.24	-0.12	-0.06	-0.13	-0.07	0.02
η_p	-0.07	0.13	0.18	0.05	-0.01	0.03	0.02	0.26	-0.1	0.08
η_q	0.13	0.03	-0.1	-0.07	-0.02	0.07	0.14	-0.01	0.09	0.07
η_r	0.05	-0.11	0.01	0.01	0.04	0.09	-0.09	0.22	0.15	0.1
η_x	0.23	-0.15	-0.03	0.11	0.38	0	-0.06	-0.1	0.02	0.39
	Between Malaysia and Thailand					Between Malaysia and US				
η_y	-0.1	-0.1	-0.06	-0.01	-0.01	-0.1	0.1	-0.1	-0.04	-0.08
η_p	0	-0.03	-0.24	-0.07	-0.11	-0.05	-0.06	0.06	0.03	-0.18
η_q	0.12	-0.23	0.12	-0.17	-0.05	0.05	-0.03	0.01	-0.13	-0.13
η_r	-0.11	0.08	-0.02	-0.23	-0.19	-0.02	0.03	-0.01	0.06	-0.17
η_x	0.17	-0.13	0.07	0.06	0.54					
	Between Philippines and Singapore					Between Philippines and Thailand				
η_y	-0.21	-0.02	0.09	0.1	0.12	0.19	-0.01	0.16	0.26	0.03
η_p	0.1	0.19	-0.1	0.07	-0.04	-0.02	-0.01	0.04	0.04	-0.02
η_q	-0.22	-0.28	-0.04	0.03	-0.04	-0.13	0	0.11	0.09	0
η_r	0.17	0.14	0	-0.23	0.07	0.14	0.2	0.11	-0.03	0
η_x	-0.01	-0.09	-0.03	-0.09	0.29	0.08	-0.18	0.1	-0.06	0.48
	Between Philippines and US					Between Singapore and Thailand				
η_y	-0.06	0.03	-0.03	0.03	-0.06	0.1	-0.08	0.1	-0.14	-0.04
η_p	0.06	-0.05	-0.1	-0.07	-0.19	0.04	0.07	0.02	0.04	-0.09
η_q	0.06	0.09	0.03	0.02	-0.08	-0.04	0.14	-0.09	-0.14	0.04
η_r	0	-0.01	-0.19	-0.09	-0.15	0.02	0.07	-0.15	-0.36	0.07
η_x						-0.04	0	0.14	0.06	0.42
	Between Singapore and US					Between Thailand and US				
η_y	-0.02	-0.09	-0.18	-0.01	0.04	-0.03	0.03	0.02	0.06	-0.07
η_p	0.02	0.03	-0.17	-0.09	-0.24	0.01	-0.02	0.01	0.04	-0.14
η_q	-0.09	0.06	-0.1	0.11	-0.04	0.07	0.06	0.01	0.11	-0.13
η_r	-0.07	0.11	-0.11	0.21	-0.28	-0.05	-0.06	-0.18	-0.09	-0.16

Note: The residuals in the row heading of cross-country correlation matrices denote the residuals of the second country. Bold indicates significance at the 5% significance level.

$$y_t^{Sin} = 0.080\mathrm{y}_t^{EA} + 0.044\mathrm{y}_t^{Japan} + 0.066y_t^{Indonesia} + 0.156y_t^{malay} + 0.022y_t^{Philippine} + 0.039y_t^{Thailand} + 0.142y_t^{us} + \ldots\ldots \quad (4.1)$$

$$p_t^{Sin} = 0.075\mathrm{p}_t^{EA} + 0.046\mathrm{p}_t^{Japan} + 0.094p_t^{Indonesia} + 0.142p_t^{malay} + 0.021p_t^{Philippine} + 0.041p_t^{Thailand} + 0.136p_t^{US} + \ldots \quad (4.2)$$

$$q_t^{Sin} = 0.032\mathrm{q}_t^{EA} + 0.019\mathrm{q}_t^{Japan} + 0.040q_t^{Indonesia} + 0.060q_t^{malay} + 0.009q_t^{Philippine} + 0.017q_t^{Thailand} + 0.058q_t^{US} + \ldots \quad (4.3)$$

Equation (4.1) shows the contemporaneous effects of foreign GDPs on Singapore's GDP. We can see that a 1% increase in Malaysia's GDP in a given quarter leads to an increase of 0.156% in Singapore's output within the same quarter. Equation (4.2) shows the international spillover of inflation and equation (4.3) shows the spillover in equity market. From these three equations, we have two primary results. First, the effects from Malaysia and the US are relatively larger than other countries. This may reflect the close trade and financial ties between Singapore and Malaysia & the US. Second, the direct effects are in general quite small, which is in stark contrast to the substantial overall effects, particularly in the equity market calculated in the next section. This suggests that indirect and multiplier effects play an important role in the transmission of shocks.

1.5 Structural Impulse Response Analysis

To study dynamic properties of the complete model and the time-profile effects of various shocks, we compute the structural impulse response function up to twenty quarters. In order to account for the relative variability of different shocks, one-standard deviation shocks are used instead of one unit shocks. There are a variety of scenarios of interest that could be investigated. Here we only consider the following ones:

*A shock to real GDP and its impact on GDP growth across countries

*A shock to equity price and its impact on equity price across countries

*A shock to US equity price and its impact on all endogenous variables

*A shock to US interest rate and its impact on all endogenous variables

1.5.1 Responses of Real GDP to One Standard Error GDP Shock across Countries

Table 1.6 summarizes the cumulative impact of one standard error positive GDP shock in each country on the GDP growth of other countries after four quarters. Countries along the top of the table are the countries where shocks originate, and the countries along the left side of the table are the impacted countries. This table shows some interesting features. First, it displays that the international transmission effects are relatively small and are largely swamped by the domestic shocks of the individual countries. For most countries, a shock from other countries can only generate a very small change in real GDP. On the contrary, domestic shocks can generate a far larger impact on growth within that country than foreign shocks. For example, for Indonesia, one positive standard error domestic shock can cause its GDP to increase by 1.5%, while any shocks from other countries can only generate a no more than 0.24% change in its GDP.[6] In addition, we find that even the transmission effects from the US, EA and Japan to ASEAN countries are smaller than expected. This suggests there is no strong evidence of business cycle transmission among the ASEAN countries, nor between the advanced developed economies and the ASEAN economies. Second, the GDP growth in the Philippines reacts negatively to the shocks to other countries but in most cases it is trivial. This may imply that something is missing in the country-specific model for the Philippines, such as dummy variables given that

[6] It is possible to compute standard errors for the structural impulse response using bootstrap techniques. But this would involve highly intensive computer works and it is not clear whether it will add much to our conclusion.

several political crises occur during 1980s. It may also be viewed that the Philippines is a fairly closed economy with relative weak external linkages with other countries. Third, the response of Singapore's GDP to shocks originated from other countries is relatively larger than the response of other countries. This is not surprising since Singapore is a small open economy which has strong international linkages. Fourth, the shocks originated from the US generally have larger predicted effects while the US is the most insulated from foreign shocks. These results are in general consistent with the findings by Abeysinghe and Forbes (2001), except that we find the scale of international business cycle transmission is not as strong as the former.

Table 1.6: Cumulative impulse responses of GDP growth to one positive standard error GDP shock across countries after four quarters (%)

	Shocks to							
	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	US
EA	0.654	-0.013	0.030	0.016	-0.014	0.040	0.014	0.043
Indonesia	0.111	1.145	0.238	0.108	0.040	0.236	0.054	0.127
Japan	0.105	0.031	0.974	0.068	0.040	0.111	0.055	0.202
Malaysia	0.148	0.172	0.384	1.360	0.175	0.613	0.164	0.304
Philippines	-0.029	0.015	-0.072	-0.100	1.338	-0.050	-0.001	-0.020
Singapore	0.154	0.178	0.336	0.374	0.139	1.825	0.253	0.472
Thailand	0.050	0.016	0.118	0.037	0.018	0.116	1.230	0.166
US	0.052	0.002	0.033	0.021	0.003	0.050	0.017	0.572

The statistics in Table 1.6 capture the total multiplier effects of a shock to one country on other countries. It may be interesting to compare the pattern predicted by these multiplier effects with the pattern predicted by the bilateral trade flows between countries. Table 1.7 shows this comparison. In the "rank by exports" columns, the table ranked the main trading partners in terms of export shares of the country listed in the heading of that section of the table. In the “ranked by multiplier” columns, the table listed the multiplier effects on the country in the heading from a shock originating in each of the countries listed in the rows. These multiplier effects are taken from Table 1.6 and then normalized by setting “own-country” multipliers to unity to remove the scaling effect

Table 1.7 shows several patterns. First, shocks to the larger economies have the greatest multiplier effect on other countries. For most countries, the US, and/or Japan/EA are at the top of the “ranked by multiplier” column. Second, it shows that the predicted impact of a shock working directly through export flows can be different from the predicted impact of a shock working through multiplier effects on output growth and trade linkages in the full sample. However, the difference is not big. On one hand, it shows shocks to a country’s most important bilateral-trade partners are less important when the full multiplier effects are considered. For example, Malaysia is Singapore’s largest export market, a shock to Malaysia would have less impact on Singapore than a shock to the US and Japan. On the other hand, it shows that the rankings by export shares don't change much from the rankings by multiplier effects. This may be attributed to the weak international output transmission we found earlier. Third, ASEAN countries, except the Philippines, are much more affected by shocks from other countries than the larger economies such as Japan and EA.

Table 1.7: Trading Partners Ranked by Export Shares and Multiplier Effects

EA				Indonesia			
Ranked by exports		Ranked by multiplier		Ranked by exports		Ranked by multiplier	
US	0.736	US	0.075	Japan	0.349	Japan	0.244
Japan	0.140	Japan	0.031	US	0.222	US	0.221
Singapore	0.048	Singapore	0.022	EA	0.165	EA	0.170
Malaysia	0.026	Thailand	0.012	Singapore	0.162	Singapore	0.129
Thailand	0.024	Malaysia	0.011	Malaysia	0.052	Malaysia	0.079
Indonesia	0.016	Philippine	-0.011	Thailand	0.030	Thailand	0.044
Philippine	0.011	Indonesia	-0.011	Philippine	0.020	Philippine	0.030
Japan				**Malaysia**			
Ranked by exports		Ranked by multiplier		Ranked by exports		Ranked by multiplier	
US	0.552	US	0.352	US	0.308	US	0.531
EA	0.203	EA	0.161	Singapore	0.263	Japan	0.395
Singapore	0.071	Singapore	0.061	Japan	0.186	Singapore	0.336
Thailand	0.055	Malaysia	0.050	EA	0.138	EA	0.226
Malaysia	0.052	Thailand	0.045	Thailand	0.056	Indonesia	0.150
Philippine	0.039	Philippine	0.030	Indonesia	0.026	Thailand	0.133
Indonesia	0.029	Indonesia	0.027	Philippine	0.023	Philippine	0.131
Philippine				**Singapore**			
Ranked by exports		Ranked by multiplier		Ranked by exports		Ranked by multiplier	
US	0.397	Indonesia	0.013	Malaysia	0.285	US	0.824
Japan	0.217	Thailand	(0.001)	US	0.259	Japan	0.345
EA	0.178	Singapore	(0.027)	EA	0.146	Malaysia	0.275
Singapore	0.097	EA	(0.044)	Japan	0.120	EA	0.236
Malaysia	0.060	US	(0.035)	Indonesia	0.080	Thailand	0.206
Thailand	0.044	Malaysia	(0.074)	Thailand	0.071	Indonesia	0.155
Indonesia	0.006	Japan	(0.074)	Philippine	0.040	Philippine	0.104
Thailand				**US**			
Ranked by exports		Ranked by multiplier		Ranked by exports		Ranked by multiplier	
US	0.330	US	0.291	EA	0.492	EA	0.079
Japan	0.240	Japan	0.121	Japan	0.290	Japan	0.034
EA	0.168	EA	0.077	Singapore	0.086	Singapore	0.027
Singapore	0.134	Singapore	0.064	Malaysia	0.051	Malaysia	0.015
Malaysia	0.066	Malaysia	0.027	Philippine	0.039	Thailand	0.013
Indonesia	0.035	Indonesia	0.014	Thailand	0.029	Philippine	0.002
Philippine	0.028	Philippine	0.014	Indonesia	0.013	Indonesia	0.002

Notes: Multipliers are normalized by setting "own-country" multipliers to unity. The country listed at top of each part of the table is the country "responding to" a normalized shock originating in each country listed in the lower part of the table. Export shares are based on the 2000-2002 export matrix

1.5.2 Responses of Equity Price to One Standard Error Equity Price Shock across Countries

Table 1.8 shows the cumulative impact of one standard error positive equity price shock in each country on the equity prices of other countries after four quarters. In contrast to Table 1.6, it displays some distinct features. First, all equity markets react strongly to domestic equity price shocks. In Indonesia, Japan, Malaysia, the Philippines and Thailand, one standard error domestic shock can generate more than 10% change in equity price in their home countries. Second, transmission among different equity markets is quite substantial. Although domestic shocks still play a major role, foreign shocks can strongly affect all equity markets except the US. Particularly, in the case of EA and Singapore, a shock originated from the US can generates a much bigger effect than their domestic shocks do. Third, a shock originated from the Philippines has much smaller effect on all equity markets than a shock originating from other countries. This suggests that the equity market in the

Table 1.8: Cumulative impulse responses of Equity price to one standard error Equity price shock across countries after four quarters (%)

	Shocks to							
	EA	Indonesia	Japan	Malaysia	Philippines	Singapore	Thailand	US
EA	6.117	0.959	2.743	1.247	0.749	0.794	0.897	8.136
Indonesia	1.058	14.943	1.636	0.595	0.488	0.846	0.558	2.540
Japan	1.597	1.684	10.243	2.127	0.906	0.962	1.203	6.852
Malaysia	2.064	2.764	5.143	16.269	1.115	2.665	1.916	8.657
Philippines	3.389	2.960	8.307	4.356	17.475	2.678	2.823	13.962
Singapore	2.401	3.664	5.391	6.935	1.530	7.477	2.336	9.428
Thailand	2.232	2.787	6.059	4.265	1.162	2.073	13.047	9.123
US	0.063	-0.365	-0.624	-0.623	-0.087	-0.197	-0.203	6.850

Philippines is relatively small and its role in international equity markets is negligible. Fourth, the reaction of the US equity market to other markets is rather insignificant, even to the shocks from big markets such as EA and Japan. This result shows that the US equity market is quite independent of other markets.

1.5.3 A Negative Shock to US Equity Price

The cumulative impulse response from one standard error negative shock to US equity price is presented in Table 1.9 and Figures 1.1 to 1.4. Table 1.9 summarizes the effects of equity price shock on real GDP growth, inflation rate, equity price, interest rate and exchange rate. We can find that the transmission of the shock to all markets is quite fast and significant. On impact, equity price falls by 5.29% in the US market, 7.5% in the Philippines market, 6.03% in Thailand, 4.53% in EA and 4.23% in Malaysia. Over time, the fall in equity price across countries start to catch up and even surpass the fall in the US market. In the long run, the equity price falls as much as 13.72% in the Philippines, 9.14% in Singapore, 8.97% in Thailand, 8.5% in Malaysia and 8.15% in EA. Although these estimates should be viewed with caution due to the long forecast horizons, this pattern of impulses is still quite informative. It confirms the prominent role of the US equity market in the global financial market.

The effects of US equity price shock on real GDP growth are negative in most countries. On impact, only the growth rate in EA and Japan tend to increase by a very insignificant amount, but over time the effects become negative. Compared with the magnitude of the effects on equity price, the real GDP effects of negative US equity price shock are rather small, with no more than 0.47% decrease in all countries, except Singapore where the long run real GDP falls by around 1.11%.

The inflation effects of a negative shock in US equity price are negative in most countries. On impact, the inflation rate effects in the Philippines, Singapore and the US are positive, though the magnitude is small. But over time the inflation rate is reduced in the case of Singapore and the US.

The effects on interest rate across countries are ambiguous, and they tend to switch signs over time. On impact, only in the case of EA and Malaysia the effects are negative, but over time, the effects on the interest rate in Indonesia, Singapore and the US also turn to be negative. The effects on exchange rate across different countries are also mixed.

Table 1.9: Cumulative impulse responses to one negative standard error shock to US equity price

	Quarters after the shock								
	0	1	2	3	4	8	12	16	19
Countries	on real GDP growth (%)								
EA	0.002	-0.051	-0.082	-0.098	-0.106	-0.103	-0.104	-0.104	-0.104
Indonesia	-0.055	-0.064	-0.036	-0.025	-0.062	-0.136	-0.134	-0.134	-0.134
Japan	0.075	0.013	-0.069	-0.102	-0.118	-0.116	-0.116	-0.116	-0.116
Malaysia	-0.056	-0.268	-0.393	-0.378	-0.349	-0.337	-0.337	-0.337	-0.337
Philippines	-0.374	-0.511	-0.443	-0.359	-0.323	-0.326	-0.323	-0.323	-0.323
Singapore	-0.340	-0.919	-1.204	-1.218	-1.144	-1.106	-1.108	-1.108	-1.108
Thailand	-0.073	-0.247	-0.352	-0.420	-0.454	-0.467	-0.468	-0.468	-0.468
US	-0.043	-0.183	-0.311	-0.361	-0.361	-0.347	-0.348	-0.348	-0.348

Table 1.9: Cumulative impulse responses to one negative S.E. shock to US equity price (Continued)									
	on inflation rate (%)								
EA	-0.031	-0.059	-0.083	-0.093	-0.090	-0.087	-0.087	-0.087	-0.087
Indonesia	-0.022	0.115	-0.090	-0.343	-0.403	-0.310	-0.318	-0.317	-0.317
Japan	-0.018	-0.089	-0.094	-0.119	-0.115	-0.113	-0.114	-0.114	-0.114
Malaysia	-0.013	-0.065	-0.121	-0.152	-0.149	-0.132	-0.133	-0.133	-0.133
Philippines	0.040	0.141	0.231	0.267	0.241	0.203	0.201	0.200	0.200
Singapore	0.022	-0.027	-0.110	-0.157	-0.160	-0.129	-0.133	-0.132	-0.132
Thailand	-0.020	-0.111	-0.285	-0.422	-0.475	-0.456	-0.460	-0.460	-0.460
US	0.034	0.038	0.009	-0.005	-0.009	-0.002	-0.002	-0.002	-0.002
	on equity price (%)								
EA	-4.535	-7.518	-8.458	-8.356	-8.136	-8.151	-8.147	-8.148	-8.148
Indonesia	-3.520	-5.078	-3.024	-2.521	-2.540	-2.527	-2.516	-2.517	-2.517
Japan	-2.606	-5.523	-6.827	-6.976	-6.852	-6.801	-6.801	-6.802	-6.802
Malaysia	-4.235	-8.762	-9.735	-9.250	-8.657	-8.509	-8.497	-8.499	-8.498
Philippines	-7.146	-11.87	-14.01	-14.37	-13.96	-13.74	-13.72	-13.72	-13.72
Singapore	-1.403	-7.803	-10.00	-10.02	-9.428	-9.142	-9.144	-9.145	-9.145
Thailand	-6.030	-8.389	-9.433	-9.283	-9.123	-8.979	-8.974	-8.973	-8.973
US	-5.299	-7.066	-7.173	-6.908	-6.850	-6.962	-6.955	-6.956	-6.956
	on interest rate (%)								
EA	-0.026	-0.051	-0.099	-0.139	-0.156	-0.157	-0.158	-0.158	-0.158
Indonesia	0.091	0.426	0.279	-0.082	-0.216	-0.150	-0.160	-0.159	-0.159
Japan	0.049	0.058	0.038	0.033	0.034	0.040	0.040	0.040	0.040
Malaysia	-0.007	-0.054	-0.099	-0.109	-0.104	-0.113	-0.112	-0.112	-0.112
Philippines	0.651	0.842	0.643	0.449	0.401	0.408	0.399	0.399	0.399
Singapore	0.032	-0.073	-0.247	-0.351	-0.389	-0.375	-0.379	-0.378	-0.378
Thailand	0.074	0.339	0.365	0.306	0.249	0.191	0.191	0.191	0.191
US	0.031	-0.091	-0.152	-0.130	-0.101	-0.090	-0.090	-0.090	-0.090
	on exchange rate (%)								
EA	-0.691	-1.356	-1.589	-1.541	-1.470	-1.471	-1.470	-1.470	-1.470
Indonesia	0.211	1.362	1.400	1.278	1.578	2.090	2.068	2.069	2.069
Japan	0.147	-0.540	-1.118	-1.121	-1.011	-0.883	-0.885	-0.885	-0.885
Malaysia	0.124	0.096	-0.119	-0.305	-0.378	-0.431	-0.432	-0.432	-0.432
Philippines	0.458	0.983	1.029	0.810	0.654	0.603	0.593	0.592	0.592
Singapore	0.075	-0.090	-0.251	-0.267	-0.208	-0.214	-0.212	-0.212	-0.212
Thailand	0.038	0.201	0.027	-0.285	-0.606	-0.897	-0.895	-0.896	-0.896

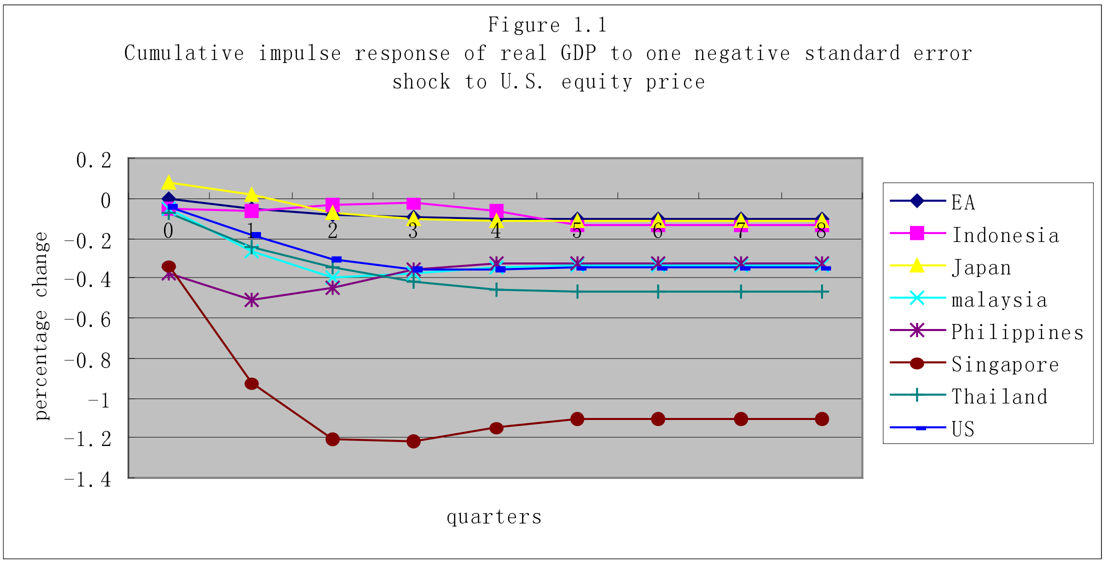


Figure 1.1
Cumulative impulse response of real GDP to one negative standard error shock to U.S. equity price
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
percentage change
0 1 2 3 4 5 6 7 8
quarters
EA
Indonesia
Japan
malaysia
Philippines
Singapore
Thailand
US

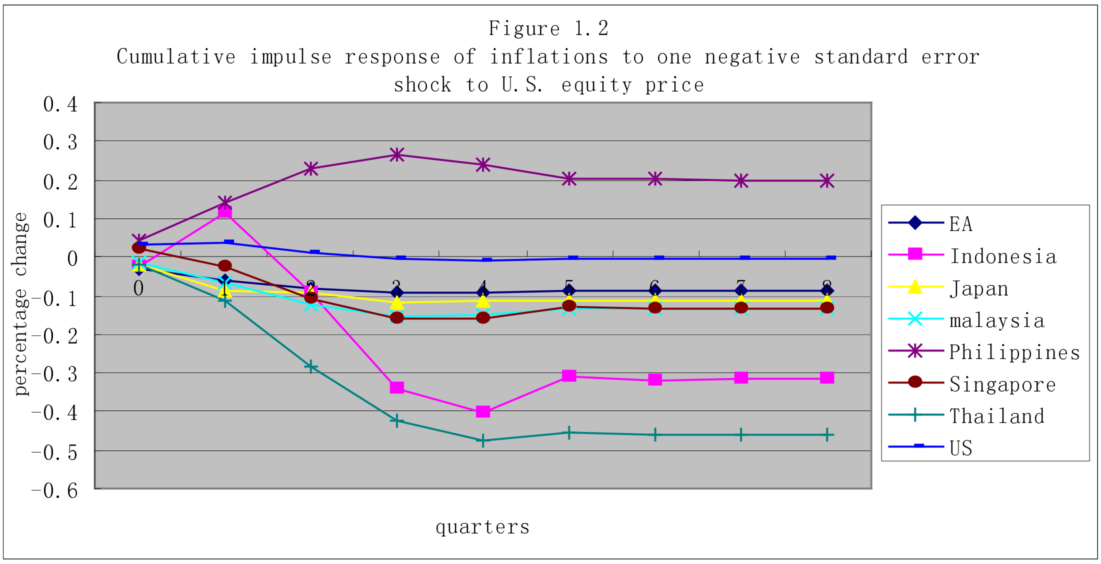


Figure 1.2
Cumulative impulse response of inflations to one negative standard error shock to U.S. equity price
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
percentage change
0 2 4 5 6 7 8
quarters
EA
Indonesia
Japan
malaysia
Philippines
Singapore
Thailand
US

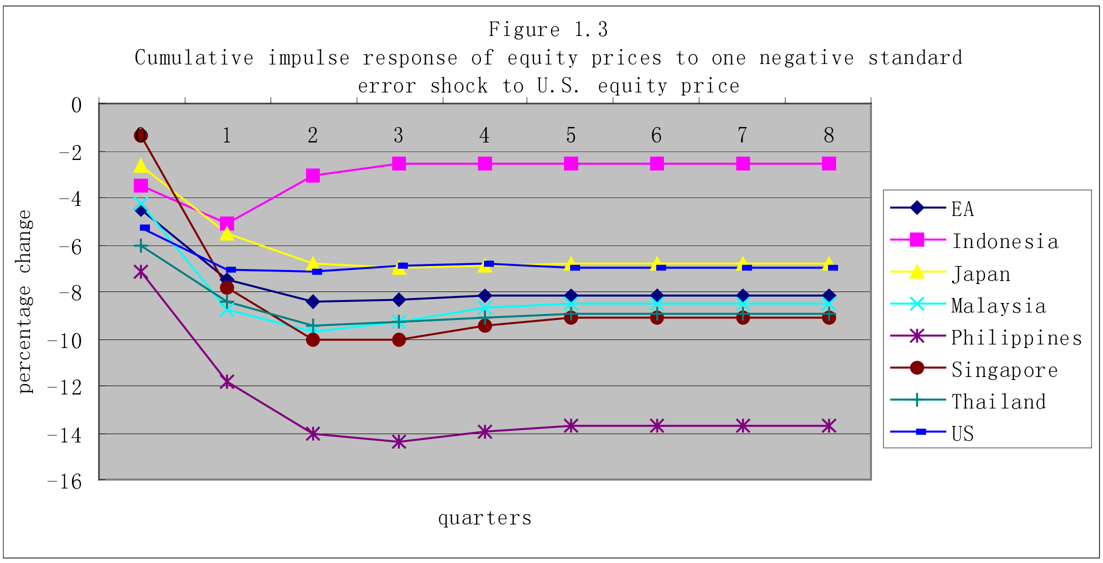
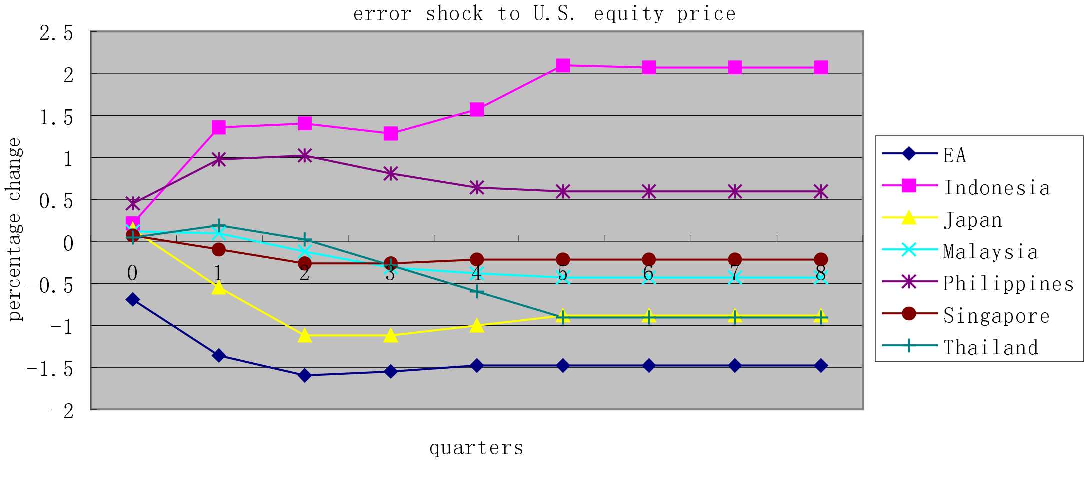


Figure 1.3
Cumulative impulse response of equity prices to one negative standard error shock to U.S. equity price
0
-2
-4
-6
-8
-10
-12
-14
-16
percentage change
0 1 2 3 4 5 6 7 8
quarters
EA
Indonesia
Japan
Malaysia
Philippines
Singapore
Thailand
US

Figure 1.4
Cumulative impulse response of exchange rates to one negative standard error shock to U.S. equity price



1.5.4 A Positive Shock to US Interest Rate

The effects of one standard error rise in the level of US interest rate on all variables across countries are presented in Table 1.10 and Figures 1.5 to 1.8. In the US, one standard error positive shock is equivalent to around 0.45% change in short-term nominal interest rate on a quarterly basis. From the table, the important role played by the US interest rate in global equity markets can be clearly seen. On impact, the increase in the US interest rate causes the equity price to decline across all markets, with the decline being most significant in ASEAN countries. After 1 quarter, Thailand market falls by as much as 4.35%, Malaysia falls by 3.62%, Philippines falls by 3.09% and Singapore falls by 3.06%. The only exception here is the Indonesian market, which initially falls but over the long run its equity price increases, though the magnitude remains limited.

