# Chapter 5

## Modelling the Volatility in Bond Returns in South-East Asia

Many studies have analysed the returns and volatility in stock markets, but there are fewer analyses of bond markets. The analysis of volatility in bond markets is useful to help investors, especially those who can bear the lower levels of risk, to understand the characteristics and behaviour of volatility and volatility spillovers across countries, and the effects of positive and negative shocks (or news) on volatility. In particular, they can diversify portfolio risk by making efficient asset allocations. Bond markets in South-East Asia grew rapidly in terms of market capitalization and trade volume following the Asian financial crisis in 1997 and it also becomes an important market for private and institutional investors.

This chapter is a revised version from the original paper presented at the Sixth International Conference on Business and Information 2009, Kuala Lumpur, Malaysia in Appendix C.

## Abstract

Bond markets have become useful for risk diversification and portfolio management, recently also for South-East Asian markets. The paper evaluates the volatility linkages and spillovers across bond markets in the South-East Asia countries of Indonesia, Philippines, Singapore and Thailand. Daily returns of bond indexes from 1 April 2004 to 13 March 2009 are used, and univariate and multivariate models are estimated to analyse returns and volatilities. The univariate volatility models suggest that asymmetric effects are present for the Indonesia and Philippines markets, whereas Singapore and Thailand display symmetric effects. Using multivariate volatility models to capture conditional correlations and spillover effects, the CCC model shows that the correlations are negative between Thailand and the other countries, so that investors can efficiently diversify the risk of their portfolio by investing in Thai bonds. The VARMA-GARCH and VARMA-AGARCH models show significant volatility spillovers. The volatility spillover effects from the Singapore market to the other markets are statistically significant, which means that hedging or speculation should be considered when the volatility in the Singapore bond market is changing. As in the case of the univariate model, asymmetry in VARMA-AGARCH also exists for Indonesia and Philippines bonds. Thus, the asymmetric model is superior to its symmetric counterpart for Indonesia and Philippines. However, rolling windows estimation suggests that the assumption of constant conditional correlations is too restrictive, as evidence from the DCC model yields statistically significant time-varying conditional correlations.

## 5.1 Introduction

Volatility is a key component in portfolio and risk management, especially in modern financial theory. Efficient portfolios rely on the correlations or covariances of pairs of assets, and may change over time. Therefore, much research in economics and finance has attempted to model the variances, covariances, and correlations of assets to construct efficient portfolios, and to adjust them over time. Bond markets in South-East Asia grew rapidly in terms of market size and trade volume after the Asian financial crisis in 1997, as shown in Figures 5.1 and 5.2. Therefore, bond markets have become important for fund managers and investors.

Many studies have analysed the returns and volatility in stock markets, but there are fewer analyses of bond markets. The analysis of volatility in bond markets is useful for investors and fund managers for understanding the characteristics and behaviour of volatility and volatility spillovers across countries, and the effects of positive and negative shocks (or news) on volatility. In particular, they can diversify portfolio risk by making efficient asset allocations.

Numerous models have been developed to capture volatility. Engle (1982) developed the Autoregressive Conditional Heterscedasticity (ARCH) model to analyse volatility, and Bollerslev (1986) generalized ARCH to the Generalized Autoregressive Conditional Heterscedasticity (GARCH) model. However, both models assume symmetric effects of positive and negative shocks. In order to accommodate differential impacts on the conditional variance of positive and negative shocks, Glosten et al. (1993) proposed the GJR model, while the EGARCH model of Nelson (1991) also captures the asymmetric effects of shocks on volatility.

Multivariate volatility models are also useful for explaining volatility. The Constant Conditional Correlation (CCC) model of Bollerslev (1990) also assumes the conditional correlations of returns are time invariant, and restricted for the volatility spillovers between different returns. Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model to allow correlations to vary over time, but did not allow volatility spillovers. The VARMA-GARCH model of Ling and McAleer (2003) and VARMA-AGARCH model of McAleer et al. (2009) are able to capture volatility spillovers, but constant conditional correlations are maintained (for further details, see McAleer (2005)).

Many papers have investigated volatility, especially volatility spillovers and correlations across countries or markets, such as Fleming et al. (1998), Fernández-Izquierdo and Lafuente (2004), Gannon (2005), Steeley (2006), Hakim and McAleer (2008), and da Veiga, Chan and McAleer (2008). In most cases, time-varying volatility and volatility spillovers across countries or markets have been found empirically.