Regarding the effects on real GDP, the increase in US interest rate immediately causes the real GDP to fall in many markets except Indonesia, Japan and the US. Over the long run, only Japan and the US remain positively affected. For most ASEAN countries, the adverse effects are quite significant, with a fall by 0.31% for Malaysia, 0.7% for the Philippines and 0.36% for Singapore.

The effects of the interest rate rise on the inflation rate are mixed. On impact, only the inflation in EA, Japan and Singapore decline, but over the long run, the inflation rate decline in all countries except the Philippines. Concerning the effects on interest rates, a rise in the US interest rate tends to increase the interest rate in all other countries. And on the exchange rate, the US interest rate shock causes the US dollar to appreciate against all other currencies except Japan.

Table 1.10: Cumulative impulse responses to one positive standard error shock to US interest rate

	Quarters after the shock								
	0	1	2	3	4	8	12	16	19
Countries	on real GDP growth (%)								
EA	-0.006	-0.002	-0.009	-0.008	-0.010	-0.011	-0.011	-0.011	-0.011
Indonesia	0.031	-0.078	-0.084	-0.033	-0.023	-0.036	-0.036	-0.036	-0.036
Japan	0.056	0.053	0.057	0.053	0.041	0.043	0.043	0.043	0.043
Malaysia	-0.168	-0.277	-0.289	-0.296	-0.314	-0.312	-0.314	-0.314	-0.315
Philippines	-0.472	-0.603	-0.685	-0.696	-0.683	-0.695	-0.697	-0.697	-0.697
Singapore	-0.129	-0.231	-0.306	-0.362	-0.371	-0.360	-0.364	-0.364	-0.364
Thailand	-0.044	-0.004	-0.041	-0.055	-0.060	-0.065	-0.065	-0.065	-0.065
US	0.047	0.195	0.165	0.135	0.130	0.134	0.134	0.134	0.134
	on inflation rate (%)								
EA	-0.006	0.001	-0.005	-0.013	-0.014	-0.013	-0.013	-0.013	-0.013
Indonesia	0.161	0.324	0.392	0.360	0.299	0.299	0.299	0.299	0.299
Japan	-0.009	-0.012	0.010	-0.013	-0.002	-0.005	-0.006	-0.006	-0.006
Malaysia	0.026	0.066	0.078	0.065	0.062	0.066	0.066	0.066	0.066
Philippines	0.206	0.389	0.538	0.648	0.686	0.740	0.751	0.753	0.753
Singapore	-0.019	-0.017	0.003	0.002	-0.008	-0.007	-0.008	-0.008	-0.008

Table 1.10: Cumulative impulse responses to one positive standard error shock to US interest rate (Continued)

				on inflation rate (%)					
Thailand	0.074	0.072	0.100	0.092	0.074	0.073	0.073	0.073	0.073
US	0.000	0.086	0.078	0.074	0.071	0.074	0.074	0.074	0.074
				on equity price (%)					
EA	-0.276	-0.963	-1.718	-1.892	-1.824	-1.799	-1.804	-1.804	-1.804
Indonesia	-0.870	0.425	0.074	0.161	0.352	0.293	0.299	0.298	0.298
Japan	-1.012	-1.906	-2.562	-2.745	-2.749	-2.714	-2.720	-2.721	-2.721
Malaysia	-1.759	-3.618	-4.180	-4.417	-4.354	-4.277	-4.297	-4.298	-4.299
Philippines	-2.205	-3.088	-4.670	-5.633	-5.698	-5.710	-5.752	-5.758	-5.759
Singapore	-0.786	-3.059	-3.870	-4.367	-4.383	-4.261	-4.283	-4.284	-4.284
Thailand	-2.848	-4.346	-4.313	-4.621	-4.547	-4.573	-4.585	-4.585	-4.586
US	-0.334	-1.117	-1.392	-1.242	-1.175	-1.152	-1.147	-1.146	-1.146
				on interest rate (%)					
EA	0.128	0.192	0.221	0.220	0.214	0.216	0.216	0.216	0.216
Indonesia	1.098	1.607	1.606	1.617	1.555	1.562	1.566	1.567	1.567
Japan	0.013	0.020	0.010	0.007	0.002	0.003	0.003	0.003	0.003
Malaysia	0.038	0.093	0.076	0.056	0.051	0.052	0.052	0.052	0.052
Philippines	0.441	0.984	1.148	1.153	1.186	1.277	1.290	1.292	1.292
Singapore	0.195	0.220	0.178	0.165	0.159	0.159	0.159	0.159	0.159
Thailand	0.585	0.779	0.823	0.818	0.820	0.819	0.822	0.822	0.822
US	0.544	0.533	0.449	0.440	0.443	0.447	0.447	0.447	0.447
				on exchange rate (%)					
EA	0.422	0.486	0.262	0.269	0.345	0.381	0.385	0.385	0.385
Indonesia	1.519	1.976	1.867	1.760	1.630	1.799	1.805	1.807	1.807
Japan	-0.007	0.015	-0.251	-0.324	-0.386	-0.322	-0.322	-0.321	-0.321
Malaysia	0.622	0.995	0.977	0.900	0.884	0.887	0.890	0.891	0.891
Philippines	0.786	1.764	2.236	2.323	2.348	2.485	2.510	2.514	2.514
Singapore	0.328	0.280	0.169	0.112	0.118	0.129	0.127	0.127	0.127
Thailand	0.291	0.274	0.273	0.287	0.272	0.210	0.212	0.212	0.212

Figure 1.5
Cumulative impulse response of real GDP to one positive standard error shock to U.S. interest rate

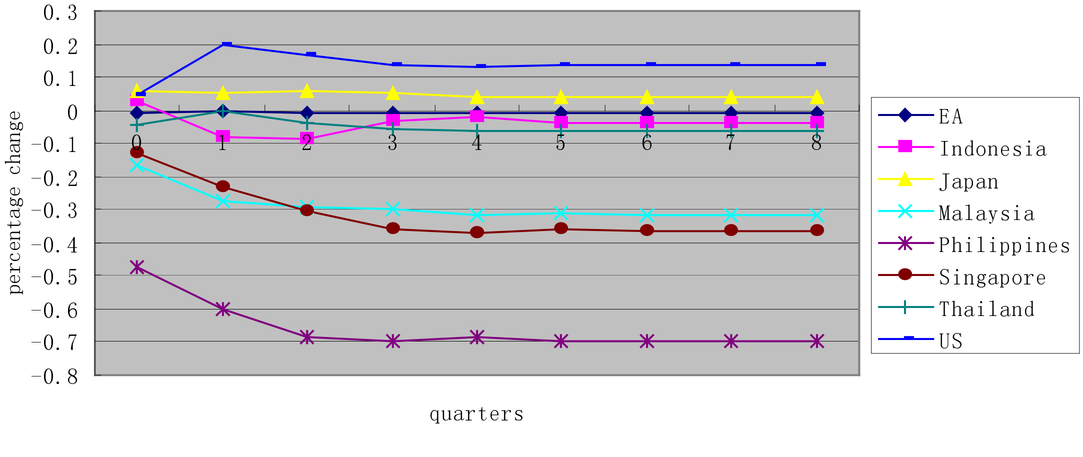


Figure 1.6
Cumulative impulse response of equity prices to one postive standard error shock to U.S. interest rate

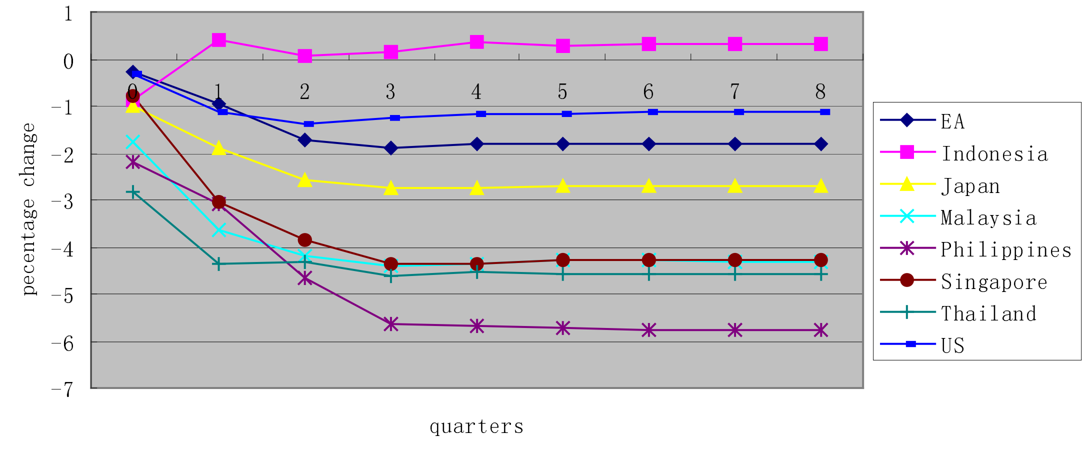


Figure 1.7
Cumulative impulse response of interest rates to one positive standard error shock to U.S. interest rate

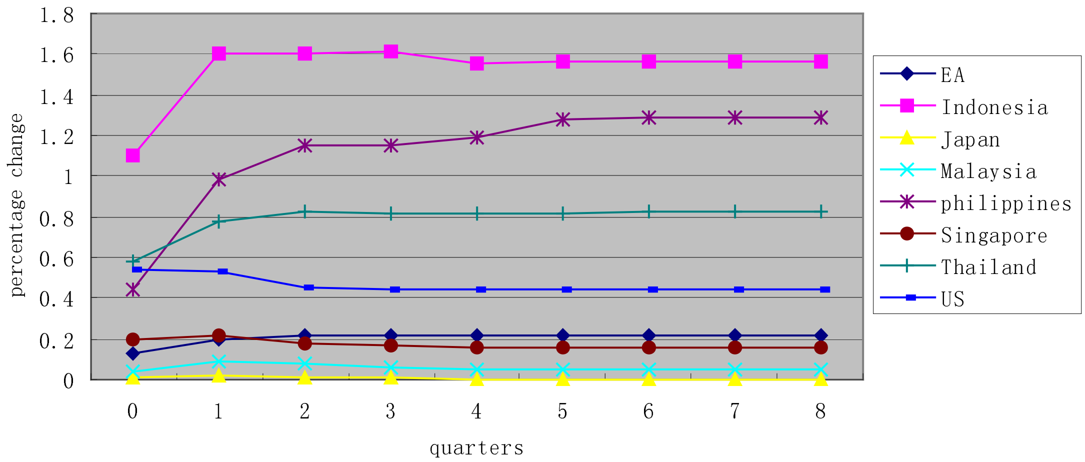
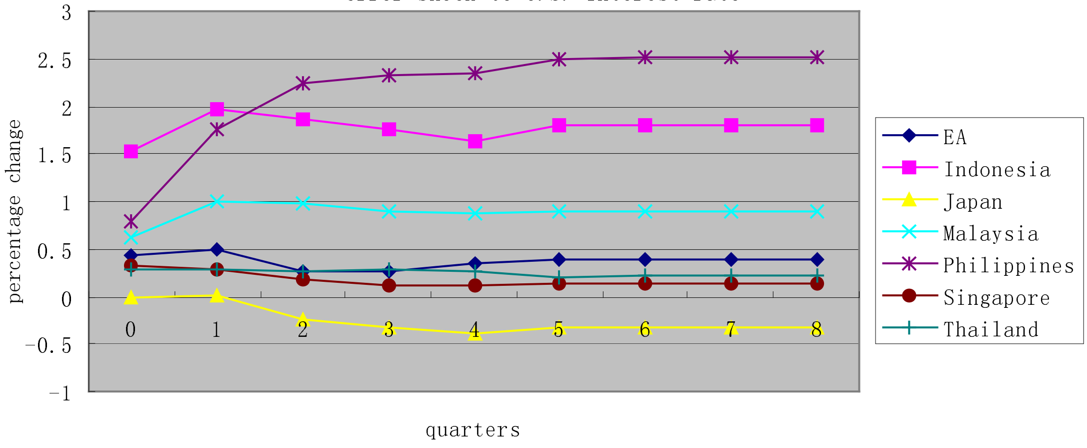


Figure 1.8
Cumulative impulse response of exchange rates to one positive standard error shock to U.S. interest rate



1.6 Conclusion

This chapter develops a framework for measuring international transmission of shocks, building on the recent advance in structural VAR literature by Abeysinghe (1999), Abeysinghe and Forebes (2001) and global econometric modeling by Pesaran, Schuermann and Weiner (2004). A key advantage of the model is that it can fully capture the interaction across sectors and countries, while remains very parsimonious. The methodology is employed in two steps. First, we link up country-specific Vector ECM models that are estimated individually. Second, we estimate the contemporaneous coefficients of endogenous variables and derive a structural VAR model.

We calculate the structural impulse response function to examine the propagation of shocks across countries. The results show that the international transmission of real shocks such as GDP shocks is not as strong as what is expected in some literature. In most cases, the foreign shocks will be swamped by shocks originated within that country. On the other hand, shocks in equity market can be transmitted to other countries rapidly and the effects are quite substantial. This suggests that equity market is rather vulnerable to foreign shocks and the spread of the Asian crisis is not that surprising. The results also confirm that the US plays a prominent role in the international propagation of shocks to ASEAN countries.

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1.8 Appendix A: Data

The variables used in this paper are real GDP, consumer price index, equity price index, exchange rate, short-term interest rate and oil price index.

A1. Real GDP

The source for Indonesia, Malaysia, the Philippines, Thailand, and the US is IMF's International Financial Statistics (IFS) GDP series. The seasonally adjusted data for Belgium, France, Germany, Japan, Italy, Netherlands, Singapore and Spain is from datastream. For Indonesia, OECD Economic indicator completes the missing recent data. Where quarterly data are not available (i.e. Indonesia, Malaysia, Philippines, Thailand), we use the interpolated quarterly series calculated by Abeysinghe, T. and Gulasekaran, R. (2004). Interpolated series are used for the period of 1980-1996 for Indonesia, 1980-1990 for Malaysia, 1980 for Philippines and 1980-1992 for Thailand. The data for Indonesia, Malaysia, the Philippines and Thailand are seasonally adjusted. Seasonal adjustment is performed with E-views, using the U.S. Census Bureau's X12 program.

A2. Consumer Price Indices

The data source for all countries is the IFS Consumer Price Index series 64 zf.

A3. Equity Price Indices

We use IFS series 62 zf for 8 countries (France, Germany, Italy, Japan, Netherlands, the Philippines, Spain, the United States). For France, the IFS data is completed with OECD Main Economic Indicator database (MEI). The data source for Belgium, Malaysia, Thailand, Singapore and Indonesia is Datastream.

A4. Exchange Rates

IFS series rf are used for all countries. For the Euro Area countries, exchange rate is the weighted average of each country currency to US dollar, multiplied with the each domestic currency-euro conversion rate, before 1999 and the Euro-US dollar since 1999.

A5. Interest Rate

The data source is the IFS series 60b (Money market rate). For six Euro Area countries, interest rate is constructed as follows: for 1980Q1-1998Q4, the short-term country-specific inter-bank rate from IFS is used. From 99Q1-04Q4, the Euro overnight inter-bank rate is used as the common short-term interest rate.

Chapter 2

Structural Oil Shocks and Their Direct and Indirect Impact on Economic Growth

2.1 Introduction

The importance of oil to the modern world is unique in character and incredibly far-reaching in scope. It is a singularly variable in the world economy, just as, if not more influential than Federal Reserve decisions, the Euro-Dollar exchange rate or conditions in the U.S. Oil availability and price affect the output capacity, rate of growth and level of inflation throughout the world. Since the first oil crisis in 1973 the macroeconomic effects of oil prices have been studied extensively. For example, Hamilton (1983) concludes that almost all recessions in the U.S have been preceded by a large increase in the price of oil.

Oil shocked the world once more when global oil prices hit a peak of around US$150 per barrel in July 2008 from around US$30 per barrel in early 2003. In addition to little excess OPEC capacity and a weak dollar, the surge in oil prices is mainly driven by the robust economic growth, especially in emerging economies such as China and India, and by the expectations that world oil demand will grow faster than supply over coming decades. This implies that the traditional analysis of macroeconomic impact of oil shocks that treats oil price shocks as exogenous, may not be - applicable anymore. The cause and effect are no longer well defined when relating changes in the real price of oil to macroeconomic outcomes. Indeed, there now appears to be reverse causality from macroeconomic aggregates to oil prices (Kilian and Barsky (2004)).

To better understand the impact of oil price on the macroeconomic outcomes, we have to move beyond studying changes in the real price of oil and address the problem of identifying the structural shocks underlying the real price of oil. The identification of such structural shocks is important not only in understanding their relative importance in determining the oil price, but also in understanding their implications for macroeconomic aggregates. It is not possible to assess the impact of higher oil prices without knowing the underlying cause of the oil price increase. In the case that different types of oil price shocks may have very different effects on the economy and on the real price of oil, regression of relating macroeconomic aggregates to innovations in the price of oil will not be valid. Implicit in the regression is the view that an increase in the price of oil has the same effect regardless of the underlying cause of that increase. The interpretation based on this assumption leads one to discuss the effects of higher oil prices as though it did not matter what drove up oil prices in the first place. Thus, there is a need to decompose oil price shocks in the first place and then study how these shocks affect the economy differently.

This chapter investigates how different types of oil price shocks affect the growth of different economies directly and indirectly. To study this question, we utilize and combine two methodologies first formulated by Kilian (2007) and Abeysinghe (1999, 2001). Kilian (2007) uses a structural near-VAR model to decompose oil price shocks into four structural shocks, namely political oil supply shocks, other oil supply shocks, aggregate demand shocks and oil-specific demand shocks, where the last component relates to the idiosyncratic features of the oil market, such as changes in the precautionary demand concerning the uncertainty about the availability of future oil supplies. Abeysinghe (2001) decomposes the direct and indirect effects of oil prices on GDP growth of 12 economies using a structural VAR model where the indirect effect is transmitted through a trade matrix. It is found that, because of the indirect effect transmitted through their trading partners, even net oil exporters like Indonesia and Malaysia cannot escape the negative influence of a high oil price. Positive direct and negative indirect effects offset each other for these two producers, so that the net effect is nil.

To study the questions at hand we utilize the data from Abeysinghe (2001), where a set of 12 economies including ASEAN-4 (Indonesia, Malaysia, the Philippines and Thailand), NIE-4 (South Korea, Hong Kong, Singapore, Taiwan), China, Japan, USA, and the rest of OECD as one country are examined. Given that many of these countries are trading economies, the indirect effect of an oil shock through trading partners will play an important role in the economic growth. Meanwhile, we will address the question how structural oil shocks affect oil exporting countries, such as Indonesia and Malaysia, and oil importing countries such as Singapore and Japan differently.

Our analysis proceeds in two steps. First, we modify the procedure of Kilian (2007) to decompose oil-price changes into three components: oil-supply shocks, aggregate demand shocks and oil-specific demand shocks. An alternative index for global aggregate demand is used in our analysis. Second, after recovering the oil-supply shocks, aggregate demand shocks, and oil-specific demand shocks from the first analysis, we then modify Abeysinghe (2001)'s structural VARX model to incorporate these structural shocks to determine their direct and indirect effects on the GDP growth in our sample of twelve countries.

The rest of the chapter is organized as follows: Section 2.2 presents an overview of oil market and a selective literature survey. Section 2.3 presents the estimation methodology in detail, and describe the Kilian (2007)'s near-structural VAR model and Abeysinghe (2001) VARX model. Section 2.4 describes the data in detail and presents empirical result. Section 2.5 adds some conclusions.

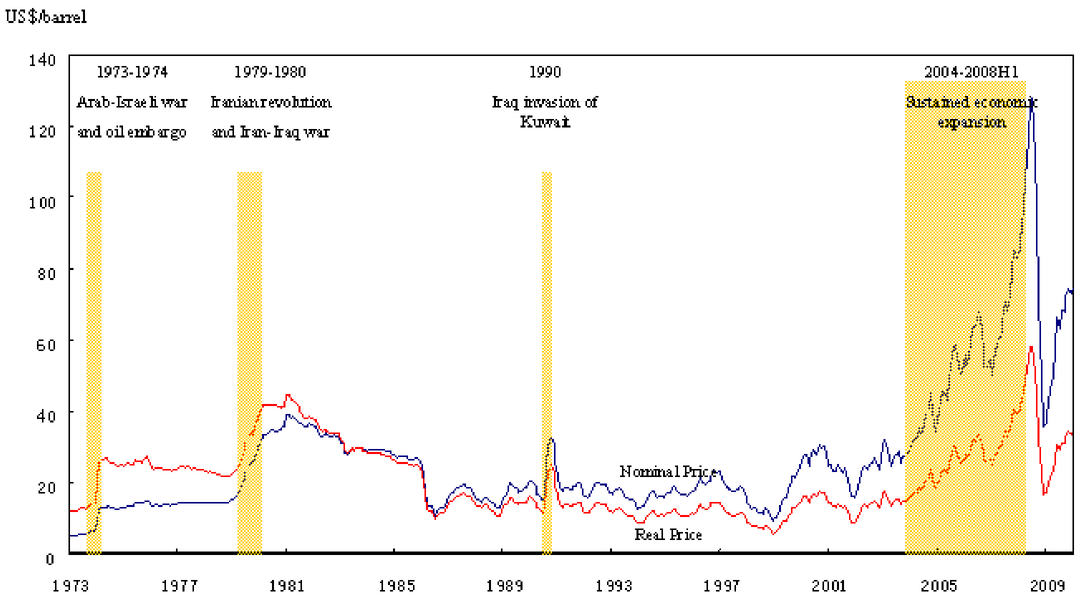
2.2 Literature Review

This section presents an overview of oil market and a review of related literature. The oil market overview reviews the behavior of oil prices over time, world oil production and consumption. This is followed by reviews on possible transmission mechanisms of oil price shocks, empirical studies on the impact of oil price shocks, and how problems arisen have led to the structural analysis of oil market.

2.2.1 Oil Market Overview

The nominal oil price, proxied by the crude oil price per barrel measured in US dollars, and the real oil price deflated by the U.S consumer price index are shown in Figure 2.1. At the peak, the average global oil price in June 2008 was about 30 times higher than in 1973, which is equivalent to 10% growth per annum over the past four decades. There was considerable volatility in oil prices and a few sharp spikes were observed. Moreover, the average annual increase in the price of oil between 2004 and –the first half of 2008 was substantially higher than in the preceding period, at over 32% p.a.

Figure 2.1: Crude Oil Prices (Feb 1973 – Dec 2009)



Earlier price spikes usually follow exogenous geopolitical events, including the 1973

Arab-Israeli war and the subsequent oil embargo, the 1979 Iranian revolution, followed by the Iran-Iraq war, and the 1990 Iraqi invasion of Kuwait (the Gulf War). However, the surge in oil prices between 2004-2008 is somewhat different, given the fact that there are no major political events during the period. Some researchers, e.g. Kilian (2007) and Hamiltion (2009) have investigated the cause of oil price surge during 2004-2008H1. In general, it is now widely believed in the literature that the latest oil spike is primarily demand driven, while earlier increases in oil prices were supply driven.

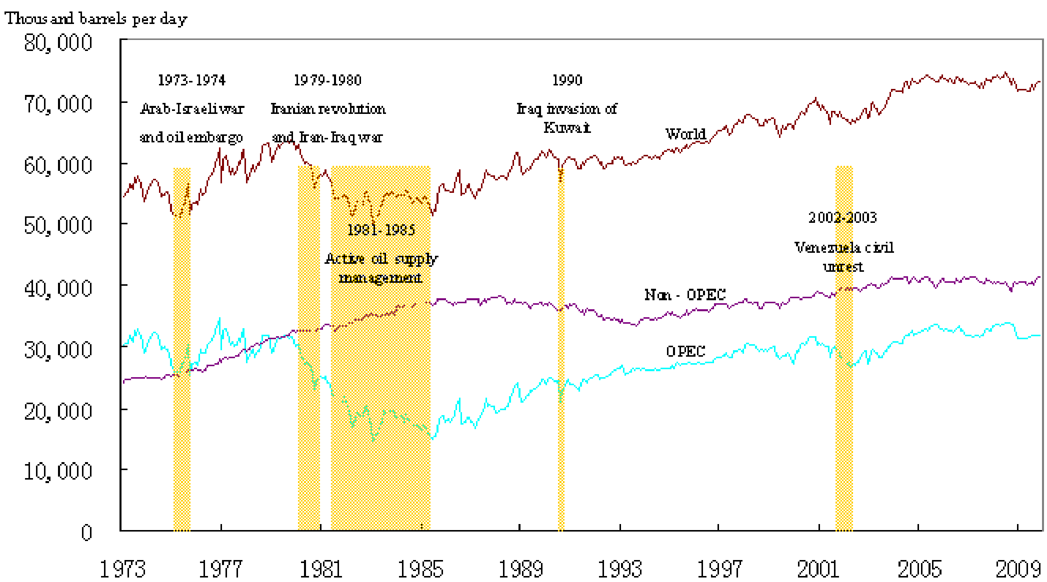
A visual inspection of nominal and real oil price shows little differences between their general movements. Changes in real oil prices have historically tended to be (1) permanent, (2) difficult to predict, and (3) governed by very different regimes at different points in time. Moreover, the real oil price seems to follow a random walk (Hamilton, 2008). The price increased by 187% within twelve months during the 1979 Iranian revolution and the subsequent Iran-Iraq war, but it could also have easily decreased by a comparable amount in another period. In fact, oil prices are amongst the most volatile goods and commodities (Regnier, 2007).

Figure 2.2 shows the oil production of OPEC and non-OPEC countries, as well as the total world oil production. It can be easily seen that the oil production from OPEC countries is much more volatile than that of Non-OPEC producers. This is due to the production disruptions following some significant political events happened in some

OPEC countries in the 1970s and 1980s, as well as the cartel behavior of OPEC producers.

A striking feature of Figure 2.2 is the dynamic production interactions of OPEC and non-OPEC oil producers, which results in a less volatile total world oil production. For example, when there is a political event leading to a reduction of oil production in affected OPEC countries, non-OPEC producers will increase production volume to react to changes in OPEC production. Thus, exogenous reduction of oil production in affected countries tends to be supplemented by an increase in production elsewhere (Kilian, 2008).

Figure 2.2: World Oil Production – OPEC and non-OPEC



This dynamic interaction can also be seen during 1980-1985, where OPEC countries cut oil productions due to active oil supply management while non-OPEC production increases gradually during the same period. This finding implies that the occurrence of oil price hikes after political events or cartel behavior of OPEC oil producers could be due to alternative mechanisms rather than actual shortfalls in oil production. Meanwhile, an absence of contraction in oil production levels after 2001 suggests that supply conditions is not the main reason for the 2004-2008 oil price hike.

2.2.2 Theories on Transmission Mechanisms of Oil Price Shocks

Oil prices may have an impact on economic activity through various transmission channels. Several theoretical models have been developed to address these transmission channels.

The first group of theories explains the classic supply-side effect of oil price shocks. According to this, rising oil prices are indicative of the reduced availability of a basic input to production, and consequently can cause a rise in production cost and slow the growth of output (see Barro, 1984; Brown and Yücel, 1999; Abel and Bernanke, 2001). The production cost effect is likely to be small due to the small proportion of energy expenditure for most economies. However, this effect can be greater under mark-up pricing[7] or capital-energy complementarities[8].

The second group argues that an increase of oil prices deteriorates terms of trade for

[7] Under mark-up pricing, an increase in oil price leads producers to mark-up the prices of final products. An increase in prices would generally reduce consumption and growth. This effect can be further compounded under dynamic mark-up pricing.

[8] When capital and energy are complementarities in production, a reduction in oil used in production due to an increase in oil prices will reduce the marginal productivity and demand of capital and thus reduces real output.

oil-importing countries (see Dohner, 1981). Thus, there is a wealth transfer from oil-importing countries to oil-exporting ones, leading to a fall of the purchasing power of firms and households in oil-importing countries. However, the total wealth transfer from the oil-importing countries to the oil-producing countries will tend to be small, given the small expenditure on foreign oil relative to GDP.

The third group focuses on the indirect effect through monetary policy response to oil price shocks (Pierce and Enzler, 1974; Mork, 1994). To mitigate the inflationary effects of oil price shocks, central banks may implement monetary tightening, which in turn reduces growth. If central banks accommodate the inflationary effects of an increase in oil price, it may lead to 'wage-price spiral' through second round effects, which in turn reduce growth.

The fourth group explains the negative effect of oil price rise on consumption and investment. Oil price increase can depress the purchase of energy-using goods such as automobiles and the resulting sector reallocation of labor imposes costs on the economy, thus reducing growth (Hamilton, 1988). On the other hand, rising oil prices introduce uncertainty and business firms will postpone investment as they attempt to find out whether the increase in the price of oil is transitory or permanent (Bernanke, 1983).

The fifth group argues that if the oil price increase is long-lasting, it can give rise to a change in the production structure and have an impact on unemployment. Indeed, a rise in oil prices diminishes the rentability of sectors that are oil-intensive and can incite firms to adopt and construct new production methods that are less intensive in oil inputs. This change generates capital and labor reallocations across sectors that can affect unemployment in the long run

2.2.3 Empirical Studies on Macroeconomic Effects of Oil Price Shocks

Since the first oil crises in 1973 the macroeconomic effects of oil prices have been studied extensively. In an influential paper, Hamilton (1983) found within a vector autoregression (VAR) framework that oil price change has a strong causal and negative correlation with real U.S. GNP growth from 1948 to 1980. These earlier studies generally put forward a linear relationship between output growth and oil price changes (see Burbidge and Harrison, 1984; Gisser and Goodwin, 1986). However, by the mid-1980s, the estimated linear relationship between oil prices and GDP began to lose significance: the declines in oil prices occurred over the second half of the 1980s were found to have smaller positive effects on economic activity than predicted by usual linear models. At the same time, evidence of non-linearity (asymmetries) in the link between output growth and oil price shocks has been established in some papers (see e.g. Mork, 1989; Mory, 1993; Mork and Olsen, 1994; Ferderer, 1996; Brown and Yücel, 2002; Hamilton, 2003). Mork (1989) was the first to provide the asymmetry of oil price shocks on economic activities. Using data from industrialized nations, Mork and Olsen (1994) again verified that there was a negative and significant relationship between an oil price increase and national output, while no statistical significance could be attributed to them when the oil price falls. Lee and Ratti (1995) estimated normalized oil shocks using the generalized autoregressive conditional heteroskedastic (GARCH) model and investigated the impacts of positive and negative oil shocks on economic activities. They came to the same conclusion that positive shocks have a statistically significant impact on economic activities, while negative shocks have no such an impact.

Similarly, Sadorsky (1999) employed a near-threshold approach and discovers that oil price increase have a greater impact on economic activities and are better able to explain the forecast error variance of real stock returns than are negative price changes. Oil price changes can explain more of the forecast error variance of real stock returns than can interest rates, especially after 1986. Beyond that, Huang et al. (2005) used a multivariate threshold model to analyze the impacts of an oil price change and its volatility on economic activities in USA, Canada and Japan during the period from 1970 to 2002. The most important finding is that in the two-regime model responses of economic activities are rather limited in regime I but are much more pronounced in regime II, where an oil price change or its volatility exceeds its threshold level.

A problem with non-linear specifications is that there are many possible functional forms. Thus, these studies have to conduct analysis with many different functional forms to ensure that the results are robust. To resolve this problem, Hamilton (2003) formulated a flexible approach for nonlinear inference by using U.S. macroeconomic data to determine the most suitable specification for the economy.

At least until recently, macroeconomists have viewed changes in the price of oil as an important source of economic fluctuations. However, a remarkable feature in the recent past is the prolonged surge in oil prices and their relatively mild impact on real economic activity and inflation. This observation casts doubt on the relevance of oil shocks for the macroeconomic performance in more recent times. In other words, the way the economy reacts to oil price shocks appears to have changed fundamentally. This conjecture has recently been confirmed in the empirical studies by Edelstein and Kilian (2007), Herrera and Pesavento (2009) and Blanchard and Galí (henceforth BG, 2007). In particular, these studies find the macroeconomic structure has changed over time and this caused a reduced impact of oil price shocks on macroeconomic aggregates. Prominent explanations for different macroeconomic consequence of oil price shocks over time discussed in the literature are improved monetary policy (e.g. BG 2007), more flexible labor markets (BG 2007), changes in the composition of automobile production and the overall importance of the US automobile sector (Edelstein and Kilian 2009), and variations in the role and share of oil in the economy over time (e.g. BG 2007; Edelstein and Kilian 2009).

Similarly, Segal (2007) assesses several arguments as to why high oil prices during the mid-2000s did not lead to a slowing of the world economy. The most important are 1) that oil prices have never been as important as commonly thought and 2) that high oil prices did not restrain growth because they no longer pass through to core inflation, which obviates the typical (growth-slowing) monetary tightening in response to positive oil price shocks.

2.2.4 Structural Analysis of Oil Price Shocks

However, a common limitation of the abovementioned analyses is that the oil price is often treated as exogenous with respect to the economy. It was widely accepted that the oil price surges between 2003 and 2008H1 were primarily driven by the robust economic growth. As a result, the traditional analysis that treats oil price shocks as exogenous may not be relevant. Indeed, there now appears to be reverse causality from macroeconomic aggregate to oil prices, which makes the identification of the endogenous component of oil price shocks necessary.

Recently, researchers began asking whether the relative importance of the driving forces behind oil price movements has changed and whether such changes can explain time-varying effects of oil price shocks. Kilian (2007) argues that oil price shocks have different effects on macroeconomic aggregates depending on their underlying causes. He decomposes the oil price changes into four structural shocks hidden behind such changes: (a) political oil supply shocks; (b) other oil supply shocks; (c) aggregate demand shocks for all industrial commodities including oil; and (d) precautionary demand shocks specific to oil. This decomposition of shocks eliminates not only the deficit of previous studies that considered oil price as an exogenous variable with respect to other variables that determine the course of the economy, but also the deficiency of those studies to document the relative importance of such differentiated shocks for the course of the economy.

Drawing on detailed data and econometric modeling to distinguish between these shocks over a four-decade period, Kilian (2007) identifies the broad characteristics of different shock-induced price hikes and their impact on macroeconomic aggregates. First, positive global demand conditions can offset the adverse effects of higher commodity prices on economic growth, which are endogenous to those demand conditions. This explains why higher oil prices in 2004H1 to? 2008 have had less impact than in the early 1980s, and why they have co-existed with strong economic growth for a relatively long period. Second, since market expectations adjust quickly to exogenous events, sharp increases in precautionary demand driven by uncertainty about future oil supply – rather than actual shortfalls in oil production – may well trigger immediate and large gains in oil prices. For example, the increase in oil prices in 1979/80 was not primarily due to supply disruptions as cutbacks associated with the Iranian revolution were largely offset by increased production elsewhere, although the outbreak of the Iran Iraq war in 1980 did initially generate a significant supply disruption. Instead, there was a strong increase in precautionary demand during that period as political instability in Iran, coupled with the Iranian hostage crisis and the

Soviet invasion of Afghanistan, heightened fears that the oil fields in Iran and Saudi Arabia might be destroyed.

Lippi (2008) identified and derived demand and supply shocks in the USA economy and those in the oil market. Using robust sign restrictions suggested by theory, he estimates the effects of different structural shocks. The estimates show that identifying the shock underlying the oil price change is important to predict the sign and the magnitude of its correlation with the U.S. production. The results offer a natural explanation for the smaller correlation between oil prices and US production in recent years compared to the 1970s. Decomposition of shocks also shows that demand shock accounted for more than half of all oil price shocks that occurred.

2.3 Estimation Methodology

We use two separate frameworks developed by Kilian (2007) and Abeysinghe (1999, 2001) respectively. This Section describes the Kilian (2007) and Abeyshinhe (2001) models and then lays out our estimation methodology.

2.3.1 Kilian's (2007) Model: Decomposition of Oil Price Shocks

Kilian (2007) uses a structural near-VAR model to decompose oil price shocks into four mutually orthogonal components. These orthogonal components come with structural economic interpretations as political oil supply shocks, other oil supply shocks, aggregate demand shocks and oil-specific demand shocks. The last component relates to the idiosyncratic features of the oil market, such as changes in the precautionary demand concerning the uncertainty about the availability of future oil supplies. The structural representation of the model, with the choice of two years lag, is as follows:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \,, \tag{3.1}$$

where $z_t = (x_t, \Delta prod_t, rea_t, rpo_t)'$, x_t denotes the series proxying the oil supply shocks driven by exogenous political events in OPEC countries, $\Delta prod$ denotes the percentage change in global crude oil production, rea_t denotes real economic activity and rpo_t refers to the real price of oil. A_i are matrix parameters to be estimated with the first row of $A_i, i = 1,...,24$ restricted to be zero to reflect the exogeneity of political oil supply shocks and its lack of serial correlation. ε_t denotes the vector of serially and mutually uncorrelated structural innovations.

Kilian (2007) postulated a recursive structure of A_0^{-1} such that the reduced form errors can be decomposed as follows:

$$e_t \equiv \begin{pmatrix} e_t^{x} \\ e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = A_0^{-1}\varepsilon_t \equiv \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{political oil \sup ply shocks} \\ \varepsilon_t^{Other oil \sup ply shocks} \\ \varepsilon_t^{aggregate demand shocks} \\ \varepsilon_t^{oil-specific demand shocks} \end{pmatrix}, \tag{3.2}$$

The assumptions that characterize the behavior of the structural shocks and the motivations are presented below.

Political oil supply shocks, henceforth *PS shocks*, are the measures of shocks to crude oil production due to the political events in the OPEC countries. They are caused by political events in OPEC countries and thus exogenous by construction. From the model, it was derived from the index proxying for political oil supply shocks, x_t, in Kilian (2008b). Contrary to conventional dummy variable method[9] of deriving political oil supply shocks, Kilian (2008b) used a historical approach to determine shock periods, affected economies and calculated the production shortfall against a counter-factual production growth path. This counter-factual production growth path is based on the growth rates of economies under similar historical circumstances during the same period. The index is then obtained by expressing production shortfall as a fraction of world production.

Other oil supply shocks, henceforth *OS shocks,* refer to oil supply shocks other than political oil supply shocks which affect the world oil production. They may be shocks due to cartel activity or oil productions in non-OPEC countries. For identification, the innovations in oil supply are allowed to respond to political oil supply shocks but not respond to changes in demand for oil in the same month. This restriction is plausible, considering the slow response of oil producing countries to oil demand changes due to supply adjustment costs and uncertainty.

[9] Conventional dummy variable method involves adding dummy variable that takes the value of one during determined periods of political oil supply shocks and zero otherwise. In comparison, Kilian (2008b) method provides more information, such as the counter-factual production level, but it is based on an element of historical judgment.

Aggregate demand shocks, henceforth *AD shocks,* are estimated by changes in real economic activity which cannot be explained by both supply shocks. It was obtained from the residual of regressing index for real global economic activity, rea_t. This index was constructed by obtaining growth rates of freight rates for various bulk dry cargoes, taking their equal-weighted average, cumulating and normalizing the series to unity in January 1968. For identification, the innovation in real economic activity is allowed to respond to the oil supply shock, but is assumed not to respond to changes in specific demand for oil in the same month. The interpretation of this exclusion restriction is that increases in the real price of oil driven by shocks that are specific to the oil market will not lower global real economic activity immediately, but with a delay of at least one month. This is consistent with the sluggish behavior of global real economic activity after each of the major oil price increases in the sample.

Oil-specific demand shocks, henceforth *OD shocks*, are shocks which account for oil price changes which cannot be explained by all the above shocks. These shocks will reflect in particular fluctuations in precautionary demand for oil driven by fears about future oil supplies, and it may also reflect other factors such as oil sector-specific inventory adjustments.

Implicit in Kilian's (2007) model are two more assumptions: First, there are no politically motivated exogenous supply shocks in industrial commodities other than oil. This assumption seems self-evident. Second, the idiosyncratic shocks to the demand or supply of dry cargoes average out in the construction of the index of real economic activity. These assumptions remain realistic and do not pose discernible problems in the analysis.

2.3.2 Abeysinghe (2001) Model: Decomposition of Direct and Indirect Impact of Oil Price Shocks

Abeysinghe (2001) developed a structural VARX model to measure the direct and indirect effects of oil shocks on growth. The model uses a new specification strategy which reduces the number of unknowns and allows varying cross-country relationships over time.

Using reduced-form bilateral export functions, Abeysinghe (2001) derived the following system of simultaneous equations to capture the inter-linkages between GDP growth rates of different economies:

$$(B_0 * W_t)y_t = \lambda + \sum_{j=1}^{p}(B_j * W_{t-j})y_{t-j} + \sum_{j=0}^{p}\Gamma_{1j}z_{1,t-j} + \sum_{j=0}^{p}\Gamma_{kj}z_{k,t-j} + \varepsilon_t \ , \tag{3.3}$$

where y_t is a (n×1) vector of GDP growth series of the different economies, the $z_i, i = 1,..,k$ are (n×1) vectors of exogenous variables, W_t is a known matrix of weights derived from bilateral export shares such that $\sum w_{ij} = 1, j = 1,2,...,n; i \neq j$. B are unknown parameter matrices, $\Gamma_1,...,\Gamma_k$ are diagonal parameter matrices, and ε_t is a random vector with zero mean and $Var(\varepsilon_t) = \Omega$. In our notation n is the number of countries considered in the model and the asterisk * stands for the element-wise (Hadamard) product of two matrices.

Using the compact notation $B^{w}(L)=(B_0 * W_t)-(B_1 * W_t)L-\cdots-(B_p * W_t)L^p$ and $\Gamma^{i}(L)=\Gamma^{i}_{0}+\Gamma^{i}_{1}L+\cdots+\Gamma^{i}_{p}L^p$ where L is the lag operator, equation (3.3) can be written as

$$y_t=\lambda^{*}+B^{w}(L)^{-1}\Gamma^{1}(L)z_{1t}+\cdots+B^{w}(L)^{-1}\Gamma^{k}(L)z_{kt}+B^{w}(L)^{-1}\Gamma^{1}\varepsilon_t\,, \qquad (3.4)$$

Using Equation (3.4), the impulse responses with respect to the i^{th} exogenous variable can be obtained from $B^{w}(L)^{-1}\Gamma^{i}(L)z_{it}$. For country i, the ii^{th} element of $B^{w}(L)^{-1}\Gamma^{i}(L)z_{it}$ provides the direct impact of oil prices on the GDP growth and the $ij^{th}(j=1,2,...n;i\neq j)$ off-diagonal terms provide the impact through the trading partners. Unlike standard VAR or VARX models, which produce fixed impulse responses, the impulse responses produced by model (3.4) change over time as the trading pattern changes. This allows one to compute impulse responses at any point in time using a given trade matrix W_t. Abeysinghe suggests using 12-quarter moving averages of export shares, so that they change slowly over time.

2.3.3 Our Estimation Methodology

Our estimation proceeds in two steps. First, we decompose oil price shocks into three structural shocks following Kilian’s (2007) procedure, namely oil-supply shocks, aggregate demand shocks and oil-specific demand shocks. Such decompositions carry a significant economic interpretation and reveal certain implications for both researchers and policy makers. In particular, the structural VAR model contains three variables, global oil production (prod), global real economic activity (rea), and real oil prices (rpo).

$$A_0\Delta z_t = \alpha + \sum_{i=1}^{p} A_i \Delta z_{t-i} + \varepsilon_t \tag{3.5}$$

where $z_t = (prod_t, rea_t, rpo_t)'$, ε_t denotes the vector of serially and mutually uncorrelated structural innovations. The recursive structure of A_0^{-1} is postulated as in Kilian (2007) such that the reduced form errors can be decomposed as follows:

$$e_t \equiv \begin{pmatrix} e_t^{prod} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = A_0^{-1}\varepsilon_t \equiv \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{Supplyshock} \\ \varepsilon_t^{aggregatedemandshock} \\ \varepsilon_t^{oilspecificdemandshock} \end{pmatrix}, \tag{3.6}$$

Our analysis follows the basic framework of Kilian's (2007) with some notable adjustments. In Kilian's (2007) paper, he estimates a structural VAR model for the four variables as follows: the percentage change in world oil production due to political events, the percentage changes in world crude oil production, global real economic activity, and the real oil prices. As we show below, the percentage change in world oil production is a stationary variable (i.e., I(0) variable) while global real economic activity and the real oil prices are non-stationary variables (i.e., I(1) variables). Thus we argue that Kilian (2007) estimates a structural VAR model that incorporates variables with different order of integration. We modify Kilian's (2007) procedure for recovering oil market shocks by estimating a three variable structural VAR model, using the first log difference of global oil production, global real economic activity, and the real price of oil. As such, our three variables have the same order of integration, i.e. I(0).

Next, after recovering the oil-supply shocks, aggregate demand shocks, and oil-specific demand shocks, we then use Abeysinghe (2001)'s structural VARX model to incorporate these structural shocks to determine their direct and indirect effects on the GDP growth in our sample of twelve countries. Specifically, we estimate

$$(B_0 * W_t)y_t = \lambda + \sum_{j=1}^{p}(B_j * W_{t-j})y_{t-j} + \sum_{j=0}^{p}\Gamma_{1j}z_{1,t-j} + \sum_{j=0}^{p}\Gamma_{2j}z_{2,t-j} + \sum_{j=0}^{p}\Gamma_{3j}z_{3,t-j} + \varepsilon_t \,, \quad (3.7)$$

where z_{1t}, z_{2t}, z_{3t} are the oil supply shocks, aggregate demand shocks and oil-specific demand shocks.

The estimation of simultaneous equations system (3.7) can be done by 1) single equation/limited information estimation methods for simultaneous equations systems - ordinary least square (OLS) and two-stage least square (2SLS) or 2) system method of estimation - three-stage least square (3SLS). 2SLS and 3SLS are instrumental variable estimation methodologies.

2.4 Empirical Results

2.4.1 Data

We collect monthly data on nominal oil prices, proxied by the U.S Crude Oil Imported Acquisition Cost by Refiners as it constitutes the longest span of available oil price data[10], the U.S. consumer price index, global oil production measured in

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[10] The oil price data is from Energy Information Administration. Other measures of crude oil prices, such as

millions of barrels per day, and global real economic activity proxied, as suggested by Kilian (2007), by the index of dry bulk cargo freight rates[11]. The nominal oil prices were deflated by the U.S. CPI to get real oil prices.

It is noteworthy that our definition of real oil prices represents a common shock to all countries. However, the economic impact of oil price shocks could be different in different countries because of changes in their exchange rates against US dollar. For simplicity, we don't estimate the model using oil prices converted to domestic currencies and deflated by each country's CPI. In fact, as pointed out by some researchers, there wouldn't be significant differences in the results.

For GDP growth series, we use log-difference of quarterly real GDP for the twelve economies from 1975Q1 to 2009Q1, seasonally adjusted to construct the weighted average of GDP growth rates. The GDP data from 1975Q1 to 2007Q1 are downloaded from Abeysinghe Tilak's website, and then extended until to 2009Q1 using data from International Financial Statistics database and various national statistical bureaus. Quarterly data on bilateral export shares are downloaded Abeysinghe Tilak's website. The trading patterns of the sample economies are summarized in Table 2.1. In accordance with Abeysinghe's (2001) methodology, countries in the model must have close trading links. In order to reduce the bias of foreign variables' estimators in each equation, each country in the data set must have

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Petroleum West Texas Intermediate and Petroleum UK Brent are only available for a later date.

[11] The index of dry bulk cargo freight rates is obtained from Dr Lutz Kilian

several of the others as its major trading partners. In this regard, the set of countries from Abeysinghe (2001) forms a logical one. Within the sample countries, Malaysia is the main oil exporter; China and Indonesia were historically net oil exporters but became net oil importers in 1993 and 2004 respectively. The rest of the economies are all net oil importers.

Each row in Table 2.1 represents the export shares of one country to all other countries, which are summed to one. It shows that Japan, USA and ROECD are major export markets to all Asian economies. Second, Singapore is a close trading partner with Malaysia and Indonesia. Third, Hong Kong and China are close trading partners, and China is the biggest export market for South Korea and Taiwan.

Table 2.1 Export Shares (12-quarter moving average at t=2006Q3)

	Importers											
Exporters	Singapore	Malaysia	Indonesia	Thailand	Philippines	S.Korea	Taiwan	HK	China	Japan	USA	ROECD
Singapore		0.16	0.10	0.05	0.02	0.04	0.03	0.11	0.10	0.07	0.13	0.19
Malaysia	0.17		0.03	0.06	0.02	0.04	0.04	0.06	0.08	0.11	0.22	0.18
Indonesia	0.11	0.05		0.03	0.02	0.08	0.06	0.02	0.08	0.24	0.14	0.18
Thailand	0.08	0.06	0.04		0.02	0.02	0.03	0.07	0.10	0.16	0.19	0.22
Philippines	0.07	0.06	0.01	0.03		0.03	0.07	0.08	0.12	0.18	0.18	0.18
S.Korea	0.03	0.02	0.02	0.02	0.01		0.06	0.08	0.27	0.10	0.19	0.20
Taiwan	0.04	0.02	0.01	0.02	0.02	0.03		0.18	0.23	0.08	0.17	0.19
Hong Kong	0.02	0.01	0.00	0.01	0.01	0.02	0.01		0.49	0.06	0.18	0.18
China	0.03	0.02	0.01	0.01	0.01	0.06	0.01	0.20		0.14	0.26	0.25
Japan	0.03	0.02	0.02	0.04	0.02	0.09	0.08	0.08	0.15		0.26	0.21
USA	0.03	0.02	0.00	0.01	0.01	0.04	0.03	0.03	0.07	0.09		0.66
ROECD	0.03	0.02	0.01	0.01	0.01	0.09	0.04	0.02	0.03	0.09	0.65	

2.4.2 Unit Root Tests

We test for unit roots in the natural logarithms of our variables. We test the null hypothesis of unit root versus the alternative hypothesis of stationary variables using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981). We employ the Akaike information criteria (AIC) to select the lag length for the ADF test. Table 2.2 reports the results with and without a trend. We can't reject the null

Table 2.2 Unit-root tests

Variables	Levels		First Differences	
	Without trend	With trend	Without trend	With trend
Prod	0.76	-1.56	-22.68***	-22.68***
Rea	-2.51**	-3.59***	-14.53***	-14.51***
Rpo	-0.27	-2.82	-12.36***	-12.35***
GDPs				
Singapore	5.35	-1.85	-3.59***	-8.29***
Malaysia	4.78	-1.84	-3.69***	-7.61 ***
Indonesia	5.16	-1.65	-4.29***	-8.55***
Thailand	5.96	-5.05***	-2.66***	-8.77***
Philippines	5.45	-0.07	-2.37**	-11.74***
South Korea	7.17	-2.00	-4.76***	-12.72***
Taiwan	5.96	-5.05 ***	-2.66***	-9.08***
Hong Kong	7.28	-3.66 ***	-3.17***	-10.87***
China	5.47	0.16	-0.94	-6.16***
Japan	5.75	-4.09 ***	-3.30***	-9.95***
US	4.91	-1.73	-2.27**	-3.58***
ROECD	3.37	-1.81	-1.98**	-8.29***
ε^{os}	-11.32***	-11.28***		
ε^{ad}	-11.71***	-11.66***		
ε^{id}	-11.92***	-11.88***		

Note: prod is the log of global oil production, rea is the log of real economic activity, rpo is the log of real oil price, GDPs are the log of seasonally adjusted GDP, $\varepsilon^{\text{oil supply shock}}$ is the structural oil supply Shock, $\varepsilon^{\text{aggregate demand shock}}$ is the structural global demand shock, and $\varepsilon^{\text{oil-specific demand shock}}$ is the structural oil-specific demand (idiosyncratic) shock. The null hypothesis H_0: has a unit root.
The critical values for tests with trend is: 1%=-3.45, 5%=-2.87, 10%=-2.56, and without trend is: 1%=-2.57, 5%=-1.94, 10%=-1.62

**Significant at 5%
***Significant at 1%

hypothesis that the global oil production and real oil price contain a unit root at the 5% significance level, suggesting that the natural logarithm of these two variables in our study are I(1). For the exception, the unit root hypothesis in real economic activity is rejected at the 5% level. On the GDP growth rate, with the exception of China, we reject the null hypothesis that GDP growths contain a unit root at 5% significance level, suggesting GDP growth rate are I(0). The null hypothesis is also rejected for the three structural oil market shocks we recovered from decomposing the changes in oil prices.

2.4.3 Variance Decomposition Tests

Table 2.3 reports the variance decompositions results for the effects of various oil market shocks on the real price of oil in our first step VAR model. We use 20 lags in the VAR model. The number reported indicate the percentage of the forecast error in real oil price that we can attribute to each of the structural innovations at different horizons (from 1 month to 60 months). We report the percentages for selected forecast horizons (1,6,12,24,36,48,60 months).

The decomposition results uncover a pattern for the three structural oil shocks. Oil supply shock contributes very little to the variation in real oil prices. In the long run, oil supply shock only produces 2% of the variation in the real oil prices. Global aggregate demand shock generates much bigger effect on the variation of oil prices than oil supply shock, accounting for 7.3% in one month forecast horizon to a high of 16.5% in the long run. On the other hand, the oil-specific shocks such as changes in expectation or precautionary demand concerning the future uncertainty of oil supply availability, generates the largest effect on the variation of real oil price. In short run (i.e. one month forecast horizon), it explains as high as 92.4% variations in oil prices. Extending to the long run, the oil-specific shock still generates as high as 81% variation in real oil prices.

Table 2.3 Variance Decomposition of Oil Price Shocks into Structural Oil Shocks

Months	OS shock	AD shock	ID shock
1	0.35	7.25	92.40
	(0.70)	(2.46)	(2.55)
6	1.04	9.38	89.58
	(1.42)	(3.45)	(3.71)
12	1.19	10.36	88.45
	(1.80)	(3.95)	(4.20)
24	1.97	13.91	84.12
	(2.31)	(5.55)	(5.61)
36	1.99	15.82	82.19
	(2.49)	(6.94)	(6.93)
48	2.00	16.37	81.63
	(2.64)	(7.71)	(7.74)
60	2.00	16.50	81.50
	(2.74)	(8.23)	(8.28)

Notes: Standard errors, estimated through Monte Carlo techniques with 1000 replications, appear in parentheses under percentage of variances explained.

2.4.4 Impulse Response of Global Oil Production, Real Economic Activity and Real Price of Oil to Structural Oil Shocks

Figure 2.3 and 2.4 show the impulse responses and cumulative impulse responses of global oil production, real economic activity and the real price of oil to one-standard deviation of structural innovations.

Oil supply shock tends to raise the level of global oil production permanently and significantly. It leads to an initial sharp increase in oil production, but the effects decline quickly and become not significant in 18 months. A positive oil supply shock reduces the real price of oil, but the reduction is small and not significant at the 5% level. The real oil price declines within the first 5 months. After that, the effect is essentially zero. A positive oil supply shock also causes a small but not significant increase in global real economic activity in second year after the shock (through their effect on the price of oil).

An aggregate demand expansion increases real economic activity significantly, but the increase drops to about one half of the initial effect after 18 months. Aggregate demand expansions temporarily increase global oil production, with a delay of half a year before production expands. The production response peaks about 8 months after the shock and is statistically significant. After 12 months the expansion ends. There is some indication that the initial increase is offset by small but persistent decreases at longer horizons, although the latter are not statistically significant. Aggregate demand expansions also cause a large and persistent increase in the real price of oil. The response of the real price of oil is significant at the 5 percent level for all horizons.

Oil-specific demand increases leads to an immediate, large and persistent increase in the real price of oil. It also shows some shooting in the real oil price in the first few months after the shock. The price increase dropped to only about half of the initial size after 18 months. Oil-specific demand increases do not cause an increase in global oil production. In fact, there is evidence of a decline in oil supply in the second year, although that decline is small and not significant at the 5 percent level. Oil-specific demand increases cause a temporary increase in real economic activity in the first year but the cumulative effect turned to be negative after 15 months, through their effect on the oil price.

2.4.5 Characteristics of Structural Oil Shocks

Figure 2.5 shows the time series of the three structural residuals of model (3.5) over a four-decade period. Oil supply shock has been historically large before 1990s and becomes substantially smaller after 1990. This reflects the global oil production has become more stable since 1990s and its importance in explaining the real oil price fluctuations has decreased over time. It also saw several large negative oil supply shocks before the 1990s, most of which coincide with political events in oil producing countries. Aggregate demand shock is on average small in size and don't exhibit large negative or positive spikes, except the sharp negative shock in second half 2008. It saw continued moderate positive aggregate demand shock during the period of 2004 to the first half of 2008. Oil-specific demand shock has been historically small before 1985 but becomes bigger over time. This suggests the fluctuations in precautionary demand in explaining the real oil price fluctuations is increasing.