This paper examines the returns and volatility characteristics, asymmetric effects of positive and negative shocks, and volatility spillovers across bond markets in South-East Asia, namely Indonesia, Philippines, Singapore and Thailand, by using various univariate and multivariate models.

The remainder of the paper is as follows. Model specifications are given in Section 5.2, data are discussed in Section 5.3, empirical results are analysed in Section 5.4, and some concluding remarks are presented in Section 5.5.

## 5.2 Model Specifications

A wide range of conditional volatility models have been used to estimate and forecast volatility and volatility spillovers with symmetric and asymmetric effects in financial markets. Univariate and multivariate conditional volatility models, namely GARCH, GJR, EGARCH, CCC, DCC, VARMA-GARCH and VARMA-AGARCH, are used in this paper to capture the volatility in bond markets in South-East Asian countries.

### 5.2.1 GARCH

Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model that volatility is affected symmetrically by positive and negative shocks of equal magnitude from previous periods. Bollerslev (1986) generalized ARCH(r) to the GARCH(r,s) model, as follows:

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \qquad (5.1)$$

where $\omega > 0$, $\alpha_i \geq 0$ for i = 1,…,r, and $\beta_j \geq 0$ for j = 1,…,s, are sufficient to ensure that the conditional variance, $h_t > 0$. The $\alpha_i$ represent the ARCH effects and $\beta_j$ represent the GARCH effects.

GARCH(r,s) shows that the volatility is not only effected by shocks but also by its own past. The model also assumes positive shocks ($\varepsilon_t > 0$) and negative shocks ($\varepsilon_t < 0$) of equal magnitude have the same impact on the conditional variance.

### 5.2.2 GJR

In order to accommodate differential impacts on the conditional variance of positive and negative shocks of equal magnitude, Glosten et al. (1993) proposed the following specification for $h_t$:

$$h_t = \omega + \sum_{i=1}^{r} \left( \alpha_i + \gamma_i I(\varepsilon_{t-i}) \right) \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \qquad (5.2)$$

where $I(\varepsilon_{t-i})$ is an indicator function that takes the value 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. The impact of positive shocks and negative shocks on conditional variance allows for an asymmetric impact. The expected value of $\gamma_i$ is positive, such that negative shocks have a higher impact on volatility than do positive shocks of equal magnitude. It is not possible for leverage to be present in the GJR model, whereby negative shocks increase volatility and positive shocks of equal magnitude decrease volatility.

If r = s = 1, $\omega > 0, \alpha_1 \geq 0, \alpha_1 + \gamma_1 \geq 0$ and $\beta_1 \geq 0$ are sufficient conditions to ensure that the conditional variance $h_t > 0$. The short run persistence of positive (negative) shocks is given by $\alpha_1$ $(\alpha_1 + \gamma_1)$. When the conditional shocks, $\eta_t$, follow a symmetric distribution, the short run persistence is $\alpha_1 + \gamma_1 / 2$, and the contribution of shocks to long run persistence is $\alpha_1 + \gamma_1 / 2 + \beta_1$.

### 5.2.3 EGARCH

Nelson (1991) proposed the Exponential GARCH (EGARCH) model, which incorporates asymmetries between positive and negative shocks on conditional volatility. The EGARCH model is given by:

$$\log h_t = \omega + \sum_{i=1}^{r} \alpha_i |\eta_{t-i}| + \sum_{i=1}^{r} \gamma_i \eta_{t-i} + \sum_{j=1}^{s} \beta_j \log h_{t-j} \qquad (5.3)$$

In equation (5.3), $|\eta_{t-i}|$ and $\eta_{t-i}$ capture the size and sign effects, respectively, of the standardized shocks. If $\gamma_i$ is less than zero, positive shocks will have a smaller effect on volatility than will negative shocks of equal magnitude. Moreover, (5.3) can allow for asymmetric and leverage effects. As EGARCH uses the logarithm of conditional volatility, there are no restrictions on the parameters in (5.3). As the standardized shocks are assumed to have finite moments, the moment conditions of (5.3) are entirely straightforward.

Lee and Hansen (1994) derived the log-moment condition for GARCH(1,1) as

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \qquad (5.4)$$

This is important in deriving the statistical properties of the QMLE. McAleer et al. (2007) established the log-moment condition for GJR(1,1) as

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \qquad (5.5)$$

The respective log-moment conditions can be satisfied even when $\alpha_1 + \beta_1 < 1$ (that is, in the absence of second moments of the unconditional shocks of the GARCH(1,1) model), and when $\alpha_1 + \gamma/2 + \beta_1 < 1$ (that is, in the absence of second moments of the unconditional shocks of the GJR(1,1) model).