Another important characteristic revealed by the structural shock series is that market

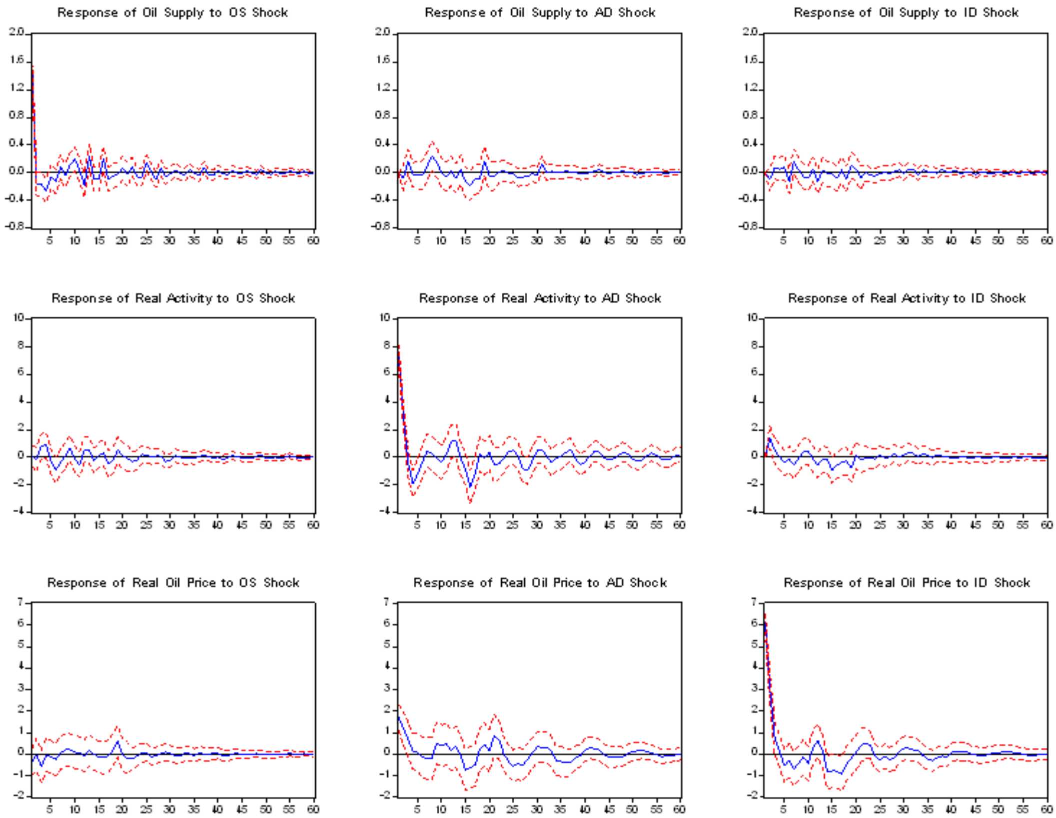


Figure 2.3: Response to One S.D. Structural Innovations with two S.E. Bands

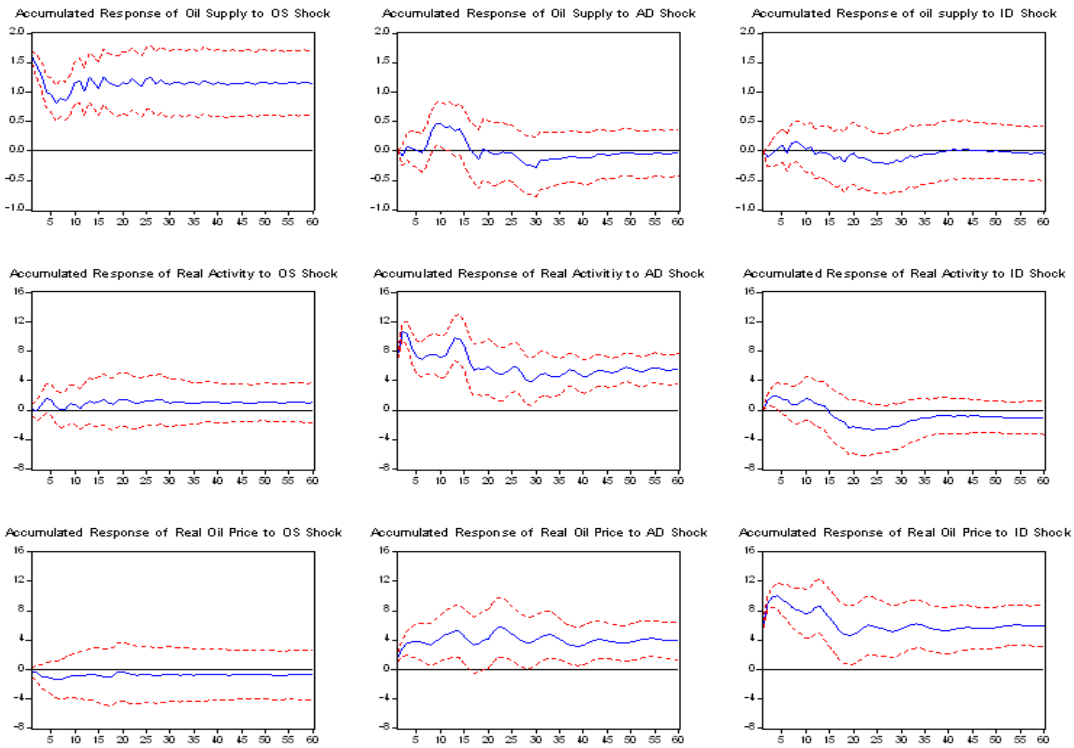
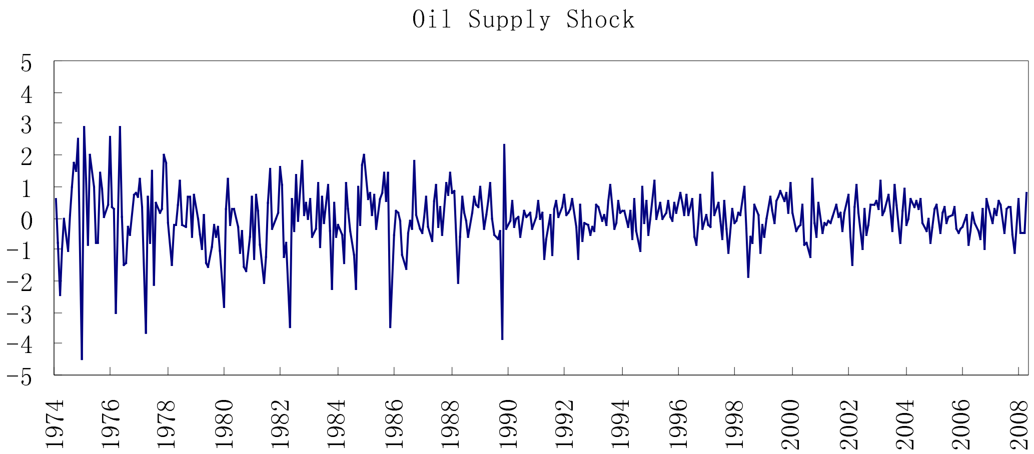
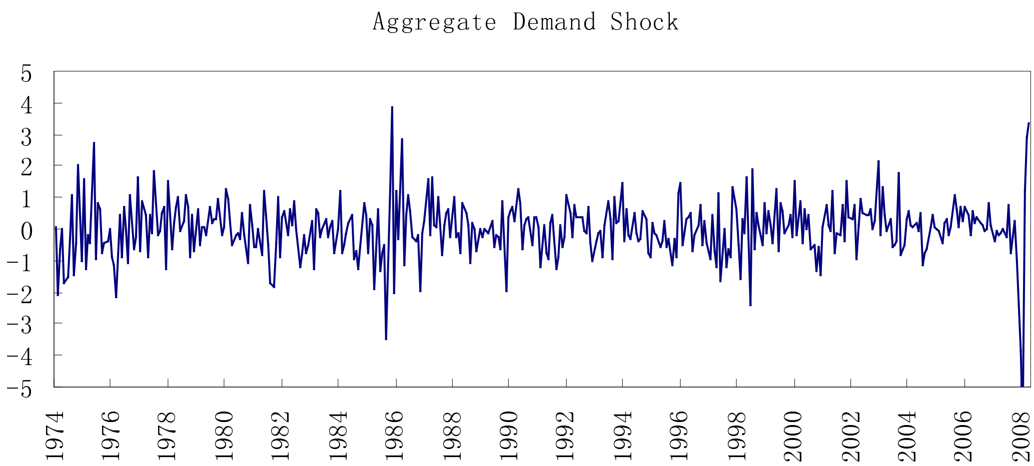
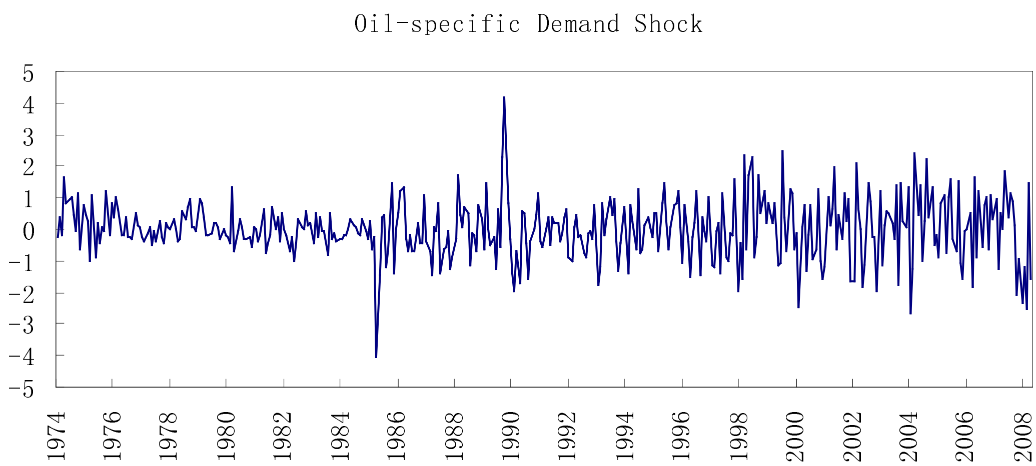


Figure 2.4: Cumulative Response to One S.D. Structural Innovations with two S.E. Bands

Figure 2.5: Monthly Time Series of Structural Oil Shocks (Nov 1974 - Feb 2009)







expectations adjust quickly to exogenous events. Sharp increases in precautionary demand driven by uncertainty about future oil supply – rather than actual shortfalls in oil production – may well trigger immediate and large gains in oil prices. For example, the increase in oil prices in 1990 after the invasion of Kuwait was almost entirely due to a spike in precautionary demand, not actual supply disruptions.

After the monthly structural oil innovations are recovered from the first step, we construct measures of quarterly shocks by adding up the monthly structural innovations for each quarter:

$$\hat{\zeta}_{jt} = \sum_{i=1}^{3} \hat{\varepsilon}_{j,t,i}\,, \quad \text{j=1,..3}$$

where $\hat{\varepsilon}_{j,t,i}$ refers to the estimated residual for the *j*th structural shock in the *i*th month of the *t*th quarter of the sample.

2.4.6 Impulse Response of GDP Growth to Structural Oil Shocks

We present results for model (3.7) estimated by OLS, as we did not find notable differences between the OLS, 2SLS and 3SLS estimations. We use one lag of GDP growth and six lags of structural oil shocks in the estimation. As a check, we performed serial correlation test for the residuals from the OLS estimation. We did not find any evidence of serial correlation for all countries except the Philippines and Japan.

After estimating the model parameters, impulse responses were generated by fixing the Wt matrix as the average for the period from quarter 3 of 2003 to quarter 3 of 2006. The cumulative impulse responses of GDP growth to one standard error increase in different structural oil shocks are plotted up to 24 quarters.

2.4.6.1 Oil Supply Shock

Oil supply (OS) shock is the measure of shock to global oil production. Figure 2.6 shows the cumulative impulse responses of GDP growth to one standard error positive OS shock. Table 2.4 provides a summary of the cumulative sums of four quarters of impulse responses and the cumulative sums for 24 quarters.

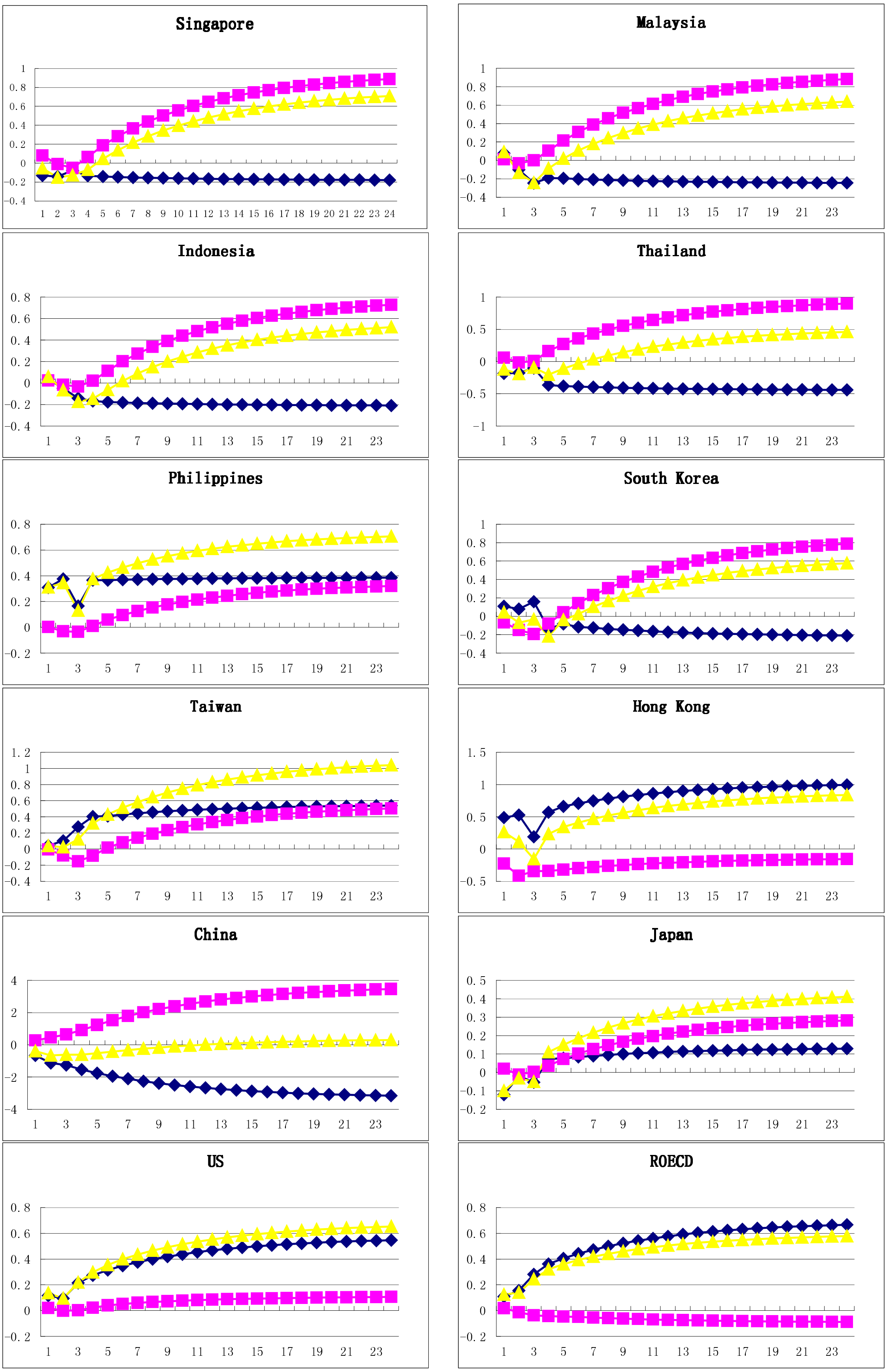
The graph shows that the OS shock has a positive total impact on all economies in the long run, though the impact is not substantial. This is intuitive and consistent with other findings since an increase in oil supply tends to reduce oil price and thus positively affects GDP growth.

The graphs also shows that the direct effects tend to become zero after a few quarters for most countries while indirect effects persist even after 20 quarters. Since indirect effects become substantial with time, it seems appropriate to examine effects until 24 quarters.

A cursory view of the impulse response graphs shows positive and negative direct and indirect effects of OS shock on different economies. The direct effects tend to be greater in the first few quarters while indirect effects gradually cumulate to become substantial after many quarters. This suggests that while direct effects are more significant in the short-run, indirect effects allow the effects of OS shock to persist over the long term. It is also noted that for the small open countries such as ASEAN5 and NIE4, the direct effect from OS shock is much smaller than the indirect effect, while for lager economies such as China and the US, the direct effect becomes much bigger. This is not surprising as small open economies are more dependent on world economy through its trading partners.

Table 2.4 shows that the direct effect of OS shock on oil importing countries such as Philippines, Taiwan, Hong Kong, Japan, US, ROECD is positive. This is intuitive that oil-importing countries will benefit from a lower oil price caused by an increase in global oil supply. On the other hand, the direct effect of OS shock on oil exporting countries such as Malaysia and Indonesia is negative. This suggests that an increase in global oil supply will adversely affect the oil exporting countries that rely on oil export revenues. The Table also shows that OS shock has a small negative direct effect on Singapore, Thailand and South Korea. A possible explanation is that the petrochemical industry in these countries is adversely hurt while other industries do not benefit from global oil supply increase, given that OS shock is not supposed to significantly change oil prices. China is also adversely affected by OS shock. This may be due to the fact that China was an oil exporting country for most of the time within our sample period.

Figure 2.6: Cumulative Impact of one S.E Oil Supply Shock on GDP Growth (%)



Direct Impact (Diamond Line), Indirect Impact (Box line), Total Impact (Triangle line)

Table 2.4: Cumulative Impact of one S.E Oil Supply Shock on GDP Growth (%)

		Direct Impact	Indirect Impact	Total Impact
Singapore	After 4 qtrs	-0.1	0.1	-0.1
	After 24 qtrs	-0.2	0.9	0.7
Malaysia	After 4 qtrs	-0.2	0.1	-0.1
	After 24 qtrs	-0.2	0.9	0.6
Indonesia	After 4 qtrs	-0.2	0.0	-0.1
	After 24 qtrs	-0.2	0.7	0.5
Thailand	After 4 qtrs	-0.4	0.2	-0.2
	After 24 qtrs	-0.4	0.9	0.5
Philippines	After 4 qtrs	0.4	0.0	0.4
	After 24 qtrs	0.4	0.3	0.7
South Korea	After 4 qtrs	-0.1	-0.1	-0.2
	After 24 qtrs	-0.2	0.8	0.6
Taiwan	After 4 qtrs	0.4	-0.1	0.3
	After 24 qtrs	0.5	0.5	1.0
Hong Kong	After 4 qtrs	0.6	-0.3	0.2
	After 24 qtrs	1.0	-0.2	0.8
China	After 4 qtrs	-1.5	0.9	-0.6
	After 24 qtrs	-3.2	3.5	0.3
Japan	After 4 qtrs	0.1	0.0	0.1
	After 24 qtrs	0.1	0.3	0.4
US	After 4 qtrs	0.3	0.0	0.3
	After 24 qtrs	0.5	0.1	0.7
ROECD	After 4 qtrs	0.4	0.0	0.3
	After 24 qtrs	0.7	-0.1	0.6
Std. Dev. $\times 10^2$	1.39			

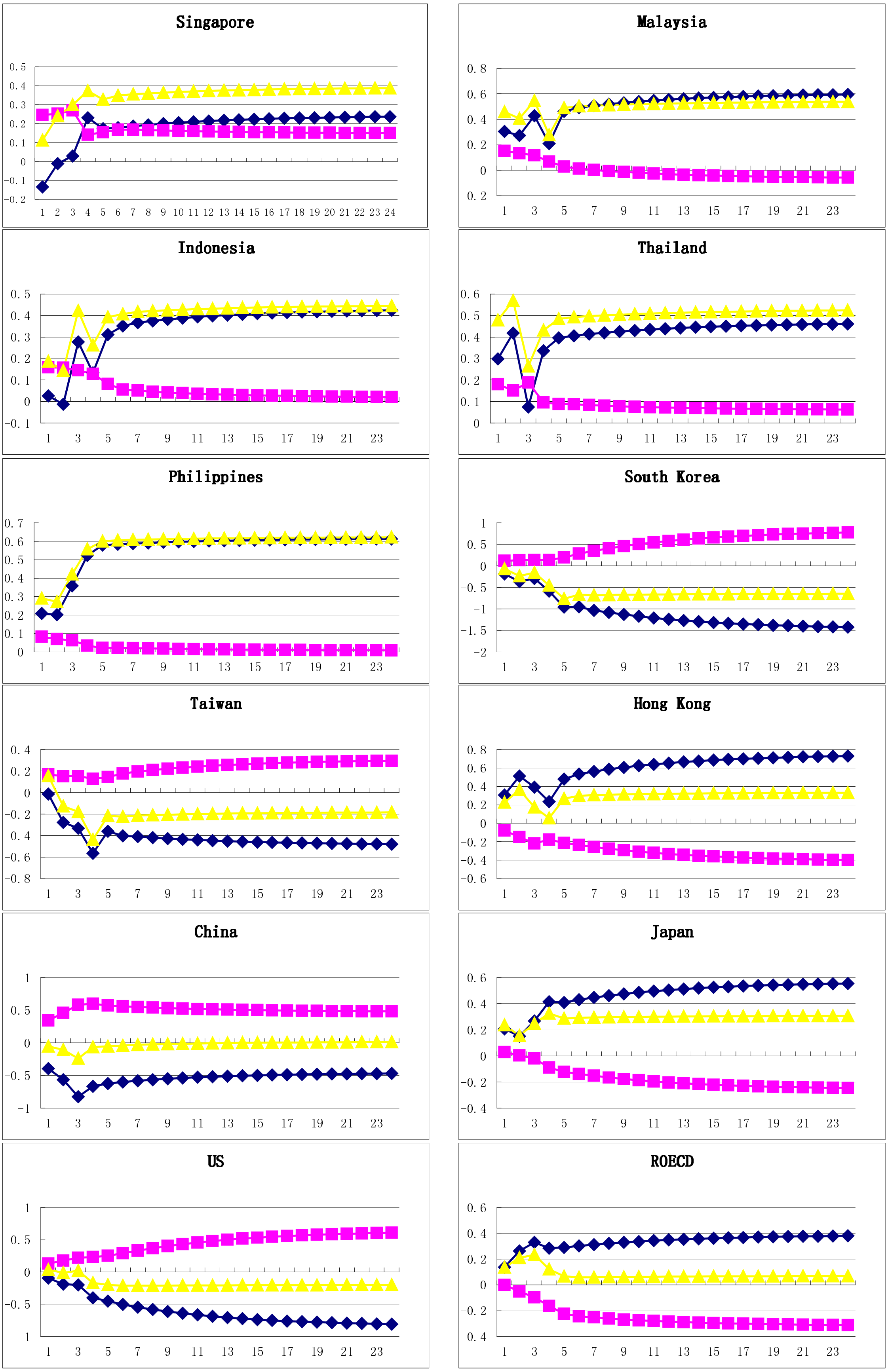
2.4.6.2 Aggregate Demand Shock

Aggregate demand (AD) shock is the oil demand shock which accounts for changes in real economic activity that cannot be explained by supply shock. Figure 2.7 shows the cumulative impulse responses of growth in response to one standard error AD shock, plotted up to 24 quarters. Table 2.5 provides the summary.

A cursory view of the impulse response graphs show positive and negative direct and indirect effects of AD shock on different economies. AD shock has positive direct effect on eight economies and negative direct effect on four economies. In most cases, a positive AD shock causes an initial increase in real GDP growth, followed by a decline in the next year. In the third year, the response reverts to near zero. This suggests aggregate demand expansion raise real GDP in the short run, but after the oil price was driven up by the aggregate demand after a few quarters, the effects trend down thereafter. In terms of total impact in the long run, the effects are slightly positive for many countries. This suggests that the increase in oil price due to aggregate demand expansion is not detrimental to economic growth. Instead, positive global demand conditions can offset the adverse effects of higher oil prices on economic growth, which are endogenous to the aggregate demand. This may explain why higher oil prices in between 2004-2008H1 have had less impact than in the early 1980s, and why they have co-existed with strong economic growth for a relatively long period.

The graphs also show that AD shock has larger direct effect than indirect effects, which is contrary to OS shock. This does not mean that there is comparatively little international transmission of AD shock, but rather the different positive and negative direct effects of AD shock on different economies produces positive and negative indirect effects that cancel each other out in the process.

Figure 2.7: Cumulative Impact of one S.E. Aggregate Demand Shock on GDP Growth (%)



Direct Impact (Diamond Line), Indirect Impact (Box line), Total Impact (Triangle line)

Table 2.5: Cumulative Impact of one Standard Error Aggregate Demand Shock on GDP Growth (%)

		Direct Impact	Indirect Impact	Total Impact
Singapore	After 4 qtrs	0.2	0.1	0.4
	After 24 qtrs	0.2	0.2	0.4
Malaysia	After 4 qtrs	0.2	0.1	0.3
	After 24 qtrs	0.6	-0.1	0.5
Indonesia	After 4 qtrs	0.1	0.1	0.3
	After 24 qtrs	0.4	0.0	0.4
Thailand	After 4 qtrs	0.3	0.1	0.4
	After 24 qtrs	0.5	0.1	0.5
Philippines	After 4 qtrs	0.5	0.0	0.6
	After 24 qtrs	0.6	0.0	0.6
South Korea	After 4 qtrs	-0.6	0.1	-0.5
	After 24 qtrs	-1.4	0.8	-0.6
Taiwan	After 4 qtrs	-0.6	0.1	-0.4
	After 24 qtrs	-0.5	0.3	-0.2
Hong Kong	After 4 qtrs	0.2	-0.2	0.1
	After 24 qtrs	0.7	-0.4	0.3
China	After 4 qtrs	-0.7	0.6	-0.1
	After 24 qtrs	-0.5	0.5	0.0
Japan	After 4 qtrs	0.4	-0.1	0.3
	After 24 qtrs	0.6	-0.2	0.3
US	After 4 qtrs	-0.4	0.2	-0.2
	After 24 qtrs	-0.8	0.6	-0.2
ROECD	After 4 qtrs	0.3	-0.2	0.1
	After 24 qtrs	0.4	-0.3	0.1
Std. Dev.$\times 10^2$	1.37			

China and US experience a negative direct effect from AD shock, while Japan and ROECD enjoy a positive direct effect. As these four economies are the major trading partners of Asian economies, this suggests the indirect effects transmitted to the Asian economies should be small. South Korea and Taiwan are the other two economies that are hit directly by AD shock, but they both enjoy a small positive indirect effect, making the total effect less negative.

Among with other countries, Malaysia and Indonesia enjoy a positive direct effect from AD shock. AD shock causes an initial increase in real GDP growth, followed by a decline in the next few quarters. After one year, the response becomes positive again. This suggests aggregate demand expansion not only raise real GDP in the short run, but also make these two economies benefit from rising oil prices in the long run.

2.4.6.3 Oil-Specific Demand Shock

Oil-specific demand (OD) shock is the oil-specific demand shock which accounts for changes in real oil price that cannot be explained by oil supply shock or aggregate demand shock. OD shock represents specific idiosyncratic features of the oil market, such as speculative oil demand or changes in precautionary demand concerning the uncertainty about the future oil supply. The cumulative impulse responses of GDP growth to one standard error increase in oil-specific demand shock are plotted up to 24 quarters in Figure 2.8. Overall the impulse responses behave as expected. Table 2.6 provides a summary of cumulative impulse response of four quarters and the long-run effects of 24 quarters.

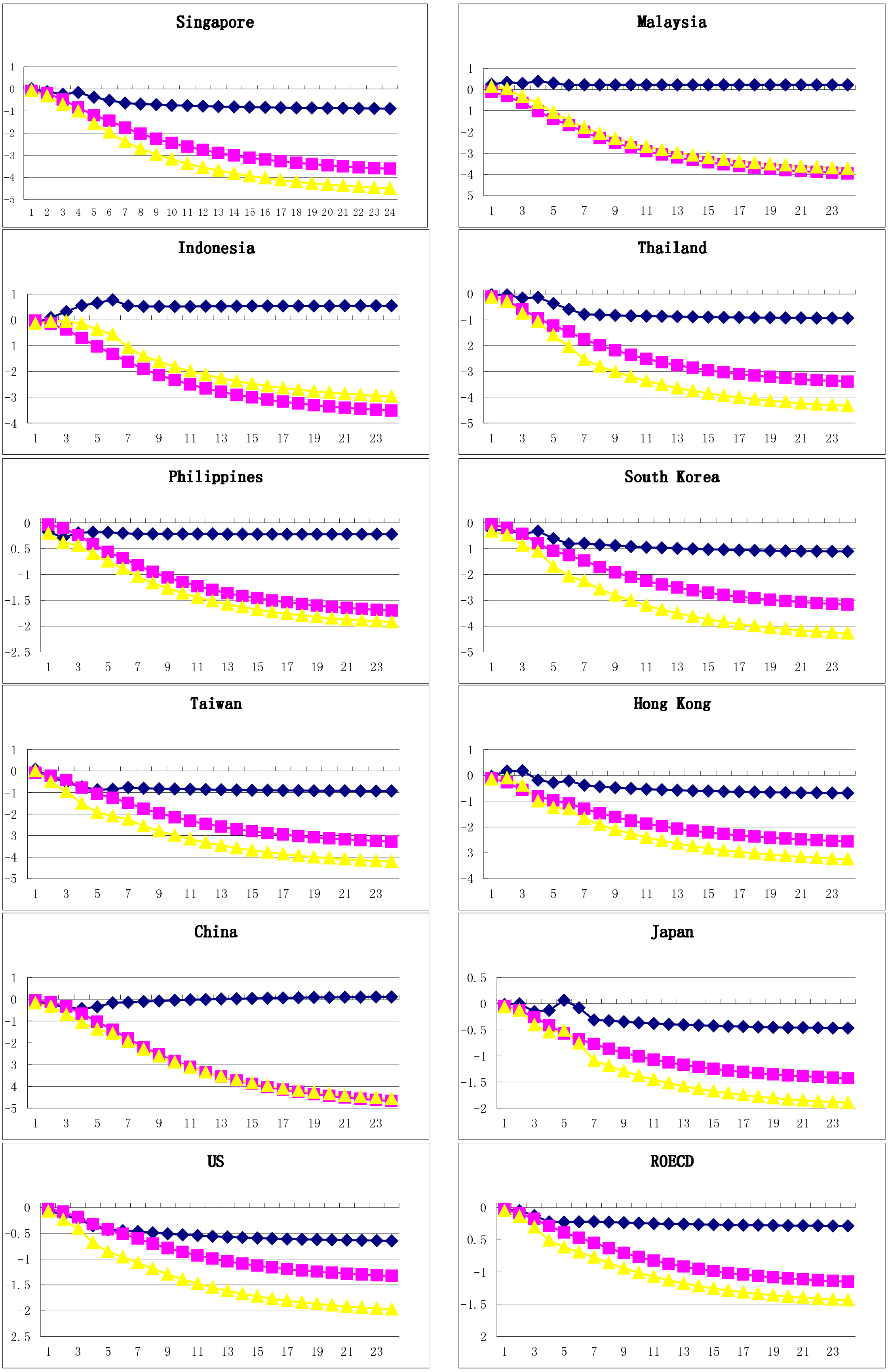
A cursory view of the impulse response graphs show that OD shock has a more consistent effect on growth, compared with OS and AD shock. There is a negative total effect on all the economies, which suggests that OD shock is detrimental to economic growth.

Malaysia and Indonesia, two net oil exporters, enjoy positive direct gain from OD shock in both short and long run. However, the magnitude of this positive effect is not big. One standard error increase in the OD shock in the current quarter leads to 0.4 and 0.6 percentage-point increases in cumulative GDP after 4 quarters respectively. On the other hand, the indirect impact from these two economies' main trading partners is negative. The indirect effect is small initially and gradually cumulates to become substantial over time. This is not surprising as higher oil price driven by OD shock is a negative supply shock to oil-importing countries, which constrains their capacity to import. This underlines one of our key results: oil exporters too can be hurt by the OD shock-induced higher oil prices even if the direct effect is positive.

In our sample, all other economies are directly hit by the OD shock. The largest negative direct effects of a positive OD shock are found for Singapore, Thailand, South Korea and Taiwan, which lead to about 1% decrease in real GDP growth in the long run. The least affected economy is China, where the direct effect was initially negative but tends to be zero after one year and a half.

Indirect effects are negative to all economies, as might be expected. In general, indirect effects through trading partners are quite significant. Countries such as Singapore, Malaysia, Indonesia, Thailand, South Korea and China are among the most affected, with GDP growth decrease by more than 3% in the long run. This

Figure 2.8: Cumulative Impact of one S.E. Oil-specific Demand Shock on GDP Growth (%)



Direct Impact (Diamond Line), Indirect Impact (Box line), Total Impact (Triangle line)

Table 2.6: Cumulative Impact of one Standard Error Oil-specific Demand Shock on GDP Growth (%)

		Direct Impact	Indirect Impact	Total Impact
Singapore	After 4 qtrs	-0.2	-0.8	-1.0
	After 24 qtrs	-0.9	-3.6	-4.5
Malaysia	After 4 qtrs	0.4	-1.0	-0.6
	After 24 qtrs	0.2	-4.0	-3.7
Indonesia	After 4 qtrs	0.6	-0.7	-0.2
	After 24 qtrs	0.5	-3.5	-3.0
Thailand	After 4 qtrs	-0.1	-0.9	-1.1
	After 24 qtrs	-0.9	-3.4	-4.3
Philippines	After 4 qtrs	-0.2	-0.4	-0.6
	After 24 qtrs	-0.2	-1.7	-1.9
South Korea	After 4 qtrs	-0.3	-0.8	-1.1
	After 24 qtrs	-1.1	-3.2	-4.3
Taiwan	After 4 qtrs	-0.7	-0.8	-1.5
	After 24 qtrs	-0.9	-3.3	-4.2
Hong Kong	After 4 qtrs	-0.2	-0.8	-1.0
	After 24 qtrs	-0.7	-2.6	-3.2
China	After 4 qtrs	-0.4	-0.7	-1.1
	After 24 qtrs	0.1	-4.7	-4.6
Japan	After 4 qtrs	-0.1	-0.4	-0.5
	After 24 qtrs	-0.5	-1.4	-1.9
US	After 4 qtrs	-0.4	-0.3	-0.7
	After 24 qtrs	-0.6	-1.3	-2.0
ROECD	After 4 qtrs	-0.2	-0.3	-0.5
	After 24 qtrs	-0.3	-1.2	-1.4
Std. Dev. $\times 10^2$	1.70	-0.3	-1.2	-1.4

suggests Asian countries are vulnerable to rising oil prices driven by OD shock as they rely largely on export markets. On the other hand, Japan, US and the rest of OECD remain least affected in terms of indirect effects.

2.5 Conclusion

In this chapter we have studied the cross-country transmission of three types of structural oil shocks. More specifically, we are interested in the direct and indirect effects of such shocks on the real GDP growth of different economies. A set of 12 economies including ASEAN-4 (Indonesia, Malaysia, the Philippines and Thailand), NIE-4 (South Korea, Hong Kong, Singapore, Taiwan), China, Japan, USA, and the rest of OECD as one country are selected for this study.

In general we find that different structural oil shocks have very different effects on economic growth. A positive oil supply shock tends to increase the real GDP growth of oil importing countries, but the magnitude is small. The direct effects for oil exporting countries such as Malaysia and Indonesia are negative but very small. The indirect effects for these two countries are positive and bigger than the direct effects in the long run, therefore leading to a positive total effect.

A positive aggregate demand shock leads to mixed results on economic growth. The direct effects of aggregate demand shock are positive for eight countries and negative for four countries in our sample. The indirect effects also follow a similar pattern. It is also found that the magnitude of the effects is small. This suggests that the increase in oil price due to aggregate demand expansion is not detrimental to economies. Instead, positive global demand conditions can offset the adverse effects of higher oil prices on economic growth, which are endogenous to the aggregate demand

It is found that the oil-specific demand shock has a negative effect on all countries, and the magnitude of this effect is much larger than the oil supply shock or aggregate demand shock. Though it has a positive direct effect on Malaysia and Indonesia, the two net oil-exporting countries, the indirect effects for these two countries through their trading partners are negative. The indirect effects accumulate over time and overwhelm the direct effect after a few quarters. In general, one standard error oil-specific demand shock leads to more than 3% GDP drop for ASEAN4 and NIE4 over the long run, while leads to 1% to 2% GDP growth drop for Japan, US and rest of OECD. The result suggests that oil-specific demand shock is detrimental to the economic growth.

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Chapter 3

Testing for Financial Contagion: A New Approach Based on Modified GARCH-in-DCC Model

3.1 Introduction

Financial crises originating in one market have tended to spread internationally and caused substantial real cost to the economies. Shocks can spread across borders because of trade and investment linkages. They also spread through financial panics, changes in investors' behavior such as herding. Financial contagion refers to the transmission of crises as a result of financial panic or changes in investors' behavior. This dissertation is concerned with a test methodology for financial contagion.

We adopt the definition of contagion introduced by Baig and Goldfain (1999) and Forbes and Rigobon (2002), where contagion is defined as a significant increase in cross-market correlation in a particular period of time (a crisis period) compared to a benchmark (non-crisis) period.[12] According to this definition, contagion does not occur if two markets show a high degree of comovement during both tranquil and crisis periods. The process of globalization has reinforced various linkages between two economies, making them more interdependent. It is important to distinguish this normal interdependence from contagion. As argued by Forbes and Rigobon (2002), this definition of contagion has several advantages. First, parameter stability tests for

[12] A list of different definitions of contagion is provided in the world bank website: (http://www1.worldbank.org/contagion/ definitions.html).

contagion defined in this way do not require one to explain the nature of the international transmission mechanism of shocks, but they do allow one to distinguish between interdependence and contagion, the two broad classes of shock transmission mechanisms. Second, this definition is different from the idea of excess comovement, where contagion is interpreted as the evidence of significant correlations in asset prices after controlling for the effects of fundamentals (see Pindyck and Rotemberg (1990) and Rodrigo Valdes (1998). As it is not an easy task to identify those fundamentals, their definition of contagion would be potentially misleading. For example, a failure to capture one important common factor may result in tests for contagion being biased towards a positive finding of contagion.

Early analyses of the existence of contagion focused on comparing the *unconditional* cross-market correlation coefficients during the stable and crisis periods, under the assumption of homogeneity in financial asset returns and constant correlation. King and Wadhwani (1990) were the first to measure contagion as a significant increase in the correlation between assets returns. Specifically, they analyzed the correlation between US, UK and Japanese equity returns around the time of the 1987 stock market crash, and found that the degree of correlation has increased after October 1987. There followed a large number of empirical studies on this type of test for contagion (see Pindyck and Rotember (1990), Lee and Kim (1993), Calvo and Reinhart (1995), Baig and Goldfajn (1998)).[13] However, this type of test, commonly

[13] For an extensive review of these type of literature, see Forbes and Rigobon (1999), and Corsetti et al (2001)

called traditional test, fails to incorporate some important facts, which might lead us to different results in testing for financial contagion.

First, it is well known that financial asset returns are conditional heteroskedastic. Second, it is also well documented that the correlation between financial asset returns are time-varying. Moreover, other studies show that there exists a positive relationship between time-varying correlation and volatility.

Boyer, Gibson, and Loretan (1999), Lorentan and English (2000) and Forbes and Rigobon (2002) pointed out cross-market correlation coefficients are conditional on the market volatility. During crises periods where markets are more volatile, estimates of correlation coefficients tend to increase and be biased upward. If tests for contagion do not adjust for this bias in the correlation coefficient, evidence in favor of contagion is likely to be found. In several different papers, Rigobon (1999) and Forbes and Rigobon (2002) show why the unadjusted correlation coefficient is biased upward and describe a simple technique to adjust for this bias. Specifically they show that, under some restrictive assumptions, the adjusted (unconditional) correlation is given by

$$\rho_y^{'} = \frac{\rho_y}{\sqrt{1 + \frac{\sigma_{y,1}^2 - \sigma_{x,1}^2}{\sigma_{x,1}^2}(1-\rho_y^2)}}, \tag{1.1}$$

where $\rho_y^{'}$ is the adjusted (unconditional) correlation coefficient, ρ_y is the unadjusted correlation in the crisis (high volatility) period, $\sigma_{y,1}^2$ is the variance of asset return in the high volatility period in the source country (denoted as country 1),

$\sigma_{x,1}^2$ is the variance in the low volatility period in country 1. They then perform the correlation test in pairs of countries under the assumption that contagion spreads from one country to another with the source countries being exogenous. The test is then performed in the reverse direction with the implicit assumption of exogeneity on the two asset returns reversed. However, performing the two tests in this way is inappropriate because it clearly ignores the simultaneity bias problem. Moreover, the argument that correlation coefficient is increasing with the volatility and the adjustment made above is actually misleading since it is also based on the assumption that there is no omitted variables or common factors. As we shall see shortly, when there is endogeneity or omitted variables, the adjusted correlation coefficient will no longer be valid, and thus the test based on the adjusted correlation coefficient may be biased as well.

Apart from the correlation analysis, several other test methodologies for contagion have been developed. Due to endogeneity issues of asset returns, these studies usually model the selected markets simultaneously. Examples include vector autoregression (VAR) approach with outlier by Favero and Giavazzi (2002), probit model by Eichengreen, Rose and Wyplosz (1996), coexceedance approach by Bae, Karolyi and Stulz (2003), VAR model with regime switching by Forbes and Rigobon (2002), the determinant of changes in the covariance matrix (DCC) approach by Rigobon (2003), latent factor approach by Dungey and Martin (2004), Corsetti, Pericoli and Sbracia (2001) and Bekaert, Harvey and Ng (2005), threshold model by Pesaran and Pick

(2007).

In this chapter, we propose a new testing methodology for contagion under the consideration of the relationship between time-varying volatility and correlation. To control for the volatility effects on return correlations, we develop a GARCH-in-DCC model based on Engle's (2002) dynamic conditional correlation (DCC) model. We then modify the proposed GARCH-in-DCC model and apply it to test for contagion during the 1997 Hong Kong stock market crash. We then compare our testing results with the results from traditional tests.

The remainder of this chapter is organized as follows. Section 3.2 discusses the relationship between volatility and correlation. It uses several hypothesized models to show that the relationship between volatility and correlation is actually dependent on the underlying data generation process. Testing for contagion based on correlation coefficient, whether unadjusted or adjusted, is inaccurate in most cases. It also employs Monte Carlo simulations to give numerical examples. Section 3.3 proposes a GARCH-in-DCC model to take into account the volatility effects on return correlations and tests the relationship between volatility and time-varying correlation. Section 3.4 proposes a test for financial contagion based on the GARCH-in-DCC model developed in Section 3.3. We apply our proposed tests to the 1997 Hong Kong market crisis and compare our results with the traditional test and Forbes & Rigobon's (2002).

3.2 The Relationship Between Volatility and Conditional Correlation

The discussion of the relationship between volatility and correlation was first motivated by Ronn (1998), which showed that the changes in volatility could bias the correlation coefficient. Boyer, Gibson, and Loretan (1999) and Forbes and Rigobon (2002) point out that measuring correlation coefficients over different time periods may introduce bias into the measured correlation coefficients due to heteroscedasticity in asset returns. When pairs of returns are divided into two groups based on the size of one or both variables, the measured "conditional" correlation can be different over different groups, although the entire sample is generated from one data-generating process with a given "unconditional" correlation. Especially they find that the "conditional" correlation coefficient is positively related to the variance ratio of the two groups. The two papers independently propose the same adjustment for the heteroskedasticity bias in the correlation coefficient. When they apply the adjusted correlation coefficient to test for contagion, Forbes and Rigobon (2002) find that there is virtually no evidence of contagion over a set of 27 countries during the 1997 Hong Kong stock market crisis, 1994 Mexican peso devaluation, and 1987 U.S. Stock market crash.

In this section, we reinvestigate the relationship between volatility and correlation in four hypothesized models. It confirms that correlation coefficients can be biased when there is heteroskedasticity in the data, but the adjusted correlation coefficient proposed by Boyer, Gibson, and Loretan (1999) and Forbes and Rigobon (2002) to control for the heteroskedasticiy bias is only accurate under rare circumstances. To illustrate how volatility may affect correlation in different ways, we consider four hypothesized models for two random variables x_t and y_t, which represent financial asset returns in different markets. We also provide a Monte Carlo simulation for each model to illustrate the magnitude of this bias.

3.2.1 Analytical Discussion: Bias in the Correlation Coefficient

Model 1: x_t exogenous, y_t endogenous, and no common exogenous factor exists

We begin with considering a pair of normally distributed variables x_t and y_t with assumptions that x_t is exogenous and y_t is endogenous. Suppose that x_t and y_t follow

$$x_t = \alpha_1 + \varepsilon_{1t} \tag{2.1}$$

$$y_t = \alpha_2 + \beta x_t + \varepsilon_{2t}, \tag{2.2}$$

where the error terms ε_{1t} and ε_{2t} have zero means and $\mathrm{var}(\varepsilon_{1t}) = \sigma^2_{\varepsilon 1t}$, $\mathrm{var}(\varepsilon_{2t}) = \sigma^2_{\varepsilon 2t}$, $\beta > 0$, $E(x_t \varepsilon_{2t}) = 0$. The conditional correlation is obtained as

$$\rho_{xy,t} = \frac{\beta \sigma_{x_t}}{\sqrt{\beta^2 \sigma^2_{x_t} + \sigma^2_{\varepsilon 2t}}}. \tag{2.3}$$

Differentiating $\rho_{xy,t}$ with respect to σ_{x_t}, we get

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{x_t}} = \beta[\sigma_{y_t} - \frac{\beta^2 \sigma^2_{x_t}}{\sigma_{y_t}}] \Big/ \sigma^2_{y_t} = \beta \frac{\sigma^2_{\varepsilon 2t}}{\sigma^3_{y_t}} \succ 0 \tag{2.4}$$

Equation (2.4) clearly shows that the correlation coefficient is increasing in the variance of x_t. Therefore, during periods of high volatility in market x, the estimated conditional correlation between y_t and x_t will be greater than the unconditional correlation. This result has direct implications for tests for contagion based on cross-market correlation coefficients. Markets tend to be more volatile during crisis period. Therefore, the conditional correlation coefficient will tend to increase during crisis period. In other words, even if the unconditional correlation coefficient remains constant during a stable period and crisis period, the conditional correlation coefficient will be greater during the crisis period. If the unadjusted conditional correlation coefficients are computed to test for contagion, it is very likely to over reject the null hypothesis of no contagion. This was confirmed by Boyer, Gibson and Loretan (1999), Lorentan and English (2000) and Forbes and Rigobon (2002). To correct for this type of heteroskedasticity bias, Forbes and Rigobon (2002) propose an adjustment to the correlation coefficient, which is shown in equation (1.1).

However, as pointed out by Forbes and Rigobon (2002), one potential problem with this adjustment for heteroskedasticity bias is that the underlining assumptions in the model are rather restrictive. First, the model ignores the issue of endogeneity between different markets. In effect, a simple model of asset return determination would augment equation (2.1) with a feedback from market y to x. Second, the model ignores any common exogenous global shocks or factors. When we test for contagion in asset return, some common factors such as US interest rate, oil price may have to be included into the structural model. Omitting such factors could cause the adjusted correlation coefficient still biased. Therefore, the adjustment proposed by Forbes and Rigobon (2002) is clearly a simplification and should be taken with care.

Model 2: x_t and y_t are exogenous to each other, but they are influenced by a common exogenous factor

Here we suppose x_t and y_t is not directly related. Instead, they are both influenced by a common factor z_t,

$$x_t = \alpha_1 + \gamma_1 z_t + \varepsilon_{1t} \qquad (2.5)$$

$$y_t = \alpha_2 + \gamma_2 z_t + \varepsilon_{2t}, \qquad (2.6)$$

where the error terms ε_{1t} and ε_{2t} have zero means and $\mathrm{var}(\varepsilon_{1t}) = \sigma^2_{\varepsilon 1t}$, $\mathrm{var}(\varepsilon_{2t}) = \sigma^2_{\varepsilon 2t}$, $\gamma_1 > 0, \gamma_2 > 0,\ E(z_t\varepsilon_{1t}) = 0, E(z_t\varepsilon_{2t}) = 0$. The conditional correlation can be obtained as

$$\rho_{xy,t} = \frac{\gamma_1\gamma_2\sigma^2_{z_t}}{\sqrt{\gamma_1^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 1t}}\sqrt{\gamma_2^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 2t}}}. \qquad (2.7)$$

Differentiating $\rho_{xy,t}$ with respect to $\sigma_{\varepsilon 1t}$, we get

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{\varepsilon 1t}} = -\frac{1}{\sigma^3_{x_t}} \frac{\gamma_1\gamma_2\sigma^2_{z_t}\sigma_{\varepsilon 1t}}{\sqrt{\gamma_2^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 2t}}} \prec 0 \qquad (2.8.1)$$

Differentiating $\rho_{xy,t}$ with respect to σ_{z_t}, we get

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{z_t}} = \frac{\gamma_1\gamma_2\sigma_{z_t}(\gamma_1^2\sigma^2_{z_t}\sigma^2_{\varepsilon 2t} + \gamma_2^2\sigma^2_{z_t}\sigma^2_{\varepsilon 1t} + 2\sigma^2_{\varepsilon 1t}\sigma^2_{\varepsilon 2t})}{(\sqrt{\gamma_1^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 1t}}\sqrt{\gamma_2^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 2t}})^3} > 0 \qquad (2.8.2)$$

Interestingly, equation (2.8.1) shows that the correlation coefficient is decreasing with volatility of ε_{1t}, while equation (2.8.2) shows that the correlation coefficient is increasing with volatility of z_t. Meanwhile, it can be easily seen from equation (2.5) that $\partial\sigma_{x_t} / \partial\sigma_{z_t} > 0, \partial\sigma_{x_t} / \partial\sigma_{\varepsilon 1t} > 0$. Therefore, during periods of high volatility in market x that is contributed from the idiosyncratic shock ε_{1t}, the estimated conditional correlation between markets y and x will be smaller than the unconditional correlation. In other words, heteroskedaticity in asset returns can cause estimates of cross-market correlation coefficients to be bias downward during crisis period. However, if the high volatility in market x is contributed from common factor z_t, the estimated conditional correlation will be biased upward during crisis period. This result points to the fact that the direction of bias in the unadjusted correlation coefficient is dependent on the underlying model by which x_t and y_t are generated, as well as originations of the shocks.

Model 3: Both x_t and y_t are endogenous, but they don't have a common exogenous factor

Here we suppose x_t and y_t have a feedback relationship, but they are not influenced by any common exogenous factor,

$$x_t = \alpha_1 + \beta_1 y_t + \varepsilon_{1t} \tag{2.9}$$

$$y_t = \alpha_2 + \beta_2 x_t + \varepsilon_{2t}, \tag{2.10}$$

where the error terms ε_{1t} and ε_{2t} have zero means and $\text{var}(\varepsilon_{1t}) = \sigma^2_{\varepsilon 1t}$, $\text{var}(\varepsilon_{2t}) = \sigma^2_{\varepsilon 2t}$, $0 < \beta_1 < 1, 0 < \beta_2 < 1$. We can rewrite equation (2.9) and (2.10) by expressing x_t and y_t as function of error terms

$$x_t = \frac{\alpha_1 + \beta_1\alpha_2 + \beta_1\varepsilon_{2t} + \varepsilon_{1t}}{1 - \beta_1\beta_2} \tag{2.9'}$$

$$y_t = \frac{\alpha_2 + \beta_2\alpha_1 + \beta_2\varepsilon_{1t} + \varepsilon_{2t}}{1 - \beta_1\beta_2} \tag{2.10'}$$

The correlation coefficient can be obtained as

$$\rho_{xy,t} = \frac{\beta_1 \sigma^2_{\varepsilon 2t} + \beta_2 \sigma^2_{\varepsilon 1t}}{\sqrt{(\beta_1^2 \sigma^2_{\varepsilon 2t} + \sigma^2_{\varepsilon 1t})(\beta_2^2 \sigma^2_{\varepsilon 1t} + \sigma^2_{\varepsilon 2t})}} \tag{2.11}$$

Differentiating $\rho_{xy,t}$ with respect to $\sigma_{\varepsilon 1t}$, we get

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{\varepsilon 1t}} = \frac{2\beta_2 \sigma_{\varepsilon 1t} \sqrt{(\beta_1^2 \sigma^2_{\varepsilon 2t} + \sigma^2_{\varepsilon 1t})(\beta_2^2 \sigma^2_{\varepsilon 1t} + \sigma^2_{\varepsilon 2t})} - (\beta_1 \sigma^2_{\varepsilon 2t} + \beta_2 \sigma^2_{\varepsilon 1t}) \dfrac{(2\beta_1^2 \beta_2^2 \sigma_{\varepsilon 1t} \sigma^2_{\varepsilon 2t} + 4\beta_2^2 \sigma^3_{\varepsilon 1t} + 2\sigma_{\varepsilon 1t} \sigma^2_{\varepsilon 2t})}{2\sqrt{(\beta_1^2 \sigma^2_{\varepsilon 2t} + \sigma^2_{\varepsilon 1t})(\beta_2^2 \sigma^2_{\varepsilon 1t} + \sigma^2_{\varepsilon 2t})}}}{(\beta_1^2 \sigma^2_{\varepsilon 2t} + \sigma^2_{\varepsilon 1t})(\beta_2^2 \sigma^2_{\varepsilon 1t} + \sigma^2_{\varepsilon 2t})}$$

……………………………………………………………………………………..(2.12)

After simple manipulation it yields

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{\varepsilon 1t}} = \frac{\beta_1^2 \beta_2 \sigma_{\varepsilon 1t} \sigma^4_{\varepsilon 2t} (1 - \beta_1 \beta_2) + \beta_2 \sigma^3_{\varepsilon 1t} \sigma^2_{\varepsilon 2t} (1 - \beta_1 \beta_2)^2}{[(\beta_1^2 \sigma^2_{\varepsilon 2t} + \sigma^2_{\varepsilon 1t})(\beta_2^2 \sigma^2_{\varepsilon 1t} + \sigma^2_{\varepsilon 2t})]^{3/2}} \succ 0 \tag{2.13}$$

Given $0 < \beta_1 < 1, 0 < \beta_2 < 1,$ equation (2.12) shows that the estimated correlation coefficient is unambiguously increasing in the variance of ε_{1t}, and in turn increasing in the variance of x_t or y_t. This result is similar to the one in Model 1, where the conditional correlation coefficient is also biased upward in the presence of heteroskedasticity. In other words, when asset returns in two markets are dependent on each other and not influenced by any exogenous factors, the conditional correlation coefficient will tend to be larger during the more volatile period. However, unlike in Model 1, there does not exist any procedure to adjust the bias in this case.

Model 4: x_t and y_t are endogenous to each other, and they have a common exogenous factor

Now we consider a model where x_t and y_t have a feedback relationship and they also are affected by a common exogenous factor z_t. Specifically, we assume

$$x_t = \alpha_1 + \beta_1 y_t + \gamma_1 z_t + \varepsilon_{1t} \tag{2.14}$$

$$y_t = \alpha_2 + \beta_2 x_t + \gamma_2 z_t + \varepsilon_{2t} . \tag{2.15}$$

where the error terms ε_{1t} and ε_{2t} have zero means and $\mathrm{var}(\varepsilon_{1t}) = \sigma^2_{\varepsilon 1t}$, $\mathrm{var}(\varepsilon_{2t}) = \sigma^2_{\varepsilon 2t}$, $E(z_t \varepsilon_{1t}) = 0, E(z_t \varepsilon_{2t}) = 0$, $0 < \beta_1 < 1,\ \ 0 < \beta_2 < 1,\ \gamma_1 > 0, \gamma_2 > 0,$

Similarly, the conditional correlation can be obtained as

$$\rho_{xy,t} = \frac{\beta_1 \sigma^2_{y_t} + \gamma_1 \dfrac{\beta_2\gamma_1 + \gamma_2}{1-\beta_1\beta_2}\sigma^2_{z_t} + \dfrac{\beta_2}{1-\beta_1\beta_2}\sigma^2_{\varepsilon 1t}}{\sigma_{y_t}\sqrt{\beta_1^2\sigma^2_{y_t} + \gamma_1^2\sigma^2_{z_t} + \sigma^2_{\varepsilon 1t} + 2\beta_1\gamma_1\dfrac{\beta_2\gamma_1+\gamma_2}{1-\beta_1\beta_2}\sigma^2_{z_t} + \dfrac{2\beta_1\beta_2}{1-\beta_1\beta_2}\sigma^2_{\varepsilon 1t}}} \tag{2.16}$$

Differentiating $\rho_{xy,t}$ with respect to σ_{y_t} , we get:

$$\frac{\partial \rho_{xy,t}}{\partial \sigma_{y_t}} = \frac{2\beta_1\sigma_{x_t}\sigma^2_{y_t} - (\beta_1\sigma^2_{y_t} + \gamma_1\dfrac{\beta_2\gamma_1+\gamma_2}{1-\beta_1\beta_2}\sigma^2_{z_t} + \dfrac{\beta_2}{1-\beta_1\beta_2}\sigma^2_{\varepsilon 1t})(\sigma_{x_t} + \beta_1^2\dfrac{\sigma^2_{y_t}}{\sigma_{x_t}})}{\sigma^2_{x_t}\sigma^2_{y_t}} .$$

$$= \frac{\beta_1\sigma^2_{x_t}\sigma^2_{y_t} - \beta_1^3\sigma^4_{y_t} - (\gamma_1\dfrac{\beta_2\gamma_1+\gamma_2}{1-\beta_1\beta_2}\sigma^2_{z_t} + \dfrac{\beta_2}{1-\beta_1\beta_2}\sigma^2_{\varepsilon 1t})(\sigma^2_{x_t} + \beta_1^2\sigma^2_{y_t})}{\sigma^3_{x_t}\sigma^2_{y_t}} \tag{2.17}$$

Unlike in the previous three models, equation (2.17) doesn't show whether the correlation is increasing with the variance or not. The sign of this derivative depends on the structural parameters β_1 , β_2 , γ_1 , γ_2 and the variances $\sigma^2_{z_t}, \sigma^2_{\varepsilon 1t}, \sigma^2_{\varepsilon 2t}$. This corroborates the result that the bias in correlation coefficient of assets returns due to heteroskedasticity is not clear-cut, and is largely dependent on the underlining dynamics between two markets. Given the unknown true data generation process, any adjustment to correlation coefficient would be inappropriate.

3.2.2 Numerical Examples.

Based on theoretical discussions earlier, it is clear that correlation coefficient is biased when the homoscedasticity assumption is violated. The direction of this bias is not known and is dependent on the underlying structural model that generates the data. To show how heteroskedasticity can bias correlation coefficients, we simulate the four models discussed in the previous section.

Table 3.1

A Simulated Example for Model 1: Heteroskedasticity and Correlation where x_t is exogenous, y_t is endogenous, and no common factor exists

$$x_t = 0.01 + \varepsilon_{1t}$$

$$y_t = 0.015 + \beta x_t + \varepsilon_{2t}$$

where ε_{1t} and ε_{2t} are independent idiosyncratic shocks. In the low volatility scenario, ε_{1t} is assumed to be normally distributed with zero mean and unit variance.. In the high volatility scenario, ε_{1t} is multiplied by 3 and therefore x_t has a mean of 0.01 and standard deviation of 3. Y_t is calculated as a normally distributed variable with mean of 0.015 and standard deviation of 1, plus β times x_t. We repeat the model one thousand times for each value of β, and obtain the corresponding means of correlation coefficients for both the low and high volatility scenarios.

β	Estimated Correlation in Low Volatility Scenario	Estimated Correlation in High Volatility Scenario
0.1	0.133	0.282
0.2	0.223	0.513
0.3	0.308	0.669
0.4	0.386	0.769
0.5	0.457	0.833
0.6	0.520	0.875
0.7	0.576	0.904
0.8	0.624	0.924
0.9	0.666	0.939

The assumptions and results of simulation for Model 1 are presented in Table 3.1. Assume that during normal periods, x_t is normally distributed variable with a mean of 0.01 and unit variance. During periods of turbulence, however, x_t becomes more volatile and is magnified threefold. Also assume that y_t has two components. One part is normally distributed random variable with mean of 0.015 and unit variance. The other part is x_t multiplied by parameter β.

The results of simulation confirm the findings in the existing literature that, correlation coefficient will be biased upward during periods of high volatility. For each given value of β, which is the transmission mechanism from x_t to y_t, estimated conditional correlation in high volatility period is much higher than that of low volatility period. For β ranging from 0.1 to 0.4, conditional correlation in high volatility period is approximately double the one in low volatility period. Intuitively, during normal periods when volatility of x_t is low, most of the variation in y_t is driven by its own idiosyncratic shock ε_{2t}. On the other hand, during periods when the volatility of x_t increase dramatically, the proportion of the variation in y_t driven by movements in x_t increases significantly. As a result, movements in x_t explain a higher portion of the variance in y_t and the conditional correlation between them increases substantially.

Next, we modify the model by dropping x_t in the equation for y_t and adding a common factor for both x_t and y_t. This enables us to examine the bias of correlation coefficient when both x_t and y_t are exogenous to each other. Table 3.2 shows the simulation results of Model 2. The first column is the values of parameters γ_2, and the last two columns show the bias in estimated conditional correlation coefficients given the parameter values. Not surprisingly, as indicated by the analytical analysis presented in previous section, we find that, for any values γ_2, the bias in correlation coefficients during high volatility period is negative if the volatility increase is due to the idiosyncratic shock, while the bias is positive if the volatility increase is due to z_t. In the case of increased volatility due to the idiosyncratic shock, the negative bias is increasing with the value of γ_2. The intuition behind this is straightforward. During normal periods when volatilities of x_t and y_t are low, much of their variations are driven by the common factor. During periods when the volatility of x_t increases dramatically due to its idiosyncratic shocks, the portion of the variation in them driven by movements in common factor decreases. As a result, movements in common factor explain a lower portion of the variations in x_t and y_t and the correlation between them decreases. On the other hand, if the variance of the common shock increases, the portion of the variation in x_t and y_t driven by movements in common factor increases and thus the correlation increases.