### 5.2.4 VARMA-GARCH

The VARMA-GARCH model of Ling and McAleer (2003) assumes symmetry in the effects of positive and negative shocks of equal magnitude on conditional volatility. Let the vector of returns on *m* ($\geq 2$) financial assets be given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{5.6}$$

$$\varepsilon_t = D_t \eta_t \tag{5.7}$$

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{5.8}$$

where $H_t = (h_{1t},...,h_{mt})'$, $\omega = (\omega_1,...,\omega_m)'$, $D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)'$, $A_k$ and $B_l$ are $m \times m$ matrices with typical elements $\alpha_{ij}$ and $\beta_{ij}$, respectively, for *i,j* = 1,…,*m*, $\mathrm{I}(\eta_t) = \mathrm{diag}(\mathrm{I}(\eta_{it}))$ is an $m \times m$ matrix, and $F_t$ is the past information available to time *t*. Spillover effects are given in the conditional volatility for each asset in the portfolio, specifically where $A_k$ and $B_l$ are not diagonal matrices. For the VARMA-GARCH model, the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$.

### 5.2.5 VARMA-AGARCH

An extension of the VARMA-GARCH model is the VARMA-AGARCH model of McAleer et al. (2009), which assumes asymmetric impacts of positive and negative shocks of equal magnitude, and is given by

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (5.9)$$

where $C_k$ are $m \times m$ matrices for $k = 1,\ldots,r$ and $I_t = \text{diag}(I_{1t},\ldots,I_{mt})$, so that

$$I = \begin{cases} 0, \varepsilon_{k,t} > 0 \\ 1, \varepsilon_{k,t} \le 0. \end{cases}$$

From equation (5.9), if $m = 1$, the model reduces to the asymmetric univariate GARCH, or GJR. If $C_k = 0$ for all $k$, the model reduces to VARMA-GARCH.

### 5.2.6 CCC

If the model given by equation (5.9) is restricted so that $C_k = 0$ for all $k$, with $A_k$ and $B_l$ being diagonal matrices for all $k$, $l$, then VARMA-AGARCH reduces to

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_i h_{i,t-l} \qquad (5.10)$$

which is the constant conditional correlation (CCC) model of Bollerslev (1990), for which the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$. As given in equation (5.10), the CCC model does not have volatility spillover effects across different financial assets, and does not allow conditional correlation coefficients of the returns to vary over time.

### 5.2.7 DCC

Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model, which allows for two-stage estimation of the conditional covariance matrix. In the first stage, univariate volatility models are estimated to obtain the conditional volatility, $h_t$, of each asset. At the second stage, asset returns are transformed by the estimated standard deviations from the first stage, and are then used to estimate the parameters of DCC. The DCC model can be written as:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, \dots, T, \tag{5.11}$$

$$Q_t = D_t \Gamma_t D_t, \tag{5.12}$$

where $D_t = diag(h_{1t}^{1/2}, \dots, h_{mt}^{1/2})$ is a diagonal matrix of conditional variances, with $m$ asset returns, and $F_t$ is the information set available at time $t$. The conditional variance is assumed to follow a univariate GARCH model, as follows:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \tag{5.13}$$

when the univariate volatility models have been estimated, the standardized residuals, $\eta_{it} = y_{it} / \sqrt{h_{it}}$, are used to estimate the dynamic conditional correlations, as follows:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta'_{t-1} + \phi_2 Q_{t-1} \tag{5.14}$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\}, \tag{5.15}$$

where S is the unconditional correlation matrix of the returns shocks, and equation (5.15) is used to standardize the matrix estimated in (5.14) to satisfy the definition of a correlation matrix. For details regarding the regularity conditions and statistical properties of DCC and the more general GARCC model, see McAleer et al. (2008).

## 5.3 Data

The data used to estimate the univariate and multivariate GARCH models are the daily returns of bond indexes of four countries in South-East Asia, namely Indonesia, Philippines, Singapore, and Thailand. The sample ranges from 1 April 2004 to 13 March 2009, with 1,262 observations. All the data are obtained from DataStream and the Thai Bond Market Association. The bond returns and their variable names are summarized in Table 5.1.

The returns of market *i* at time *t* are calculated as follows:

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \tag{5.16}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of market *i* for days *t* and *t-1*, respectively. Each bond price index is denominated in the local currency. The plots of the daily returns for all series are shown in Figure 5.3, which shows that all returns have a constant mean but time-varying variances.

Stationary of the data are tested by using the Augmented Dickey-Fuller (ADF) test, which is given as follows:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (5.17)$$

The null hypothesis is $\theta = 0$ which, if rejected, means that the series $y_t$ is stationary. The estimated values of $\theta$ and the t-statistics of all the returns are significantly less than zero at the 1% level, as given in Table 5.2, which shows that all series are stationary.

## 5.4 Empirical Results

Three univariate models, namely GARCH(1,1), GJR(1,1), and EGARCH(1,1), are estimated to determine the conditional mean equations and conditional variance equations, with three types of conditional mean equations. The results are given in Tables 5.3-5.5. From Table 5.3, the coefficients in the conditional variance equations are all significant in both the short and long run. The asymmetric effects of positive and negative shocks on conditional volatility in GJR are significant only for Indonesia, while the rest are insignificant. For the EGARCH model, Indonesia and Philippines show asymmetric effects and leverage, $\gamma < 0$ and $\gamma < \alpha < -\gamma$, whereby negative shocks increase volatility and positive shocks decrease volatility, except for ARMA(1,1)-EGARCH(1,1), which has no leverage. Therefore, asymmetric models of univariate volatility are preferred to GARCH for Indonesia and Philippines. Moreover, many empirical evidences suggest that the changes in volatility are correlated with the variation in the term structure of interest.

For multivariate volatility, the results for CCC in Table 5.6 show that the estimated constant conditional correlations are significant, except between Singapore and Thailand, where it is insignificant. The correlations for South-East Asian countries lie between -0.12 and 0.46. Moreover, the correlations between the Thai bond market and other markets are negative, which means portfolios constructed by including Thai bonds can diversify portfolio risk efficiently.

The VARMA-GARCH and VARMA-AGARCH models are used to determine the linkages and spillovers across countries because they can estimate time-varying volatility, and also test for volatility spillovers and the asymmetric effects of positive and negative shocks of equal magnitude. The results of VARMA-GARCH and VARMA-AGARCH are shown in Tables 5.7-5.8, for which the number of volatility spillovers and asymmetric effects are summarized in Table 5.9. The results show that volatility spillovers are evident in both models. Table 5.7 shows that the Singapore bond market volatility has spillovers to the other bond markets, such that the volatility of a developed country affect the volatility of developing countries. Therefore, investors and fund managers should be aware of these results if they invest in developing countries when the volatility in the developed country is rising, except for Thailand, which has a negative impact.

Speculators may operate in developing countries, particularly Indonesia and Philippines, to earn capital gains from volatile markets. Furthermore, volatility in Thailand is affected by volatility in Indonesia. In Table 5.8, the asymmetric effects in the multivariate volatility model lead to the same results as in the univariate volatility model, EGARCH. Thus, asymmetric effects exist in the Indonesia and Philippines bond markets, so that positive and negative shocks of equal magnitude have different impacts on conditional volatility. Therefore, we can conclude that VARMA-

AGARCH is superior to VARMA-GARCH for the Indonesia and Philippines bond markets, whereas the reverse holds for the Singapore and Thailand bond markets.

Rolling windows are used to examine time-varying conditional correlations through the VARMA-GARCH and VARMA-AGARCH models. The rolling window size is set at 1,000 for all pair of assets, and the results are shown in Figures 5.4 and 5.5, respectively. For the VARMA-GARCH model, the correlations of all pairs of assets are not constant over time, so that the assumption of constant conditional correlations may be too restrictive. However, the changes in the estimated correlations are small. The correlation between the pair, Indonesia and Philippines, is the largest (at around 0.4-0.5), while the rest are smaller than 0.15 in absolute terms. The VARMA-AGARCH model shows similar results to VARMA-GARCH in that the correlations vary over time.

The DCC estimates and t-ratios are shown in Table 5.10. The value of $\hat{\phi}_2$ is significantly different from zero and not approach to 1, which means that the conditional correlations are time varying, so that constant condition correlations do not hold. However, the parameter $\hat{\phi}_1$ is only marginally significant. Moreover, the value of parameter $\hat{\phi}_1$ and $\hat{\phi}_2$ are approach to zero and one, respectively. Therefore, the conditional correlations are very tiny change over time, which means that consideration in time-varying conditional correlation is not necessary in practice.