This example demonstrates that the effects of heteroskedasticity on correlation coefficients are dependent on the specific data generation process and the origin of the increased volatility. Supposes asset returns in two small markets are exogenous to each other and are influenced by a large common market. Then the correlation between these two small markets will decrease instead of increasing in the crisis (high volatility) period if the common exogenous factors remain relatively stable.

Table 3.2

A Simulated Example: Heteroskedasticity and Correlation where there is no endogeneity between x_t and y_t but has a common exogenous factor

$$x_t = 0.01 + z_t + \varepsilon_{1t}$$

$$y_t = 0.015 + \gamma_2 z_t + \varepsilon_{2t}$$

where ε_{1t} and ε_{2t} are independent idiosyncratic shocks with $\varepsilon_{2t} \sim N(0,1)$, and z_t is an independent exogenous variable. In the low volatility scenario, ε_{1t} and z_t are normally distributed with zero mean and unit variance. For the high volatility case, we assume two scenarios. In scenario one, we assume the volatility increase in x_t is purely due to its idiosyncratic shock ε_{1t}. In this regard, we multiply 3 to ε_{1t} while z_t remains constant. In scenario two, the volatility increase in x_t is assumed to be purely from z_t. Therefore z_t is multiplied by 3 and ε_{1t} stays constant. We repeat the model one thousand times for each value of γ_2, and obtain the corresponding bias in the estimated conditional correlation during high volatility period

γ_2	Bias in Estimated Correlation in High Volatility Scenario 1	Bias in Estimated Correlation in High Volatility Scenario 2
0.1	-0.008	0.072
0.2	-0.016	0.115
0.3	-0.023	0.126
0.4	-0.029	0.120
0.5	-0.035	0.109
0.6	-0.040	0.097
0.7	-0.045	0.087
0.8	-0.049	0.079
0.9	-0.053	0.072

We next simulate Model 3 where there is endogeneity between x_t and y_t but no common exogenous factors. Table 3.3 presents the assumptions and results of this simulation.

Table 3.3

A Simulated Example: Heteroskedasticity and Correlation when there is endogeneity between x_t and y_t but no common factor

$$x_t = 0.01 + \beta_1 y_t + \varepsilon_{1t}$$

$$y_t = 0.015 + \beta_2 x_t + \varepsilon_{2t}$$

where ε_{1t} and ε_{2t} are independent shocks with $\varepsilon_{2t} \sim N(0,1)$. In the low volatility scenario, ε_{1t} is normally distributed with zero mean and unit variance. In the high volatility scenario, ε_{1t} is multiplied by 9. As a consequence, the volatilities of x_t and y_t both increase due to endogenous relationship between them. We repeat the model one thousand times for each pair of β_1, β_2, and obtain the corresponding conditional correlation for low volatility and high volatility scenario, as well as the bias in estimated conditional correlation coefficients during high volatility period.

β_1	β_2	Estimated Correlation in Low Volatility Scenario	Estimated Correlation in High Volatility Scenario	Bias in Estimated Correlation in High Volatility Scenario
0.2	0.2	0.389	0.884	0.077
	0.4	0.552	0.969	0.026
	0.6	0.678	0.987	0.012
	0.8	0.771	0.993	0.006
0.4	0.2	0.548	0.894	0.070
	0.4	0.692	0.975	0.022
	0.6	0.799	0.990	0.009
	0.8	0.872	0.996	0.004
0.6	0.2	0.672	0.903	0.062
	0.4	0.797	0.979	0.018
	0.6	0.883	0.993	0.006
	0.8	0.938	0.997	0.002
0.8	0.2	0.764	0.913	0.055

0.4	0.870	0.983	0.014
0.6	0.938	0.996	0.004
0.8	0.976	0.999	0.001

It can be seen from Table 3.3 that the estimated conditional correlations in high volatility period are biased upward for any value of β_1 and β_2. The positive bias is decreasing with the value of β_1 or β_2. It is also noted that the estimated conditional correlations in the case of endogeneity are much larger than those in Model 1.

We next simulate the model with both endogeneity and common exogenous factors. The assumptions and results of this simulation are presented in Table 3.4. In most cases, the estimated conditional correlations are biased upward in high volatility period. The larger the γ_2, or in other words, the larger the x_t and y_t are influenced by common exogenous factor z_t, the smaller the positive bias is. When γ_2 becomes large enough and β_2 is small enough, the estimated conditional correlation in high volatility period becomes downward biased instead of upward. The intuition behind is analogous to the previous three models. In the case where x_t and y_t face a weak common factor and strong endogeneity, the increased idiosyncratic shock in x_t will make variations in x_t and y_t more correlated due to feedback system within x_t and y_t. On the other hand, in the case where x_t and y_t face a strong common factor and weak endogeneity, the increased idiosyncratic shock in x_t will cause the portion of variation in x_t and y_t driven by the common factor decreases, thus results in a decreased correlation between x_t and y_t.

Table 3.4

A Simulated Example: Heteroskedasticity and Correlation when x_t and y_t are interdependent and have a common factor

$$x_t = 0.01 + \beta_1 y_t + z_t + \varepsilon_{1t}$$

$$y_t = 0.015 + \beta_2 x_t + \gamma_2 z_t + \varepsilon_{2t}$$

where ε_{1t} and ε_{2t} are independent idiosyncratic shocks with $\varepsilon_{2t} \sim N(0,1)$, and z_t is an independent exogenous variable following N(0,1). In the low volatility scenario, ε_{1t} is normally distributed with zero mean and unit variance. In the high volatility scenario, we assume the increased volatility in x_t is contributed from its idiosyncratic shock. In this regard, ε_{1t} is multiplied by 3 in the high volatility period. We repeat the model one thousand times for each pair of γ_2, β_1 and β_2, and obtain the the corresponding conditional correlation for low volatility and high volatility scenario, as well as the bias in estimated conditional correlation coefficients during high volatility period.

γ_2	β_1	β_2	Estimated Correlation in Low Volatility Scenario	Estimated Correlation in High Volatility Scenario	Bias in Estimated Correlation in High Volatility Scenario
0.2	0.2	0.2	0.507	0.600	0.055
		0.4	0.675	0.826	0.056
		0.6	0.785	0.914	0.038
		0.8	0.856	0.952	0.024
0.4	0.4	0.2	0.684	0.727	0.024
		0.4	0.807	0.862	0.033
		0.6	0.883	0.937	0.022
		0.8	0.929	0.968	0.013
0.6	0.6	0.2	0.805	0.804	0.000
		0.4	0.891	0.892	0.016
		0.6	0.941	0.955	0.011
		0.8	0.970	0.981	0.006
0.8	0.8	0.2	0.882	0.834	-0.016
		0.4	0.940	0.917	-0.005
		0.6	0.973	0.971	-0.001
		0.8	0.990	0.991	0.000
0.9	0.8	0.2	0.892	0.839	-0.020
		0.4	0.945	0.917	-0.006
		0.6	0.975	0.970	-0.001
		0.8	0.990	0.991	0.000

To sum up, the correlation coefficient is biased when the homoscedasticty assumption is violated. The direction of this bias is not known and is dependent on the underlying structural model that generates the data. The stronger the endogenous relationship between two markets, the stronger the positive relationship between volatility and correlation. On the other hand, the stronger the common exogenous factor, the stronger the negative relationship between volatility and correlation, under the condition that the volatility of exogenous common factor is not time-varying. In the case where there is a positive relationship between volatility and correlation, the estimated conditional correlation is biased upward in high volatility period, and the evidence in favor of contagion would be more likely detected if we don't adjust for it. On the other hand, in the case where there is negative relationship between volatility and correlation, the estimated conditional correlation will be biased downward in high volatility period, and evidence of no contagion will be more likely detected.

3.3 Estimation of GARCH-in-DCC Model and Test for Volatility Effects on Correlations

3.3.1 Multivariate GARCH Model and Conditional Correlation

The general representation of the MGARCH model

$$\begin{aligned} r_t &= \mu_t(\theta) + \varepsilon_t \\ \varepsilon_t \mid \Omega_{t-1} &\sim N(0, H_t) \end{aligned} \tag{3.1}$$

where r_t is a $K \times 1$ vector of returns, $\mu_t(\theta)$ is the conditional mean vector with a finite vector of parameters θ, ε_t is the vector of residuals that is assumed to be conditionally normal with mean zero and a conditional variance-covariance matrix H_t, and Ω_{t-1} is the information set up to time t-1. H_t is a symmetric positive definite matrix with elements h_{ijt} $(i \neq j)$ for the off-diagonal terms (covariance) and h_{iit} for the diagonal terms (variance). The standardized residual vector u_t is defined as

$$u_t = D_t^{-1}\varepsilon_t, \tag{3.2}$$

where $D_t = diag(H_t)^{1/2}$, a K×K diagonal matrix with elements $h_{11t}^{1/2}, h_{22t}^{1/2}, \ldots . h_{kkt}^{1/2}$.

Bollerslev, Engle, and Wooldridge (1988) introduced the general framework for the multivariate GARCH model. They extended the univariate GARCH representation to the vectorized conditional variance-covariance matrix H_t. A difficulty in extending to multivariate GARCH model in this way is that the number of parameters to be estimated increases tremendously as the number of variables increase even moderately. To reduce the number of parameters, early multivariate GARCH researches focus on ways of imposing restrictions and simplifying the variance-covariance matrix while guaranteeing it to be positive definite. Examples include the diagonal VECH model of Bollerslev *et al* (1988), the BEKK model of Engle and Kroner (1995) and the principal component ARCH model of Kohn (1992). However, a common problem of this class of multivariate GARCH models is that the number of parameters to be estimated explodes for higher dimensions, making estimation costly and computationally intractable.

On the other hand, noting that:

$$R_t = E_{t-1}(u_t u_t^{'}) = D_t^{-1} E_{t-1}(\varepsilon_t \varepsilon_t^{'}) D_t^{-1} = D_t^{-1} H_t D_t^{-1}, \tag{3.3}$$

where R_t is the K×K conditional correlation matrix. Given (3.3), the conditional covariance matrix can be partitioned as:

$$H_t = D_t R_t D_t \tag{3.4}$$

Then one can write the dynamics of H_t by specifying variance (D_t) and correlation matrix (R_t) separately. This nonlinear approach was first proposed by Bollerslev (1990) in the constant conditional correlation (CCC) model, where he assumes R_t to be constant over time.

However, the assumption that the conditional correlations are constant may seem unrealistic in many empirical applications. Kroner and Ng (1998) noted that the CCC restriction is not valid in most cases and thus the constant assumption of conditional correlation need to be relaxed. Tse and Tsui (2002) have proposed the first time-varying conditional correlation model where

$$R_t = (1 - \theta_1 - \theta_2)\bar{R} + \theta_1 \psi_{t-1} + \theta_2 R_{t-1}, \tag{3.5}$$

follows an ARMA analogue. Their varying-correlation or VC MGARCH model result in acceptable parameter estimates for small sample sizes in simulation studies. On the other hand, Engle (2002) extended the work of Boillerslev (1990) and proposed a Dynamic Conditional Correlation (DCC) model. He has shown that DCC is most often accurate compared to other MGARCH models including the BEKK, Moving Average and the Orthogonoal GARCH models.

The proposed dynamic correlation structure of the Engle's (2002) DCC(1, 1) model is specified as follows:

$$Q_t = (1-\delta_1-\delta_2)\overline{Q} + \delta_1 u_{t-1}u_{t-1}^{'} + \delta_2 Q_{t-1}, \tag{3.6}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3.7}$$

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{kkt}} \end{bmatrix} \tag{3.8}$$

where $\overline{Q}$ is the sample covariance matrix of standardized residual vector u_t, q_{iit} is the $(i,i)^{th}$ element of Q_t and the Q_t^* is introduced to ensure that R_t is a correlation matrix with diagonal elements being unity and off-diagonal elements being within (-1,1). δ_1, δ_2 are parameters that satisfy the condition of positive definiteness of Q_t and in effect ensure the positive definiteness of R_t, proof of which is provided by Engle and Sheppard (2001).

Unlike in the VC MGARCH model, the DCC model does not formulate the conditional correlation as a weighted sum of past correlations. Indeed, the matrix Q_t is written like a GARCH equation, and then transformed to a correlation matrix. Interestingly, DCC models can be estimated consistently using a two-step maximum likelihood approach, which makes this approach feasible when the dimension is high.

A drawback of DCC models is that δ_1, δ_2 are scalars, so that all the conditional correlations obey the same dynamics. This restriction is imposed technically to ensure that the correlation matrix is positive definite through sufficient conditions on the parameters. In this respect, several variants of the DCC model are proposed in the literature. For example, Billio, Caporin and Gobbo's (2004) propose a block-diagonal structure where the dynamics is constrained to be identical only within each block. Pelletier (2003) proposes a model where the conditional correlations follow a switching regime driven by an unobserved Markov chain so that the correlation matrix is constant in each regime but may vary across regimes. Another extension proposed by Engle (2002) consists of changing equation (3.6) into

$$Q_t = \overline{Q} \circ (\iota\iota' - aa' - bb') + aa' \circ u_{t-1}u_{t-1}' + bb' \circ Q_{t-1}, \tag{3.9}$$

where ι is a vector of ones and $\circ$ is the Hadamard product of two identically sized matrices which is computed simply by element-by-element multiplication. a and b are K×1 parameter vectors with $a = (a_1, ..., a_k)'$ and $b = (b_1, ..., b_k)'$. This model adds great flexibility compared to standard DCC type models while maintaining the parameter numbers at a feasible level at the same time.

3.3.2 GARCH-in-DCC Model

As indicated in Section 3.2, the time-varying volatilities have an important influence on the time-varying correlations. To capture the volatility effects on time-varying conditional correlations, we propose a GARCH-in-DCC model by changing equation (3.6) into

$$Q_t = (1 - \delta_1 - \delta_2)\overline{Q} + \delta_1 u_{t-1}u_{t-1}' + \delta_2 Q_{t-1} + \delta_3 (D_{t-1}ii'D_{t-1} - \overline{D}ii'\overline{D}), \tag{3.10}$$

where $D_{t-1} = diag(H_{t-1})^{1/2}$, i is a $K \times 1$ vector of ones, $\overline{D}$ is the sample mean of conditional standard deviation D_t. The restrictions on the parameters are given by: $\delta_1, \delta_2 \geq 0$, $\delta_1 + \delta_2 < 1$.

Equation (3.10) introduces a volatility term into the dynamics of conditional correlation. The idea of adding the GARCH term originates from the GARCH-in-mean model in the univariate GARCH modeling. In order to ensure that the estimation is conducted within the valid parameter space, the model must be specified to maintain the positive definiteness of Q_t. According to Engle and Sheppard (2001), a sufficient but not necessary condition for Q_t to be positive definite is for all the parameters to be positive. However, we don't impose δ_3 to be positive in the estimation. Theoretically, δ_3 can be either positive or negative. A positive δ_3 indicates there is a positive relationship between volatility and correlation, and a negative δ_3 indicates a negative relationship between volatility and correlation. In empirical applications, we find the value of parameter δ_3 is small, while the sum of parameters δ_1 and δ_2 are so large that Q_t is positive definite even when δ_3 is negative.

3.3.3 Estimation of GARCH-in-DCC Model

Estimation of the GARCH-in-DCC model can be performed by Quasi Maximum likelihood (QML). A nice feature of the DCC model and its variants is that they can be estimated consistently using a two-step approach. Engle and Sheppard (2001) show that the log likelihood can be written as the sum of a mean and volatility part (depending on a set of unknown parameter vector θ) and a correlation part (depending on δ). The likelihood function is maximized with respect to the first set of parameters then the parameters estimates of the first set serve as input to the second stage where the next set of parameters is estimated. As shown in Neway and McFadden (1994), White (1994), and also Engle and Sheppard (2001), the estimates obtained using this two-step procedure are consistent and asymptotically normal under some standard assumptions.

Let θ denotes the parameter vector in D_t, and δ denotes the parameter vector in R_t, then the log likelihood function is

$$\ell(\theta,\delta)=\sum_{t=1}^{T}\ell_t(\theta,\delta), \tag{3.11}$$

where

$$\ell_t(\theta,\delta)=-\frac{k}{2}\log(2\pi)-\frac{1}{2}(\log|D_tR_tD_t|+\varepsilon_t^{'}D_t^{-1}R_t^{-1}D_t^{-1}\varepsilon_t) \tag{3.12}$$

Rearrange terms in (3.12) such that

$$\ell_t(\theta,\delta)=-\frac{k}{2}\log(2\pi)-\frac{1}{2}(2\log|D_t|+\varepsilon_t^{'}D_t^{-1}D_t^{-1}\varepsilon_t+\log|R_t|-u_t^{'}u_t+u_t^{'}R_t^{-1}u_t). \tag{3.13}$$

Thus we can decompose the likelihood function into variance part

$$\ell_{V,t}(\theta)=-\frac{k}{2}\log(2\pi)-\frac{1}{2}(2\log|D_t|+\varepsilon_t^{'}D_t^{-1}D_t^{-1}\varepsilon_t), \tag{3.14}$$

and correlation part

$$\ell_{C,t}(\theta,\delta)=-\frac{1}{2}(\log|R_t|-u_t^{'}u_t+u_t^{'}R_t^{-1}u_t), \tag{3.15}$$

so that

$$\ell_t(\theta,\delta)=\ell_{V,t}(\theta)+\ell_{C,t}(\theta,\delta). \tag{3.16}$$

In the first step, the variance part $\ell_V(\theta)=\sum_{t=1}^{T}\ell_{V,t}(\theta)$ is maximized, and then given the maximizing value $\hat{\theta}$, the correlation part $\ell_C(\hat{\theta},\delta)=\sum_{t=1}^{T}\ell_{C,t}(\hat{\theta},\delta)$ is maximized with respect to δ.

As a remark here, because D_t is a diagonal matrix, the variance part in equation (3.14) is the sum of individual GARCH likelihoods.

$$\ell_V(\theta)=-\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{K}(\log(2\pi)+\log(\sigma_{it}^2)+\frac{\varepsilon_{it}^2}{\sigma_{it}^2}), \tag{3.17}$$

which implies that in the first step the GARCH model can be estimated separately for each series.

3.3.4 Empirical Results and Tests for Volatility Effects on Conditional Correlations

We now apply the GARCH-in-DCC model to the data. The countries we consider are U.S.-Canada, UK-France-Germany, and Japan-Hong Kong-Singapore.

3.3.4.1 Description of Data

The source of our data is Datastream. Data are daily stock price index denominated in local currencies from January 2, 1996 to January 4, 2006 with 2612 observations. We analyze the return series calculated from $r_{it}=100*(\log p_{it}-\log p_{it-1})$, where p_{it} is the stock price index for country i at time t.

Table 3.5 presents summary statistics for return series. The mean returns are positive for all countries except Japan, but are small compared to their standard deviations. All returns exhibit non-zero skewness. While returns of the developed countries are negatively skewed, the returns of the emerging markets (HK and Singapore) are positively skewed. Notably all series exhibit substantial excess kurtosis, in excess of the normal distribution's benchmark value of 3. This indicates that the daily stock index returns we consider are not normally distributed. The rejection of Jarque-Bera test for normality with p-values less than 0.001 corroborates this finding. We provide Ljung-Box statistics in the last two columns. $Q_1(20)$ represents the Ljung-Box statistic for up to 20th-order serial correlation for each return series, while $Q_2(20)$ represents the statistic for the squared return series. Except the U.S. and Japan, the $Q_1(20)$ statistics show that all series exhibit serial correlations at the 1% level of significance (the critical value at the 1% level is 37.57). $Q_2(20)$ statistics show that the squared stock return series have a very strong serial correlation in all markets, and this indicates a GARCH-type modeling may be required for each return series

Table 3.6 presents the unconditional correlation among the various stock index return series. Overall the stock markets are reasonably correlated with a mean correlation of 0.412. However, there is a wide range of correlations among the markets, ranging from 0.23 to 0.82. In the sample, the markets within the same region, namely North America, Europe and Asia (except Japan) are highly correlated, with the highest correlation of 0.82 between Germany and France, while the markets in the different regions are less correlated.

Table 3.5: Summary Statistics for Daily Stock Market Returns

Country	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p value	$Q_1(20)$	$Q_2(20)$
U.S.	0.028	1.105	-0.226	7.131	1878.726	0.000	22.23	642.81
Canada	0.034	0.987	-0.703	9.266	4486.049	0.000	43.05	560.35
U.K.	0.017	1.116	-0.178	5.881	916.509	0.000	74.540	2595.20
Germany	0.025	1.521	-0.251	5.651	792.255	0.000	44.82	2102.20
France	0.036	1.407	-0.111	5.783	848.296	0.000	48.98	2325.50
Japan	-0.007	1.404	-0.030	5.230	541.518	0.000	18.18	521.73
Hong Kong	0.015	1.664	0.127	14.857	15302.450	0.000	49.04	1030.40
Singapore	0.008	1.380	0.360	14.259	13848.520	0.000	78.57	686.45

Returns are in percentage term. $Q_1(20)$ is the Ljung-Box statistics for up to 20^{th}-order serial correlation of Return series, while $Q_2(20)$ is the same statistics of the square of returns. It is asymptotically distributed as a $\chi^2(20)$ degrees of freedom. The 1% critical value of the statistics is 37.57.

Table 3.6: Unconditional Correlations of Daily Stock Market Returns

	U.S.	Canada	U.K.	Germany	France	Japan	Hong Kong	Singapore
U.S.	1.000	0.613	0.410	0.459	0.440	0.300	0.363	0.328
Canada		1.000	0.445	0.466	0.472	0.276	0.331	0.306
U.K.			1.000	0.720	0.807	0.236	0.328	0.298
Germany				1.000	0.816	0.233	0.347	0.295
France					1.000	0.237	0.312	0.283
Japan						1.000	0.420	0.365
Hong Kong							1.000	0.636
Singapore								1.000

The lag returns of the US and Canada are used when we calculate their correlations with the three Asian countries, Japan, Hong Kong and Singapore, due to the non-synchronous trading times.

3.3.4.2 Estimation Results

The first stage of the estimation consists of selecting a model for each series. Given the Ljung-Box Q test indicating the presence of conditional heteroskedasticity and autocorrelation, a univariate AR-GARCH model is used for each series. We select an initial lag order of 20 for the mean equation. The final autoregressive terms are chosen by the backstep selection method. That is, a model with autoregressive order 20 is initially fitted and then all the non-significant autoregressive parameters are sequentially removed. For the variance equation, we use the GARCH(p,q) model with order p=1, q=1 because of its simplicity and reasonable success.

The estimated univariate AR-GARCH models for each return series are given by:

$$r_{it} = a_i + \sum_{j=1}^{20} b_{ij} r_{it-j} + \varepsilon_{it}, \qquad i = 1,.....6 \tag{3.18}$$

$$h_{it} = k_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1}, \tag{3.19}$$

The estimation results are presented in Table 3.7. It can be seen that the U.S., Germany and Japan don't exhibit autoregressive behavior in the returns series, while Canada, Hong Kong and Singapore have first order serial correlation. In the conditional variance equations, the coefficient estimates α and β are statistically significant at the 1% level for all return series. Persistence in volatility, measured by $\alpha + \beta$, is nearly equal to one for all series, which indicates that the time-varying volatility in national stock market returns is highly persistent. To check the suitability of the univariate AR-GARCH model, we conduct the Ljung Box Q test for the standardized residuals and the squared standardized residuals. Both of them exhibit no significant correlations.

Table 3.7: Maximum Likelihood Estimates of the AR-GARCH(1,1) Model

Coefficient	U.S.	Canada	UK	Germany	France	Japan	HK	Singapore
a	0.0493	0.0792	0.0395	0.0650	0.0692	0.0317	0.0506	0.0358
	(0.0180)	(0.0166)	(0.0154)	(0.0219)	(0.0198)	(0.0237)	(0.0243)	(0.0216)
b_1		0.0950					0.0528	0.0944
	-	(0.0221)	-	-	-	-	(0.0216)	(0.0206)
b_2	-	-	-	-	-	-	-	-
b_3			-0.0449		-0.0541			
	-	-	(0.0201)	-	(0.0195)	-	-	-
k	0.0127	0.0082	0.0076	0.0188	0.0117	0.0308	0.0136	0.01901
	(0.0034)	(0.0016)	(0.0023)	(0.0040)	(0.0033)	(0.0069)	(0.0034)	(0.0032)
α	0.0774	0.0927	0.0739	0.0963	0.0672	0.0762	0.0669	0.1152
	(0.0064)	(0.0060)	(0.0074)	(0.0089)	(0.0066)	(0.0082)	(0.0057)	(0.0072)
β	0.9149	0.9046	0.9207	0.8977	0.9278	0.9106	0.9299	0.8826
	(0.0073)	(0.0048)	(0.0077)	(0.0086)	(0.0066)	(0.0092)	(0.0060)	(0.0057)
Log likelihood	-3703.7	-3286.6	-3549.1	-4363.8	-4202.9	-4429.3	-4538.3	-4065.1

Numbers in parenthesis are standard errors.

After fitting the univariate GARCH for each series, the dynamic conditional correlation equations were estimated. We estimate the DCC equations for pairs of countries in the same region, as well as for the pair of the U.S. and each country in Europe and Asia. The estimation results are reported in Table 3.8.

It can be seen that the coefficient estimates of DCC equations, δ_1 and δ_2, are all significant at the 1% level. This indicates that the correlations are significantly time-varying. Time-varying correlations are highly persistent. The intensity of correlation persistence measured by $\delta_1 + \delta_2$ is more than 0.85 for all pairs of countries.

Notably, incorporating the GARCH term seems to improve over the standard DCC model. The GARCH term (δ_3) is significant at the 1% level for all countries. Incorperation of the GARCH term does not alter the estimates of δ_1 and δ_2 much. It also seems that the likelihood value improves significantly for many pairs of countries after we incorporate the GARCH term in the DCC equation. We also report the estimation result of the standard DCC model, and then we perform the likelihood ratio (LR) test. The LR tests favor the GARCH-in-DCC model at the 5% level for 9 out of 13 pairs of countries under estimation. It provides another justification that the GARCH term may be necessary when we model the dynamic conditional correlation among financial time series. It is worth noting that, according to the LR test, which is actually a test of null hypothesis, $H_0 : \delta_3 = 0$, a few pairs of countries are not able to reject at the 5% level of significance. The result is different from the coefficient significance test based on the t statistic. This may be either due to the fact that the coefficient of Q_{t-1} term is so over-dominating in the conditional correlation equation (bigger than 0.8 for all pairs of countries) that the coefficient of GARCH term is very small in absolute value, causing the explanatory power of GARCH term becomes small and the improvement in log likelihood by adding the GARCH term not substantial, or due to the way that the standard errors were computed for t test. Nevertheless, the LR test confirms that adding the GARCH term improves the estimation in most cases.

Table 3.8: Estimation of Conditional Correlation Equation of GARCH-in-DCC Model

Country Pair	Base DCC Model		Garch-in-DCC Model			LR Test
	δ_1	δ_2	δ_1	δ_2	δ_3	
U.S/Canada	0.0330	0.9381	0.0346	0.9307	0.0038	2.49
	(0.0003)	(0.0018)	(0.0002)	(0.0020)	(0.0000)	
UK/Germany	0.0464	0.9408	0.0478	0.9371	0.0010	0.51
	(0.0003)	(0.0007)	(0.0003)	(0.0009)	(0.0000)	
UK/France	0.0384	0.9544	0.0391	0.9503	0.0026	**4.20**
	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0000)	
Germany/France	0.0208	0.9792	0.0205	0.9785	0.0006	**4.20**
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	
Japan/HK	0.0438	0.8140	0.0436	0.8150	-0.0002	0.00
	(0.0003)	(0.0082)	(0.0003)	(0.0088)	(0.0000)	
Japan/Singapore	0.0280	0.9298	0.0259	0.9407	-0.0014	1.17
	(0.0002)	(0.0010)	(0.0003)	(0.0020)	(0.0000)	
HK/Singapore	0.0440	0.9167	0.0499	0.8506	0.0108	**11.78**
	(0.0001)	(0.0004)	(0.0002)	(0.0026)	(0.0000)	
U.S/UK	0.0000	0.9608	0.0000	0.9702	0.0035	**10.90**
	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0000)	
U.S/Germany	0.0102	0.9873	0.0058	0.9897	0.0016	**11.20**
	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	
U.S/France	0.0069	0.9868	0.0031	0.9826	0.0026	**15.60**
	(0.0000)	(0.0003)	(0.0000)	(0.0003)	(0.0000)	
U.S(-1)/Japan	0.0029	0.9946	0.0006	0.9994	0.0003	**6.27**
	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	
U.S(-1)/HK	0.0082	0.9675	0.0086	0.9563	0.0034	**6.36**
	(0.0000)	(0.0007)	(0.0000)	(0.0006)	(0.0000)	
U.S(-1)/Singapore	0.0361	0.9015	0.0000	0.8998	0.0102	**5.34**
	(0.0005)	(0.0005)	(0.0001)	(0.0034)	(0.0000)	

The LR test is the likelihood ratio statistic for the null hypothesis of δ_3 =0. It is asymptotically distributed as a χ^2 with 1 degree of freedom. 5% critical value is 3.84. For estimation of coefficients, we report the standard errors in parenthesis.

Turning to the interpretation of coefficient estimates of the GARCH term, we noticed that the coefficient is positive in most cases. Specifically, the coefficient for Japan/Hong Kong, and Japan/Singapore is negative. This may be the result that the endogeneity between Japan and Hong Kong, Japan and Singapore is weak, while they both face a strong common exogenous factor (eg. the U.S market). As pointed out in Section 3.2, the stronger the common exogenous factor, the stronger the negative relationship between volatility and conditional correlation. The coefficient between the U.S and each country in Europe and Asia is positive. This may be the result that the U.S market is exogenous to all the other countries, and they may not have any common exogenous factor, or the common exogenous factor is weak. This scenario is similar to the Model 1 in Section 3.2, where the conditional correlation is increasing with the volatility. Last, the coefficient for all pairs of countries in the same region (except Japan/HK and Japan/Singapore as mentioned above) is positive. This may be the result that the countries in the same region exhibit strong endogenous correlation, though they are also affected by some common exogenous factors (such as the the U.S market). The endogenous effect may outweigh the common exogenous factor and thus the conditional correlation is still increasing with the volatility.