## 5.5 Concluding Remarks

The paper estimated conditional volatility, covariances and correlations in bond markets in South-East Asian countries, namely Indonesia, Philippines, Singapore and Thailand, using univariate and multivariate volatility models. The univariate volatility models suggested that negative shocks in Indonesia and Philippines made bond markets more volatile than did positive shocks of similar magnitude, or if asymmetric effects existed.

For multivariate volatility, the CCC model provided constant conditional correlations, except for an insignificant correlation between Singapore and Thailand. The correlations between Thailand and the other countries were negative, which meant that investors could diversify the risk of their portfolio efficiently by investing in Thai bonds. The VARMA-GARCH and VARMA-AGARCH models showed that volatility spillovers were evident in both models. The volatility spillover effects from the Singapore market to the other markets were statistically significant, so that the volatility of a developed country will affect the volatilities of developing countries. This means that investors and fund managers should be wary if they invest in developing countries when the volatility in the developed country is changing, while speculators may engage in developing countries, such as Indonesia and Philippines, to earn capital gains from the volatile markets.

Asymmetric effects are significant in the Indonesia and Philippines bond markets, so that positive and negative shocks of equal magnitude do not have the same impacts on conditional volatility. Thus, VARMA-AGARCH is superior to VARMA-GARCH for the Indonesia and Philippines bond markets. However, the rolling windows suggest that the assumption of constant conditional correlations is too restrictive in practice as the evidence from the DCC model shows that statistically significant time-varying conditional correlations are present.

Table 5.1 Summary of Variable Names

| **Variables** | **Index Names** |
|---|---|
| indob | CGBI ESBI Indonesia Bond Index |
| philb | CGBI ESBI Philippines Bond Index |
| singb | JPM GBI Singapore Bond Index |
| thaib | Thai Government Bond Index |

Table 5.2  ADF Test of Unit Roots in Returns

| Returns | Coefficient | t-statistic |
|---|---|---|
| indob | -0.9461 | -33.6104 |
| philb | -0.8963 | -31.9584 |
| singb | -0.9127 | -32.3937 |
| thaib | -0.6093 | -23.4788 |

Table 5.3 Univariate GARCH(1,1)

| | Mean equation | | | Conditional variance equation | | | AIC | SC |
|---|---|---|---|---|---|---|---|---|
| | C | AR(1) | MA(1) | ω | α | β | | |
| indob | **0.0005** | | | **5.16E-07** | **0.1439** | **0.8667** | -8.0161 | -7.9998 |
| | **5.8216** | | | **6.4458** | **3.0814** | **37.3688** | | |
| | **0.0004** | **0.1764** | | **4.84E-07** | **0.1354** | **0.8772** | -8.0325 | -8.0121 |
| | **4.7782** | **3.4705** | | **7.019** | **3.1205** | **39.7361** | | |
| | **0.0004** | -0.2257 | **0.4062** | **4.86E-07** | **0.1308** | **0.8704** | -8.0324 | -8.0080 |
| | **5.0098** | -1.2093 | **2.4356** | **5.1216** | **3.1899** | **39.6790** | | |
| philb | **0.0006** | | | 1.55E-07 | **0.0657** | **0.9337** | -8.2027 | -8.1863 |
| | **6.0527** | | | 0.9735 | **2.7148** | **51.1790** | | |
| | **0.0006** | **0.0863** | | 1.55E-07 | **0.0656** | **0.9336** | -8.2073 | -8.1869 |
| | **5.6272** | **2.6505** | | 1.2579 | **2.6652** | **52.1571** | | |
| | **0.0006** | 0.4663 | -0.3746 | 0.52E-07 | **0.0652** | **0.9341** | -8.2081 | -8.1836 |
| | **5.3106** | 1.6498 | -1.2778 | 0.8678 | **2.6559** | **52.0800** | | |
| singb | -0.0002 | | | **7.44E-07** | **0.0729** | **0.9148** | -7.1672 | -7.1509 |
| | -1.7291 | | | **2.6405** | **4.2579** | **50.7758** | | |
| | -0.0002 | 0.0208 | | **7.15E-07** | **0.0718** | **0.9163** | -7.1653 | -7.1449 |
| | -1.6877 | 0.7053 | | **2.6587** | **4.2539** | **53.2086** | | |
| | -0.0002 | 0.4201 | -0.3925 | **7.19E-07** | **0.0720** | **0.9161** | -7.1642 | -7.1397 |
| | -1.6354 | 0.6667 | -0.6136 | **2.8513** | **4.2428** | **54.3361** | | |
| thaib | **0.0002** | | | **2.33E-07** | **0.3908** | **0.6549** | -9.6384 | -9.6220 |
| | **5.7671** | | | **2.4409** | **4.7366** | **17.5952** | | |
| | **0.0002** | **0.4509** | | 1.01E-07 | **0.2066** | **0.7969** | -9.8015 | -9.7811 |
| | **3.3058** | **12.4297** | | 1.0420 | **5.0458** | **23.3535** | | |
| | **0.0002** | **0.4405** | 0.0130 | 1.01E-07 | **0.2067** | **0.7968** | -9.7999 | -9.7754 |
| | **3.3344** | **5.7340** | 0.1613 | 1.3862 | **5.0925** | **27.1606** | | |