Figure 3.1 plots the estimated dynamic conditional correlation between the daily stock market returns. It can be seen that the correlation between countries in the same region is greater than that of countries across regions. When comparing the intra-region correlations, countries in the Europe and America exhibit much higher correlations than Asian countries. This may indicate that the markets in North America and Europe are more integrated than its Asian peers. In panel (b-3) in Figure 3.1, the correlation between France and Germany, the member countries of the euro shows an apparent upward trend since the inception of the euro in 1999. However, this upward trend is not shown in the correlations of U.K.-France and U.K-Germany, where U.K. is not a member of the euro. This upward trend was also not found in the correlations among any other countries in the same region.

Turning to the cross-region conditional correlation, or the correlations of the U.S and countries in Europe or Asia in our estimation, the correlation is less volatile than those of intra-region. There is no significant time trend in the correlation, but the correlations increase substantially from the second half of 2002 until early 2003, and then dropped back to their historical levels. The correlation hike at the end of 2002 may be due to the U.S's war against Iraq. At the time, the Dow Jones Industrials Index dropped by 14.9% from 28 November 2002 to 12 March 2003.

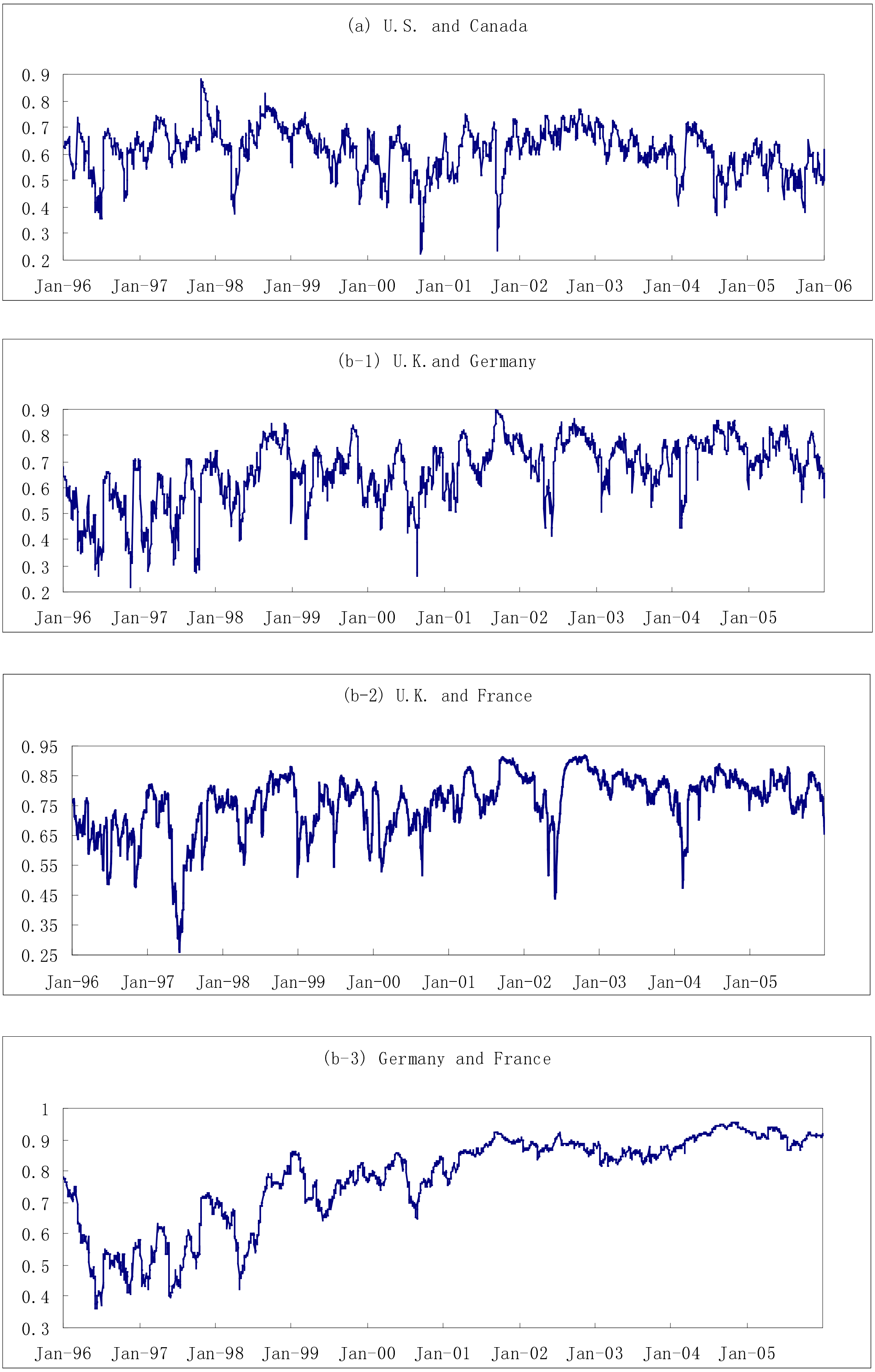
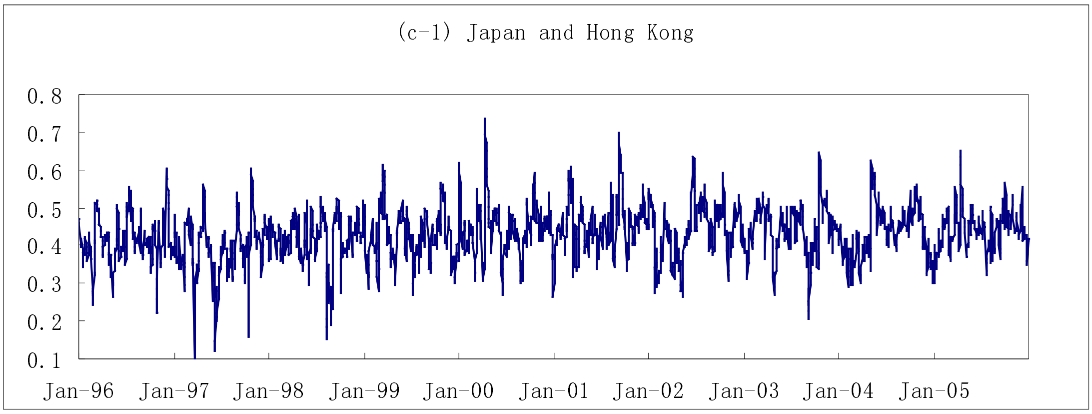
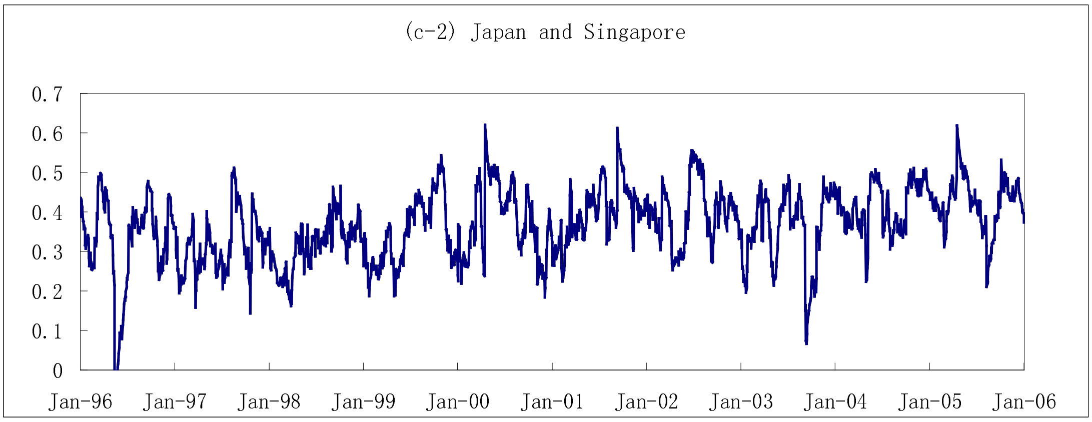
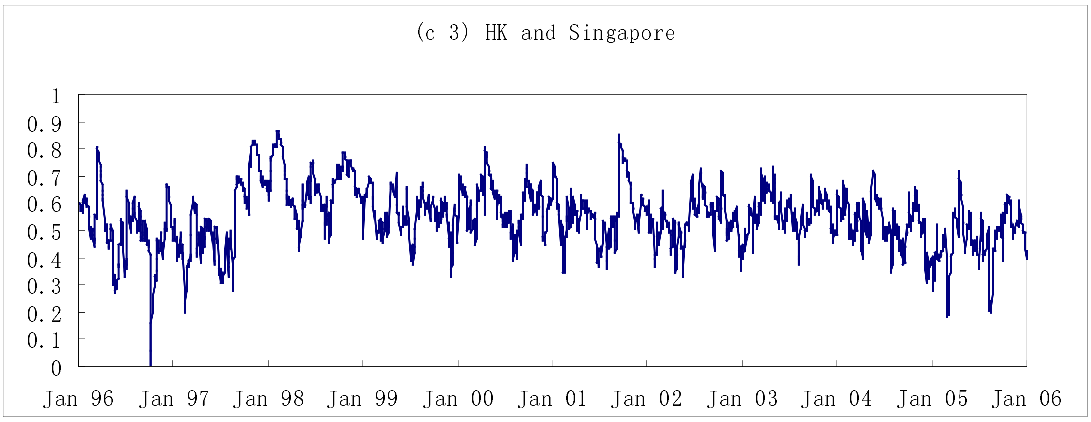


Figure 3.1 Time-varying Conditional Correlation between Daily Stock Market Return







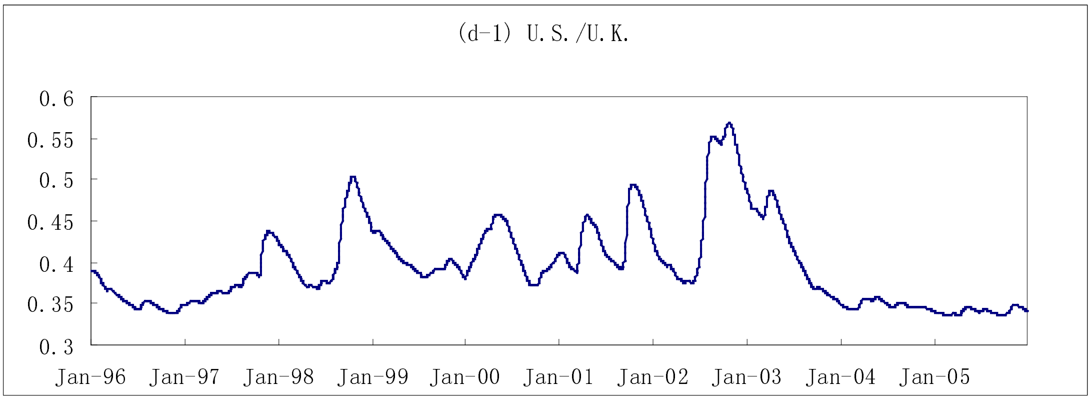
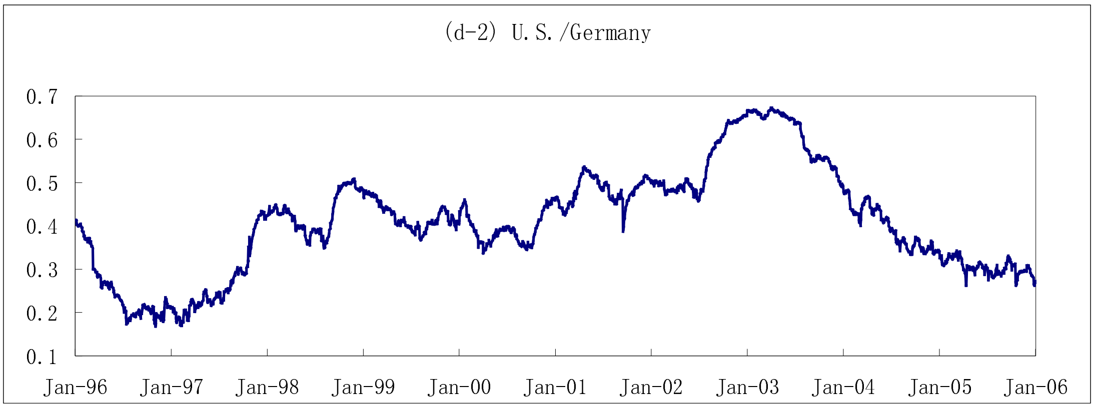
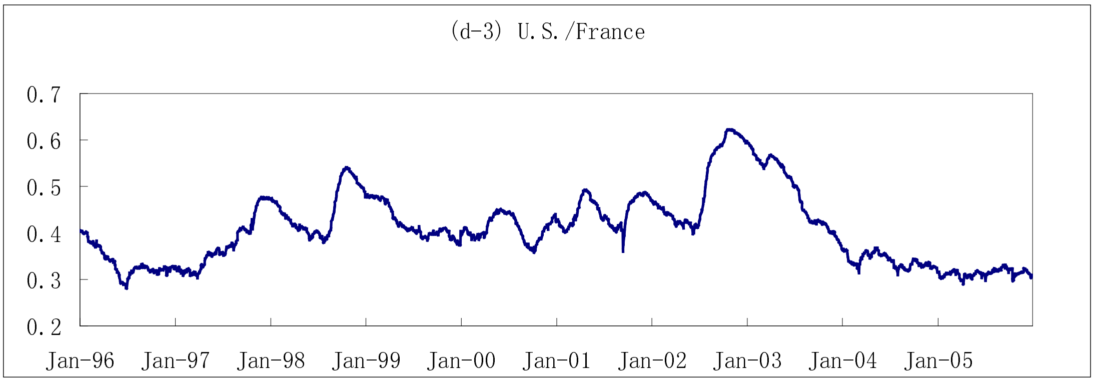
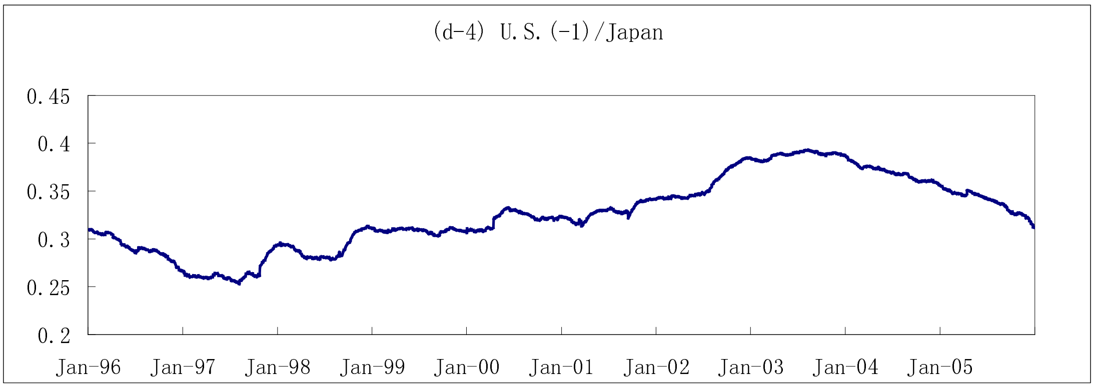


Figure 3.1 (Continued)







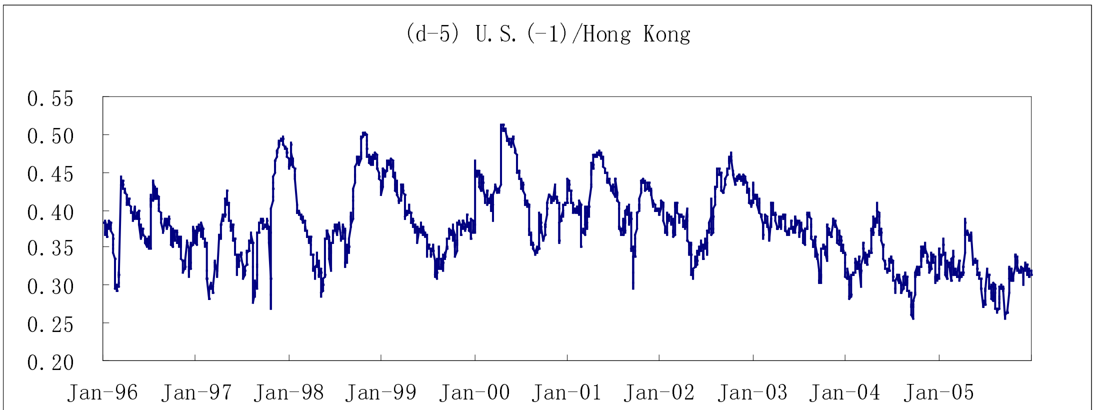


Figure 3.1 (Continued)

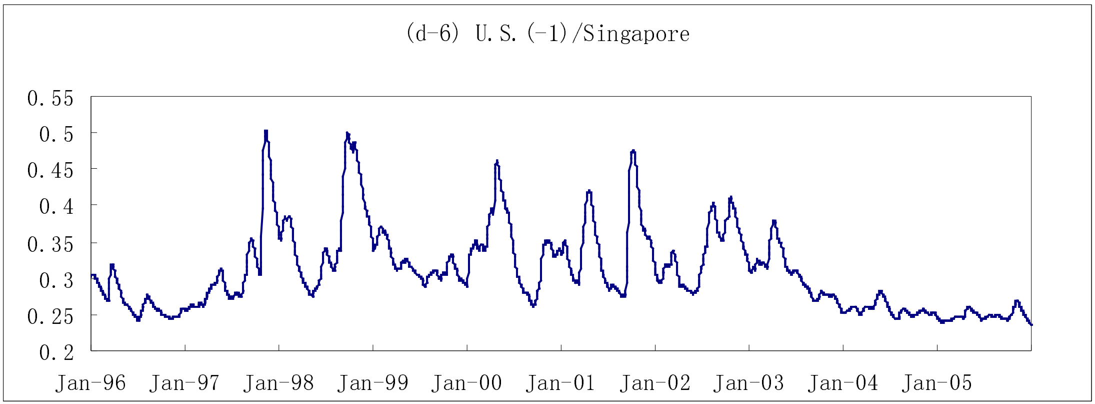


Figure 3.1 (Continued)

3.4 Tests for Financial Contagion

We test for financial contagion from Hong Kong to the rest of world during the Hong Kong market meltdown. As discussed in Section 3.1, the definition of contagion is a significant increase in cross-market correlation after a crisis in one country. First we perform the traditional test of comparing the two sample correlation coefficients between the stable and crisis period. Next, we propose a new test methodology by modifying the GARCH-in-DCC model and apply it to the Hong Kong crisis. We compare our test results with those from the traditional tests. We start by defining the period of Hong Kong market crisis.

3.4.1 Empirical Definition of the Hong Kong Crisis

While there is a broad agreement as to when the Hong Kong market crisis started, there is more ambiguity and disagreement as to the exact ending date of the crisis. The Hong Kong market lost about a quarter of its value in four trading days starting on 17 October 1997, and it continued to decline until the end of November. In our empirical study, we follow the same definition of Forbes and Rigobon (2002). We define the crisis period starts on 17 October 1997 and ends on 14 November 1997. We also define the stable period as 4 January 1996 to 16 October 1997. The stable period is immediately followed by one month long crisis period. Thus, the full period considered in our test is from 4 January 1996 to 14 November 1997.

3.4.2 Description of the Data

The source of our data is Datastream. We examine daily stock market index returns over a two-year period, 4 January 1996 to 14 November 1997 (484 observations).[1] Returns are denominated in local currencies and measured in logarithmic differences multiplied by 100. The series are 10 countries (including Australia) in Asia, 9 countries from Europe, and 6 countries from America.

Table 3.9 presents summary statistics for return series. Most Asian countries have negative mean returns during the sample period, while most European and American countries have positive mean returns. This is due to a series of financial crises in South East Asia during the period. Most countries' returns are negatively skewed, and all returns exhibit excess kurtosis, in excess of the normal distribution's benchmark value of 3. This indicates that the daily stock index returns we consider are not normally distributed. The Jarque-Bera normality tests were rejected for all countries. The $Q_1(20)$ statistics reveal that while there is no strong evidence of serial

[1] Removed holidays are December 25-26 and 1 January, total 3 days a year.

correlation in returns of most developed countries (the critical value at the 1% level is 37.57), the returns of the emerging markets show the opposite. $Q_2(20)$ statistics indicate that the squared stock return series have a very strong serial correlation in all markets except Canada and Chile.

Table 3.9: Summary Statistics of 25 Stock Market Returns

Country	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	$Q_1(20)$	$Q_2(20)$
Hong Kong	-0.009	1.853	-0.086	29.658	14332.51	69.63	296.80
Indonesia	-0.036	1.429	0.112	15.988	3402.84	79.14	185.64
Japan	-0.057	1.219	-0.176	4.569	52.15	23.81	74.97
Korea	-0.111	1.551	-0.136	7.668	440.89	40.77	225.22
Malaysia	-0.085	1.383	1.164	18.195	4765.32	55.31	120.62
Philippines	-0.073	1.431	-0.529	10.200	1068.16	64.12	72.47
Singapore	-0.046	1.156	-0.754	18.253	4737.44	75.34	190.31
Taiwan	0.077	1.429	-0.546	6.458	265.13	31.66	62.76
Thailand	-0.220	1.810	0.559	6.018	208.92	58.44	178.91
Australia	0.019	0.859	-1.151	20.152	6039.54	15.32	156.62
Belgium	0.072	0.804	-0.255	5.369	118.45	37.69	84.48
France	0.068	1.089	-0.085	6.077	191.57	18.36	91.81
Germany	0.085	1.163	-1.065	10.833	1328.81	25.56	172.80
Italy	0.092	1.208	-0.311	9.471	852.30	22.24	114.86
Netherlands	0.110	1.147	-0.342	5.963	186.50	45.67	273.99
Spain	0.109	1.078	-0.388	6.259	226.40	23.99	94.18
Sweden	0.102	0.613	-0.877	7.547	479.04	28.25	81.00
Swiss	0.098	1.019	-0.203	6.158	204.45	28.08	95.37
U.K.	0.050	0.745	-0.250	4.579	55.35	37.291	72.26
Argentina	0.015	1.737	-1.962	15.667	3546.25	12.80	117.14
Brazil	0.129	2.244	-1.232	12.872	2087.70	15.88	175.31
Canada	0.078	0.773	-1.448	14.395	2787.69	35.74	10.34
Chile	-0.034	0.565	0.044	5.120	90.81	56.41	16.66
Mexico	0.085	1.471	-1.065	27.562	12257.74	14.49	100.40
U.S.	0.078	0.980	-0.915	11.145	1405.55	20.40	48.10

Returns are in percentage term. Q1(20) is the Ljung-Box statistics for up to 20th order serial correlation of return series, while Q2(20) is the same statistics of the square of returns. It is asymptotically distributed as a x2 with 20 degrees of freedom. The 1% critical value of the statistics is 37.57

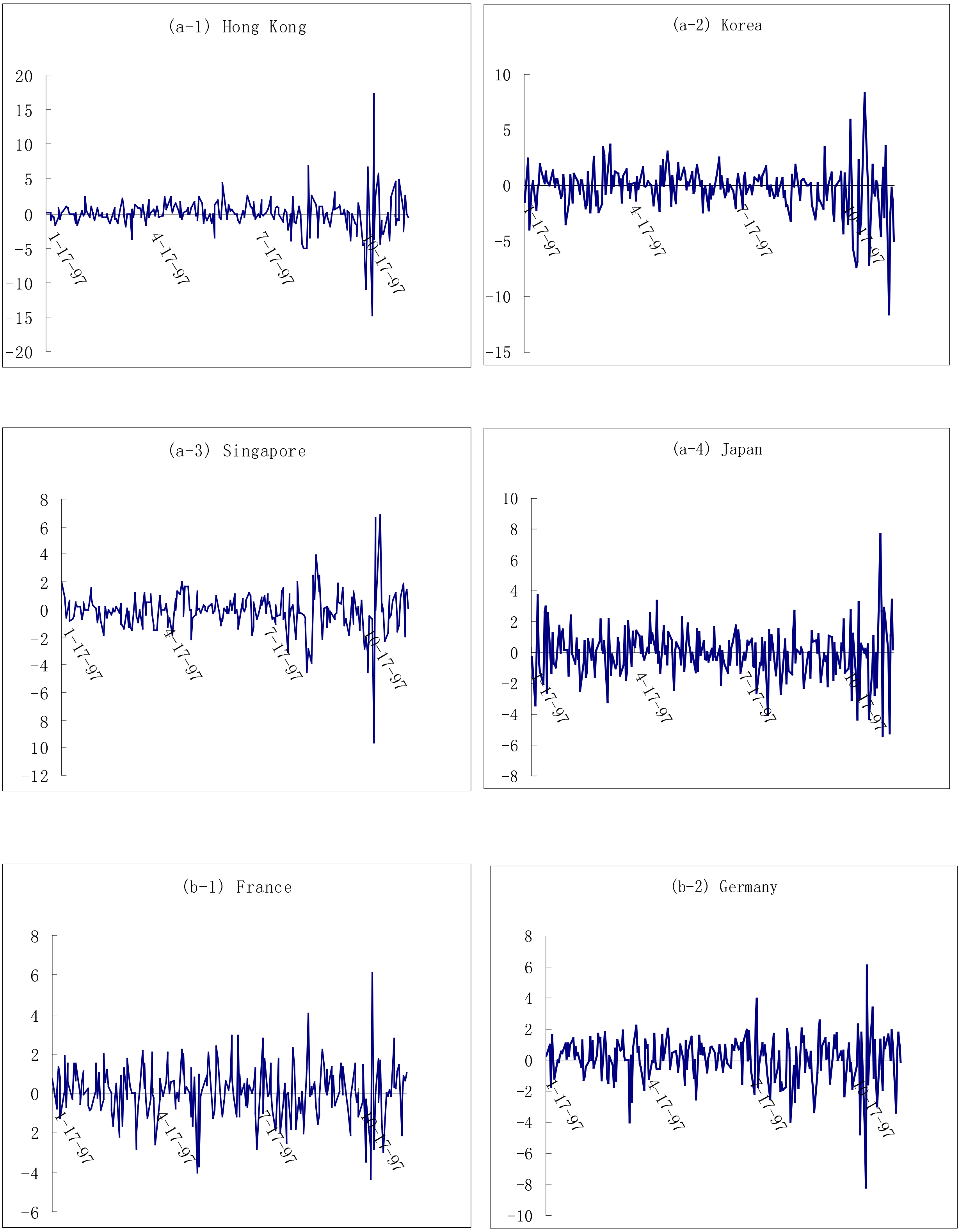


Figure 3.2 Daily Stock Market Return (%)

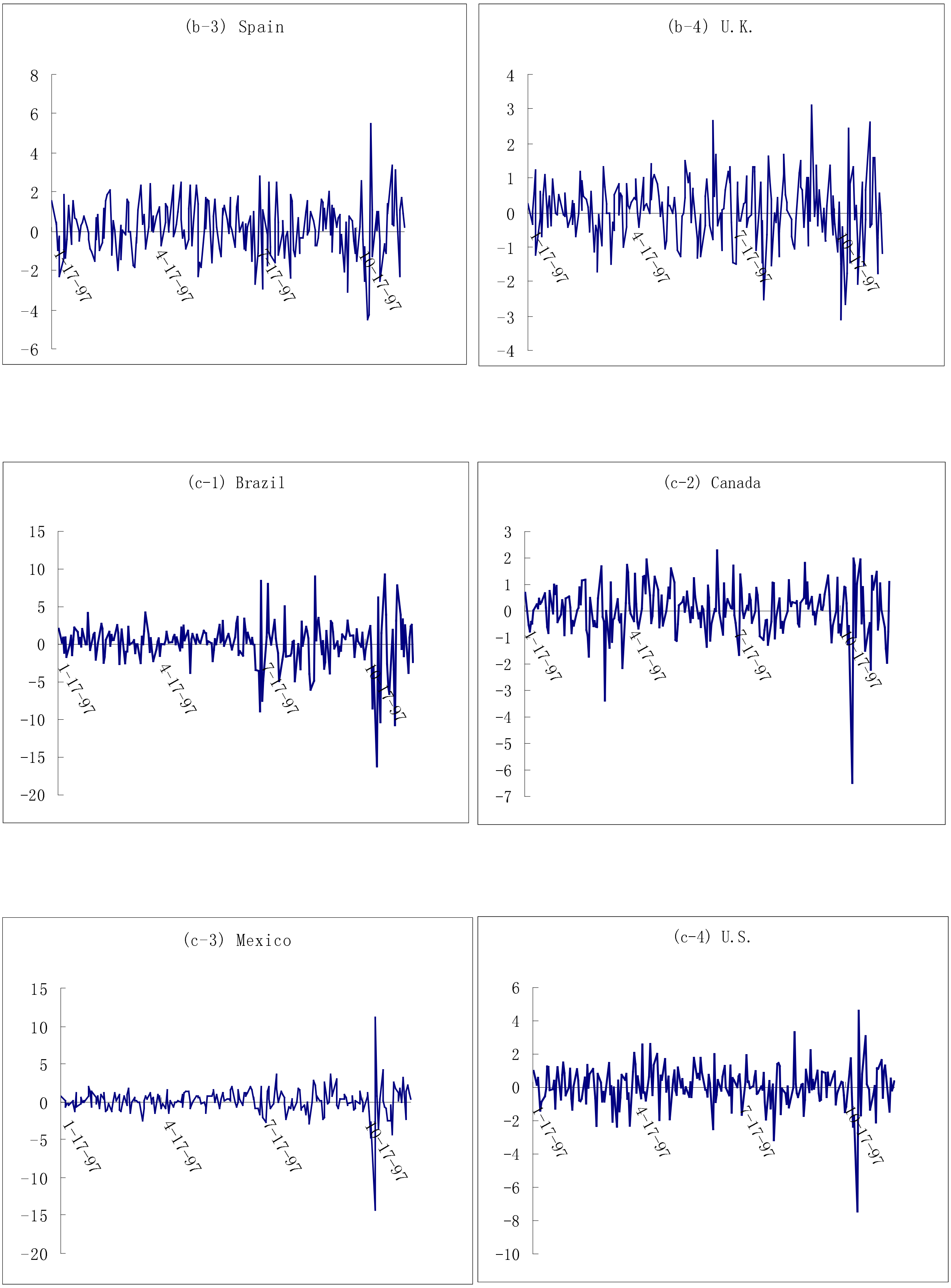


Figure 3.2 Daily Stock Market Return (%) (Continued)

Figure 3.2 plots the return paths of various stock markets surrounding the October 1997 Hong Kong market crisis. All markets around the world seemed to respond to the turmoil in Hong Kong market. However, most markets seemed surprisingly not responsive to the collapse of the Thai Baht on 2 July 1997. It is interesting to note that even the markets such as Mexico and Brazil, which seem have no tie with the Hong Kong market, observed a volatile period during the Hong Kong crisis. Major financial markets such as Germany, the U.K. and the U.S also exhibit a short period of high volatility during the crisis. As shown in panel (a-2), the Korea market enters into an intense volatile period immediately after the Hong Kong market crash.

In summary, a visual inspection of the raw data suggests that a transmission of shock from Hong Kong to the rest of the world seemed to occur during the Hong Kong crisis. However, this does not mean that contagion has happened in these countries. Next, we apply the traditional and our proposed test to examine which countries are subject to contagions from the Hong Kong Crisis.

3.4.3 Traditional Test for Financial Contagion: z-Test

3.4.3.1 Description of Traditional Test

The traditional testing procedure is straightforward. We first divide the entire sample period into the stable and crisis period. Then we compute the correlation coefficient between Hong Kong and each other country in the sample for the two periods. The test hypotheses are:

$$\begin{aligned} H_0 &: \rho^C_{i,hk} \le \rho^S_{i,hk} \\ H_1 &: \rho^C_{i,hk} \succ \rho^S_{i,hk} \end{aligned}, \tag{4.1}$$

where $\rho^C_{i,hk}$ and $\rho^S_{i,hk}$ are the correlation coefficients between country i and Hong Kong for the crisis and stable periods. Under the assumption that two samples are drawn from two bivariate normal distributions[2] with the same correlation coefficient, Anderson (1985) shows that the Z statistic converges to a normal distribution with zero mean and unit variance. Z statistic is defined as

$$Z_0 = \frac{|z_C - z_S|}{\sqrt{\frac{1}{(n_C - 3)} + \frac{1}{(n_S - 3)}}}, \tag{4.2}$$

where $z_p = \frac{1}{2}\log\frac{1+\hat{\rho}_p}{1-\hat{\rho}_p}(p = s, c)$, and $\hat{\rho}_p$ is estimated correlation coefficients. n_c and n_s are the number of observations for crisis period and non-crisis period, respectively. One-sided tests are performed to test the hypothesis (4.1) examining if the cross-market correlation coefficient during the crisis period is significantly greater than that of the stable period. If this is true, it is regarded as evidence of contagion

The traditional test is simple though, it has some advantages compared with some other testing methods. As discussed earlier, two countries' asset returns can co-move because fundamentals between countries are related, or two countries respond to an exogenous global factor at the same time. Given that one is never sure of how many fundamental variables or common exogenous factors are enough to explain the

[2] As we saw in Table 3.9, the data that we examine are not normally distributed.

cross-market correlation, any modeling of asset returns or correlations on a set of explanatory variables involves the risk of misspecification. The traditional test can avoid such misspecification by computing the correlation directly and examine the difference of them during the stable and crisis period.

3.4.3.2 Test Results

The estimated correlation coefficients for the stable and crisis periods are presented in Table 3.10. Z-test statistics are presented in the last column. Significant test statistics at the 5% level of significance are highlighted in the bold face.

During the stable period, most Asian and European countries are weakly correlated with Hong Kong, except Singapore, with average correlations of 0.285 for the Asian countries and 0.242 for the European countries. An exception is Singapore, whose correlation with Hong Kong in the stable period stands at 0.54. For the American countries, the causality[14] from Hong Kong is very low, with an average of 0.124. During the crisis period, the correlation increases substantially for most countries in the sample. The average correlations with Hong Kong are 0.513 fro the Asian countries, 0.79 for the European countries, and 0.16 for the American countries.

According to the z-test results, 15 out of 25 countries show evidence of contagion from the October 1997 Hong Kong market crash. Contagion occurred to Japan,

[14] The stock markets in American countries open only after Hong Kong market closes, therefore we define this as causality from Hong Kong to America

Table 3.10 Contagion Tests Based on the z-test

Region	Country	Sample Correlation Coefficient		Test Statistic	p-value
		Stable	Crisis		
Asia	Indonesia	0.385	0.577	1.045	0.148
	Japan	0.278	0.626	**1.867**	**0.031**
	Korea	0.108	0.278	0.739	0.230
	Malaysia	0.318	0.638	**1.775**	**0.038**
	Philippines	0.287	0.750	**2.819**	**0.002**
	Singapore	0.540	0.867	**2.974**	**0.001**
	Taiwan	0.121	0.103	-0.074	0.529
	Thailand	0.130	0.064	-0.280	0.610
	Australia	0.401	0.714	**1.958**	**0.025**
Europe	Belgium	0.196	0.702	**2.802**	**0.003**
	France	0.181	0.822	**4.077**	**0.000**
	Germany	0.353	0.845	**3.618**	**0.000**
	Italy	0.261	0.850	**4.120**	**0.000**
	Netherlands	0.271	0.830	**3.791**	**0.000**
	Spain	0.182	0.685	**2.726**	**0.003**
	Sweden	0.358	0.749	**2.479**	**0.007**
	Swiss	0.180	0.832	**4.222**	**0.000**
	U.K.	0.195	0.797	**3.720**	**0.000**
America	Argentina	0.098	0.011	-0.363	0.642
	Brazil	0.110	0.094	-0.068	0.527
	Canada	0.157	0.285	0.561	0.287
	Chile	0.105	0.472	**1.695**	**0.045**
	Mexico	0.183	0.032	-0.637	0.738
	U.S.	0.088	0.059	-0.122	0.549

This table presents the cross-market correlation coefficients for Hong Kong and each country in the sample. The stable period is defined as from 4 January 1996 to 16 October 1997. The crisis period is defined as from 17 October 1997 to 14 November 1997. The test statistics are for the one-sized z-tests examining if the correlation coefficient during the crisis period is greater than during the stable period. The critical values are 1.65 at the 5% level. The p-values of the test statistics are reported in parenthesis in the last column

Malaysia, the Philippines, Singapore, Australia, Belgium, France, Germany, Italy, the Netherlands, Spain, Sweden, Swiss, Russia, the U.K. and Chile. 5 out of 9 Asian countries, all 9 out of 9 European countries, and 1 out of 6 American countries were affected by the Hong Kong crisis. Forbes and Rigobon (2002) find the very similar results when they examine the case of Hong Kong crisis using the traditional test. They find that 4 out of 9 Asian countries, 9 out of 10 European countries are subject to contagion.

3.4.4 Contagion Tests Based on the Modified GARCH-in-DCC Model

3.4.4.1 The Modified GARCH-in-DCC Model

To capture the shift in the conditional correlation as the contagion effects, we extend the GARCH-in-DCC model by adding a dummy variable to allow for structural breaks in the mean. The modified GARCH-in-DCC parameterization used in the test is given by:

$$Q_t = (1-\delta_1-\delta_2)\overline{Q} + \delta_4(\overline{Q}_2-\overline{Q})d_t + \delta_1 u_{t-1}u_{t-1}^{'} + \delta_2 Q_{t-1} + \delta_3(D_{t-1}ii^{'}D_{t-1} - \overline{D}ii^{'}\overline{D}), \quad (4.3)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$$
$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 \\ 0 & \sqrt{q_{22t}} \end{bmatrix} \quad (4.4)$$

where d_t is a scalar crisis dummy variable, with $d_t = 0$ during the stable period and $d_t = 1$ during the crisis period. $\overline{Q}_2$ is the sample covariance matrix of the standardized residual vector u_t during the crisis period. R_t is a (2x2) correlation matrix. The restrictions on the DCC parameters are given by:

$$\delta_1, \delta_2, \delta_4 \geq 0,$$
$$\delta_1 + \delta_2 + \delta_4 \leq 1, \quad (4.5)$$

Equation (4.3) is a function of the standardized residual vector u_t and conditional variance D_t. After the volatility effect on the return correlation is controlled for, the shift in correlation during the crisis period will be captured as structural breaks in equation (4.3). To test the significance of the crisis dummy variables, we perform the LR tests.

We first select the models to be used in the tests. The conditional mean equation is given in equation (3.18). We select an initial autoregressive order of 3 for all the countries and then all the non-significant autoregressive parameters are removed. For the conditional variance and correlation equations, we choose GARCH(1,1) and GARCH-in-DCC(1,1,1) for all the countries.

3.4.4.2 Test Results

The null GARCH-in-DCC model is given in equation (3.10) in Section 3.3, and the alternative model is given in equation (4.3). The LR tests for the null hypothesis, $H_0 : \delta_4 = 0$, is presented in Table 3.11. The test statistic is given in the last column. The p-value is given in parenthesis under the LR statistic. The test statistic is distributed as a χ^2 with 1 degree of freedom, and its critical value at the 5% level of significance is 3.84. Standard errors of coefficient estimates are reported in parenthesis under the estimations.

Overall, when the volatility effects on the correlations are controlled for, the 15 cases of contagion found under the z-tests reduce to 9 cases. Among the Asian countries, only the Philippines was subject to contagion by the Hong Kong market crisis. We noticed that the estimated coefficients of GARCH term for Asian countries are mostly positive, which indicates there exists a positive relationship between volatility and conditional correlation. This positive relationship may indicate that the Hong Kong markets and other Asian markets share some similar fundamentals within the region and thus exhibit some degree of endogenous correlation. After the positive effects are controlled for, the 5 cases of contagion found under the z-test reduced substantially to only 1 case.

For the European countries, all are subject to contagion except Spain. This is similar to the z-tests, where all European countries are found to be under contagion. Interestingly, it can be seen that the estimated coefficients of the GARCH term for most European countries are negative, which may suggest that the endogeneity between the Hong Kong market and European markets are weak, while they may face some strong common exogenous factors. After this negative relationship is controlled for, most European markets show strong evidence of contagion at the 5% significance level. Belgium and Sweden are significant at the 10% level.

For the American countries, none of them are found to be subject to contagion, while the z-test shows Chile is under contagion. It can be seen from Table 3.11 that the estimated coefficients of the GARCH term are positive for all American countries. This may be due to the fact that American markets will only open after Hong Kong market closes, which effectively makes Hong Kong market exogenous to American markets. After this positive relationship between volatility and correlation is controlled for, no evidence of contagion is found for American countries.

Figure 3.3 shows that the crisis affected countries exhibit structural changes in correlation dynamics. It plots correlations estimated from the null of the GARCH-in-DCC model and the alternative modified model for 6 selected countries in the sample, with 3 countries are subject to crisis under the LR test, while 3 countries are not subject to contagion under the LR test but subject to contagion under z-tests.

Panel (a) of Figure 3.3 plots the correlation dynamics for countries that are subject to contagion under the LR test. For all 3 countries under examination, the null of GARCH-in-DCC model indicates that there is an increase in correlation when the Hong Kong crisis begins on October 17. The increase is well captured by introducing the GARCH term into standard DCC model. When the modified GARCH-in-DCC model is estimated, the estimated correlations between Hong Kong and 3 other countries jumped suddenly to a much higher level of more than 0.8. Also, the correlation dynamics estimated under the modified GARCH-in-DCC model are less volatile than that of the GARCH-in-DCC model during the stable period for all cases. This implies a structural break did occur during the crisis period.

Table 3.11: Contagion Tests Based on the Modified GARCH-in-DCC Model

Country	GARCH-in-DCC Model			Modified GARCH-in-DCC Model				LR Test (p-value)
	δ_1	δ_2	δ_3	δ_1	δ_2	δ_3	δ_4	
Indonesia	0.0337	0.4970	0.0360	0.0337	0.4951	0.0362	0.0000	0.002
	(0.0014)	(0.0275)	(0.0003)	(0.0014)	(0.0377)	(0.0003)	(0.0719)	(0.964)
Japan	0.0065	0.9686	-0.0022	0.0376	0.7774	-0.0045	0.0291	1.076
	(0.0003)	(0.0003)	(0.0000)	(0.0048)	(0.0102)	(0.0000)	(0.0146)	(0.300)
Korea	0.0696	0.1149	0.0171	0.0696	0.1149	0.0171	0.0000	0.000
	(0.0072)	(1.2599)	(0.0004)	(0.0048)	(1.2599)	(0.0005)	(11.73)	(1.000)
Malaysia	0.0183	0.9557	0.0012	0.0000	0.9989	0.0006	0.0673	2.444
	(0.0002)	(0.0024)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.118)
Philippines	0.0000	0.4605	0.1082	0.0000	0.4983	0.0236	0.6575	**3.900**
	(0.0525)	(0.1794)	(0.8107)	(0.0025)	(0.1868)	(0.0025)	(0.1279)	**(0.048)**
Singapore	0.0916	0.7351	0.0393	0.0916	0.7351	0.0393	0.0000	0.000
	(0.0016)	(0.0084)	(0.0006)	(0.0015)	(0.0123)	(0.0005)	(0.0154)	(1.000)
Taiwan	0.0000	0.4520	0.0138	0.0000	0.4496	0.0138	0.0000	0.000
	(0.0210)	(0.2719)	(0.0005)	(0.0103)	(1.5087)	(0.0005)	(2.8006)	(0.989)
Thailand	0.0103	0.9538	-0.0023	0.0120	0.9566	-0.0025	0.0424	0.392
	(0.0010)	(0.0122)	(0.0000)	(0.0003)	(0.0020)	(0.0000)	(0.0815)	(0.531)
Australia	0.0887	0.6265	-0.0018	0.0887	0.6265	-0.0018	0.0000	0.000
	(0.0058)	(0.0376)	(0.0000)	(0.0053)	(0.0351)	(0.0000)	(0.0215)	(1.000)
Belgium	0.0293	0.9372	-0.0030	0.0189	0.9584	-0.0003	0.1517	**3.054**
	(0.0002)	(0.0006)	(0.0000)	(0.0001)	(0.0003)	(0.0000)	(0.0048)	**(0.081)**
France	0.0231	0.8949	0.0037	0.0000	0.6855	-0.0039	0.5026	**10.486**
	(0.0010)	(0.0211)	(0.0015)	(0.0009)	(0.0080)	(0.0000)	(0.0475)	**(0.001)**
Germany	0.0647	0.8525	0.0078	0.0589	0.8673	-0.0018	0.1249	**7.374**
	(0.0014)	(0.0066)	(0.0002)	(0.0017)	(0.0064)	(0.0000)	(0.0038)	**(0.007)**
Italy	0.0332	0.9519	-0.0006	0.0250	0.9689	-0.0040	0.2654	**9.334**
	(0.0005)	(0.0016)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0162)	**(0.002)**

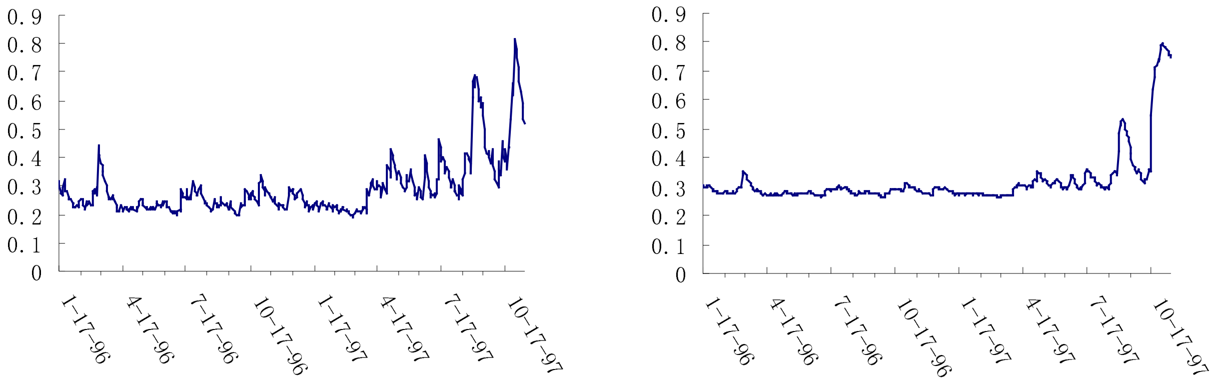
Table 3.11: Contagion Tests Based on the Modified GARCH-in-DCC Model (Continued)

Country	GARCH-in-DCC Model			Modified GARCH-in-DCC Model				LR Test
	δ_1	δ_2	δ_3	δ_1	δ_2	δ_3	δ_4	(p-value)
Netherlands	0.0000	0.6134	0.0495	0.0130	0.9660	-0.0019	0.1644	**7.634**
	(0.0048)	(0.0227)	(0.0008)	(0.0002)	(0.0018)	(0.0000)	(0.0022)	**(0.006)**
Spain	0.0559	0.6160	0.0673	0.0559	0.6158	0.0673	0.0000	0.000
	(0.0017)	(0.0066)	(0.0007)	(0.0016)	(0.0148)	(0.0019)	(0.7643)	(1.000)
Sweden	0.0307	0.9343	-0.0027	0.0242	0.9397	-0.0022	0.1636	**2.814**
	(0.0003)	(0.0018)	(0.0000)	(0.0003)	(0.0016)	(0.0000)	(0.0178)	**(0.093)**
Swiss	0.0283	0.4211	0.1205	0.0101	0.7927	-0.0018	0.6353	**5.576**
	(0.0023)	(0.0485)	(0.0036)	(0.0003)	(0.0127)	(0.0000)	(0.0752)	**(0.018)**
U.K.	0.0386	0.9280	-0.0026	0.0257	0.9374	0.0017	0.2254	**4.096**
	(0.0005)	(0.0023)	(0.0000)	(0.0003)	(0.0018)	(0.0000)	(0.0067)	**(0.043)**
Argentina	0.0016	0.8576	0.0060	0.0016	0.8576	0.0060	0.0000	0.000
	(0.0017)	(0.0169)	(0.0001)	(0.0018)	(0.0162)	(0.0001)	(0.6141)	(1.000)
Brazil	0.1283	0.0114	0.0000	0.0152	0.0465	0.0003	0.4432	0.154
	(0.0100)	(0.0002)	(0.0149)	(0.0004)	(0.0186)	(0.0000)	(4.9837)	(0.695)
Canada	0.0000	0.8632	0.0351	0.0000	0.8558	0.0379	0.0000	0.167
	(0.0019)	(0.0633)	(0.0071)	(0.0027)	(0.1797)	(0.0214)	(0.4998)	(0.683)
Chile	0.1275	0.0104	0.3003	0.1276	0.0106	0.3003	0.0000	0.176
	(0.0072)	(0.0576)	(0.0373)	(0.0082)	(0.0475)	(0.0341)	(1.1169)	(0.674)
Mexico	0.0000	0.8491	0.0124	0.0000	0.8491	0.0124	0.0000	0.000
	(0.0086)	(0.1829)	(0.0014)	(0.0096)	(0.2113)	(0.0017)	(0.2352)	(1.000)
U.S.	0.0131	0.7442	0.0318	0.0131	0.7442	0.0318	0.0000	0.860
	(0.0022)	(0.0208)	(0.0010)	(0.0021)	(0.0271)	(0.0014)	(0.0040)	(0.354)

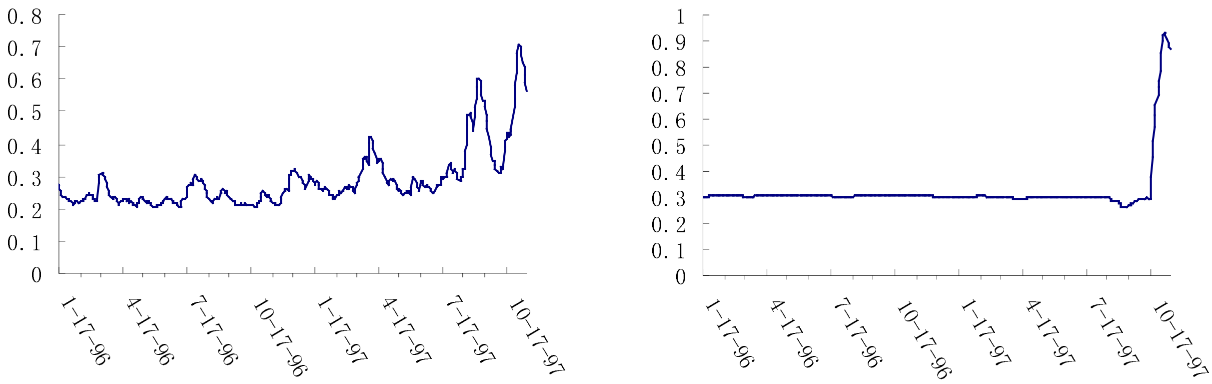
The LR test tests the null hypothesis, $H_0 : \delta_4 = 0$. The LR statistic is distributed as a χ^2 with one degree of freedom. Its 5% and 10% critical values are 3.84 and 2.71 respectively. The p-value is reported under the LR statistic. The bold numbers indicate significant at the 10% level. For estimation of coefficients, we report standard errors in parenthesis.

GARCH-in-DCC　　　　Modified GARCH-in-DCC

(a-1) Philippines



(a-2) Netherlands



(a-3) U.K.

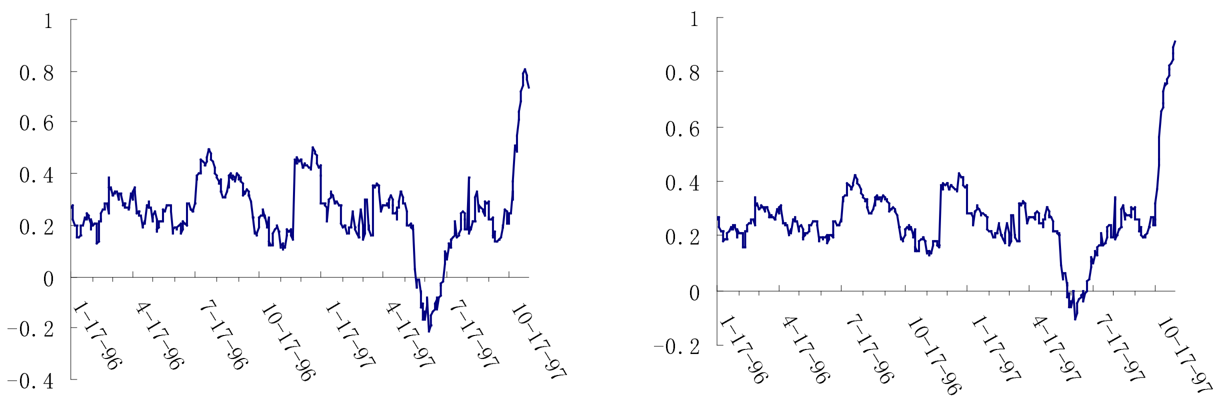
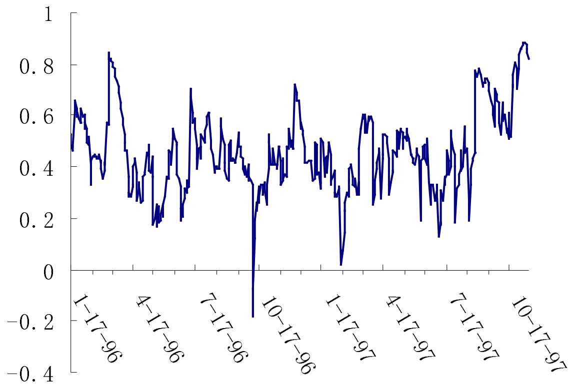
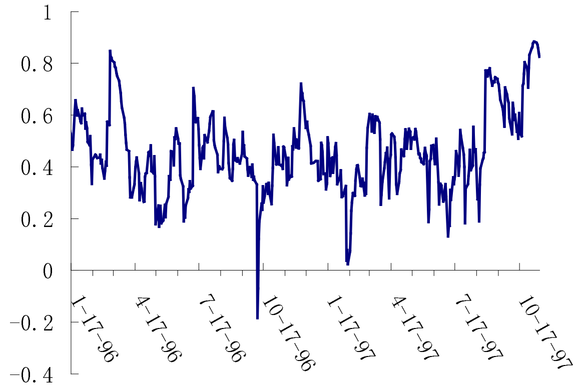


Figure 3.3 Comparison of the Conditional Correlation Dynamics: Null vs. Alternative
(It is the correlation with Hong Kong)

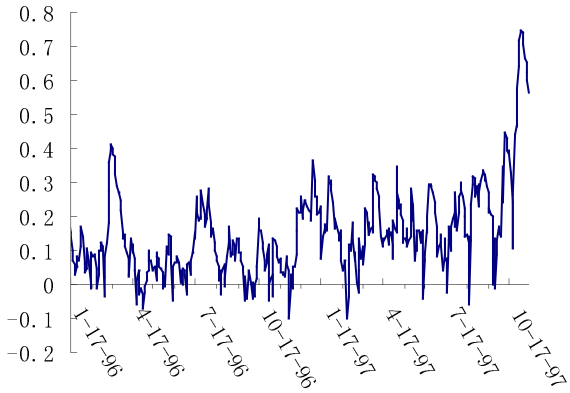
GARCH-in-DCC Modified GARCH-in-DCC

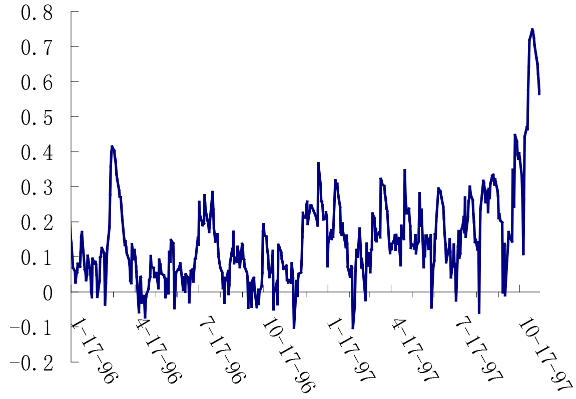
(b-1) Singapore



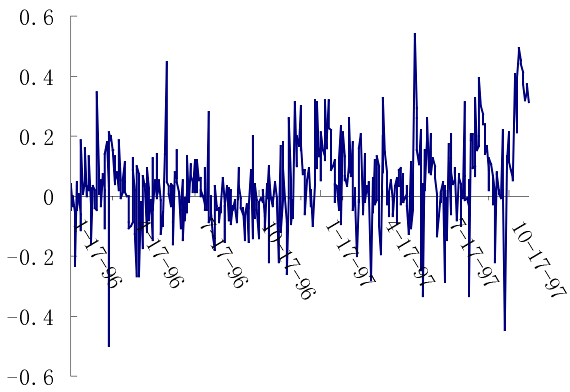


(b-2) Spain





(b-3) Chile



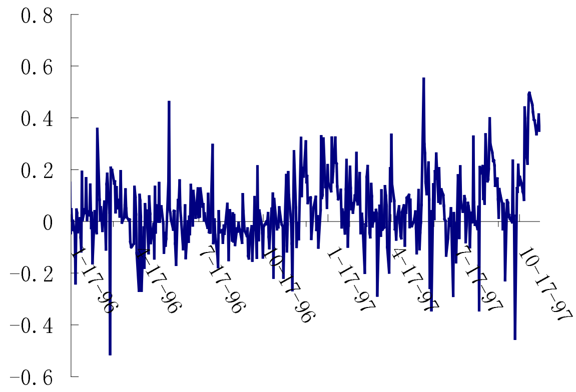


Figure 3.3 Comparison of the Conditional Correlation Dynamics: Null vs. Alternative (Continued)
(It is the correlation with Hong Kong)

Panel (b) plots the correlation dynamics for countries that are not subject to contagion under the LR test but are subject to contagion under the z-tests. Similar to the countries in Panel (a), all countries under examination exhibit an increase in correlation when the Hong Kong crisis begins on October 17. The increases were captured by the GARCH term in conditional correlation equation. When the modified GARCH-in-DCC model with crisis dummy variable is estimated, the correlation dynamics don't change much from the null model. In other words, after the volatility effects on the correlation are controlled for in the null model, there is no more evidence of contagion found in these countries.

3.5 Conclusion

In this chapter, we reinvestigate the relationship between time-varying correlation and volatility. By using extensive simulation studies, we have shown that the relationship is actually dependent on the underlying data generation process, which is contrary to several studies that have documented that there exists a positive relationship between time-varying correlation and volatility. To model the volatility effects on return correlations, we extend the standard dynamic conditional correlation (DCC) model by introducing a GARCH term to the model. We find strong evidence of volatility effects on conditional correlations between stock markets returns, although the effects are presented in different manners. The proposed GARCH-in-DCC model is preferred in most cases to the standard DCC model using likelihood ratio test.

After controlling for the volatility effects on return correlations in the proposed GARCH-in-DCC model, we further modify the model by introducing a dummy variable to allow for structural breaks in correlations. We then apply the modified GARCH-in-DCC model to test for contagion during the 1997 Hong Kong stock market crash

We compare our test results with the traditional test. The traditional methodology of testing for contagion computes the sample cross-market correlation coefficients during the stable and crisis period, and then examines if the correlation coefficients increase significantly after a crisis. Since the traditional test assumes that return dynamics are homoscedastic, it fails to take into accounts the volatility effects on correlations. Under the traditional test, we find 15 cases of contagion among a set of 25 countries. When we apply our methodology, we find only 9 cases of contagion. This result indicates that controlling for volatility effects is important in tests for contagion. In several cases, we find the increased correlations in the crisis period are actually due to the strong positive effects of increased volatility. After the volatility effects are controlled for, the evidence of contagion under the traditional test substantially weakens.

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