Note: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge robust t-ratios.

(2) Entries in bold are significant at the 95% level.

Table 5.4 Univariate GJR(1,1)

| | Mean equation | | | Conditional variance equation | | | | AIC | SC |
|---|---|---|---|---|---|---|---|---|---|
| | C | AR(1) | MA(1) | ω | α | γ | β | | |
| indob | **0.0003** | | | **4.37E-07** | 0.0277 | **0.1658** | **0.8882** | -8.0693 | -8.0489 |
| | **3.7777** | | | **3.4477** | 1.0057 | **2.1177** | **38.24** | | |
| | **0.0002** | **0.1789** | | **4.19E-07** | 0.0224 | **0.1713** | **0.8911** | -8.0876 | -8.0631 |
| | **2.3929** | **3.3590** | | **7.2959** | 0.8751 | **2.2889** | **48.1731** | | |
| | 0.0002 | **0.5823** | **-0.4310** | **4.25E-07** | 0.0200 | **0.1786** | **0.8907** | -8.0879 | -8.0593 |
| | 1.7220 | **4.4827** | **-3.1207** | **4.7258** | 0.7183 | **2.1921** | **45.0876** | | |
| philb | **0.0004** | | | 2.04E-07 | 0.0145 | 0.0778 | **0.9390** | -8.2335 | -8.2131 |
| | **4.4734** | | | 1.88736 | 0.6908 | 1.7425 | **51.2571** | | |
| | **0.0004** | 0.0648 | | 2.02E-07 | 0.0169 | 0.0767 | **0.9378** | -8.2358 | -8.2113 |
| | **4.4955** | 1.8188 | | 1.1698 | 0.7101 | 1.5856 | **41.9317** | | |
| | **0.0004** | 0.5262 | -0.4531 | 1.97E-07 | 0.0167 | 0.0774 | **0.9383** | -8.2369 | -8.2084 |
| | **3.8935** | 1.7942 | -1.4928 | 1.0522 | 0.6705 | 1.4833 | **42.5874** | | |
| singb | -0.0002 | | | **8.90E-07** | **0.0865** | -0.0393 | **0.9157** | -7.1685 | -7.1481 |
| | -1.2822 | | | **2.9609** | **3.8041** | -1.5373 | **51.8116** | | |
| | -0.0002 | 0.0190 | | **8.63E-07** | **0.0856** | -0.0380 | **0.9166** | -7.1664 | -7.1419 |
| | -1.2460 | 0.6465 | | **2.8186** | **3.7749** | -1.5062 | **51.3207** | | |
| | -0.0002 | 0.4784 | -0.4544 | **8.65E-07** | **0.0860** | -0.0385 | **0.9165** | -7.1652 | -7.1366 |
| | -1.2091 | 0.8664 | -0.8106 | **3.0624** | **3.7122** | -1.5054 | **50.3725** | | |
| thaib | **0.0002** | | | **2.33E-07** | **0.3954** | -0.0072 | **0.6546** | -9.6368 | -9.6164 |
| | **5.7394** | | | **3.6122** | **4.9482** | -0.0723 | **16.9922** | | |
| | **0.0002** | **0.4509** | | 1.01E-07 | **.02071** | -0.0011 | **0.7971** | -9.7999 | -9.7754 |
| | **3.2437** | **12.3193** | | 1.3977 | **3.4456** | -0.0137 | **27.1457** | | |
| | **0.0002** | **0.4406** | 0.0129 | 1.01E-07 | **0.2070** | -0.0008 | **0.7969** | -9.7983 | -9.7698 |
| | **3.2614** | **5.7280** | 0.1602 | 1.3719 | **3.5162** | -0.0100 | **26.5800** | | |

Note: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge robust t-ratios.

(2) Entries in bold are significant at the 95% level.

Table 5.5 Univariate EGARCH(1,1)

| | Mean equation | | | Conditional variance equation | | | | AIC | SC |
|---|---|---|---|---|---|---|---|---|---|
| | C | AR(1) | MA(1) | ω | α | γ | β | | |
| indob | **0.0007** | | | -0.1072 | 0.0726 | **-0.1188** | **0.9953** | -8.0865 | -8.0061 |
| | **5.0362** | | | -1.6333 | 1.7261 | **-4.0525** | **267.9606** | | |
| | **0.0005** | **0.2029** | | -0.0771 | 0.0372 | **-0.1246** | **0.9956** | -8.0557 | -8.0312 |
| | **3.3679** | **3.0696** | | -1.9216 | 1.3156 | **-3.4613** | **363.1264** | | |
| | **0.0005** | **1.0138** | **-0.9973** | **-0.2343** | **0.2122** | -0.0546 | **0.9897** | -8.0159 | -7.9873 |
| | **6.7259** | **168.7703** | **-1109.24** | **-2.4637** | **4.3400** | -1.2510 | **131.7278** | | |
| philb | **0.0003** | | | **-0.1042** | 0.0233 | **-0.0949** | **0.9918** | -8.2399 | -8.2195 |
| | **3.6664** | | | **-3.2770** | 1.4073 | **-4.7759** | **347.2820** | | |
| | **0.0002** | **0.0596** | | **-0.1508** | 0.0409 | **-0.1086** | **0.9882** | -8.2331 | -8.2086 |
| | **2.3726** | **1.4813** | | **-2.9756** | 1.6226 | **-4.3448** | **231.8719** | | |
| | **0.0005** | **0.9884** | **-0.9974** | **-18075** | **0.2158** | **-0.1794** | **0.8475** | -8.1572 | -8.1286 |
| | **9.4750** | **101.7960** | **-551.0198** | **-2.0862** | **2.3740** | **-2.9739** | **11.3435** | | |
| singb | -0.0001 | | | **-0.2443** | **0.1464** | 0.0341 | **0.9868** | -7.1606 | -7.1402 |
| | -1.0390 | | | **-3.8380** | **4.8901** | 1.8130 | **180.1993** | | |
| | -0.0001 | 0.0137 | | **-0.2401** | **0.1452** | 0.0336 | **0.9871** | -7.1584 | -7.1339 |
| | -1.0277 | 0.4651 | | **-3.8017** | **4.8132** | 1.7630 | **182.2945** | | |
| | -0.0001 | **0.8738** | **-0.8667** | **-0.2474** | **0.1477** | 0.0352 | **0.9866** | -7.1577 | -7.1291 |
| | -1.0633 | **2.8742** | **-2.7851** | **-3.8800** | **4.9471** | 1.8038 | **179.4170** | | |
| thaib | **0.0002** | | | **-1.0707** | **0.4860** | 0.0035 | **0.9409** | -9.6474 | -6.6270 |
| | **6.7923** | | | **-5.2962** | **7.2456** | 0.0908 | **66.1295** | | |
| | **0.0002** | **0.4327** | | **-0.7770** | **0.3650** | -0.0002 | **0.9590** | -9.8116 | -9.7871 |
| | **3.5762** | **12.0128** | | **-4.9232** | **6.7812** | -0.0055 | **88.3754** | | |
| | **0.0002** | **0.4309** | 0.0023 | **-0.7756** | **0.3646** | -0.0003 | **0.9590** | -9.8100 | -9.7814 |
| | **3.5675** | **5.5293** | 0.0277 | **-4.9044** | **6.7886** | -0.0082 | **88.1437** | | |

Note: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge robust t-ratios.

(2) Entries in bold are significant at the 5% level.

Table 5.6  Constant Conditional Correlations between Returns

| Returns | indob | philb | singb |
|---|---|---|---|
| philb | **0.4576** | | |
| | **19.8532** | | |
| singb | **0.0655** | **0.0812** | |
| | **3.2632** | **4.2918** | |
| thaib | **-0.1209** | **-0.1163** | 0.0229 |
| | **-6.3326** | **-5.2512** | 0.8932 |

Notes: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge (1992) robust t-ratios.

(2) Entries in bold are significant at the 5% level.

Table 5.7  Estimates for VARMA-GARCH(1,1)

| Returns | $\omega$ | $\alpha_{indob}$ | $\alpha_{philb}$ | $\alpha_{singb}$ | $\alpha_{thaib}$ | $\beta_{indob}$ | $\beta_{philb}$ | $\beta_{singb}$ | $\beta_{thaib}$ |
|---|---|---|---|---|---|---|---|---|---|
| indob | **-1.09E-06** | **0.0930** | 0.0033 | 0.0178 | **-0.0191** | **0.8177** | 0.0109 | **0.0368** | **0.0893** |
| | **-77.3670** | **2.9968** | 0.2154 | 1.3993 | **-2.2659** | **23.3354** | 0.5557 | **3.2169** | **2.4105** |
| philb | -2.76E-07 | -0.0027 | **0.1068** | -0.0085 | 0.1109 | 0.0126 | **0.8382** | **0.0254** | -0.0203 |
| | -1.7273 | -0.2488 | **2.9085** | -1.7308 | 1.1459 | 0.6597 | **17.4841** | **2.7924** | -0.2370 |
| singb | 3.10E-07 | -0.0089 | -0.0082 | **0.0692** | -0.0516 | 0.0025 | 0.0123 | **0.9201** | **0.1229** |
| | 0.9154 | -1.1992 | -0.6840 | **3.8622** | -1.1937 | 0.3638 | 0.7472 | **44.7504** | **2.0903** |
| thaib | **2.29E-07** | -7.34E-05 | 0.0027 | 0.0006 | **0.2522** | **0.0011** | -0.0017 | **-0.0025** | **0.7333** |
| | **7.2968** | -0.8892 | 0.9217 | 0.9172 | **5.1276** | **2.8459** | -1.0311 | **-4.1930** | **20.9733** |

Note:  (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge robust t-ratios.

(2) Entries in bold are significant at the 95% level.

Table 5.8 Estimates for VARMA-AGARCH(1,1)

| Returns | $\omega$ | $\alpha_{indob}$ | $\alpha_{philb}$ | $\alpha_{singb}$ | $\alpha_{thaib}$ | $\gamma$ | $\beta_{indob}$ | $\beta_{philb}$ | $\beta_{singb}$ | $\beta_{thaib}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| indob | **-1.06E-06** | 0.0377 | -0.0074 | **0.0259** | -0.0132 | **0.1116** | **0.8158** | 0.0181 | **0.0322** | 0.0569 |
| | **-82.4782** | 1.3276 | -0.9594 | **2.3140** | -1.6161 | **2.0029** | **26.5608** | 1.1106 | **3.4256** | 1.9554 |
| philb | **-4.12E-07** | -0.0033 | 0.0163 | **-0.0109** | 0.0914 | **0.1889** | 0.0024 | **0.8483** | **0.0351** | -0.0195 |
| | **-5.2189** | -0.4527 | 0.5309 | **-3.4487** | 1.2811 | **2.8935** | 0.3047 | **25.0780** | **5.6777** | -0.3453 |
| singb | 4.72E-07 | -0.0082 | -0.0112 | **0.0836** | -0.0573 | -0.0366 | 0.0021 | 0.0193 | **0.9180** | **0.1178** |
| | 1.3760 | -1.1625 | -0.9566 | **3.6573** | -1.3119 | -1.4581 | 0.3193 | 1.1441 | **44.7494** | **1.9679** |
| thaib | **2.62E-07** | -8.14E-05 | 0.0026 | 0.0008 | **0.2638** | 0.0319 | **0.0012** | -0.0018 | **-0.0028** | **0.7053** |
| | **8.7534** | -0.9018 | 0.8583 | 1.1482 | **3.5412** | 0.2977 | **2.9725** | -0.9960 | **-4.5885** | **19.6180** |

Note: (1) The two entries for each parameter are their respective estimate and Bollerslev and Woodridge robust t-ratios.

(2) Entries in bold are significant at the 95% level.

Table 5.9 Summary of Volatility Spillovers and Asymmetric Effects

| Returns | Number of volatility spillovers | | Asymmetric effects |
|---|---|---|---|
| | VARMA-GARCH | VARMA-AGARCH | |
| indob | 2 | 1 | Yes |
| philb | 1 | 1 | Yes |
| singb | 1 | 1 | No |
| thaib | 2 | 2 | No |

Table 5.10  DCC Estimates

| Parameter | Estimate |
|---|---|
| $\hat{\phi}_1$ | 0.0199 |
| | 1.6901 |
| $\hat{\phi}_2$ | 0.6085 |
| | 2.3211 |

Note: The two entries for each parameter are their respective estimate and Bollerslev and Woodridge (1992) robust t-ratios.

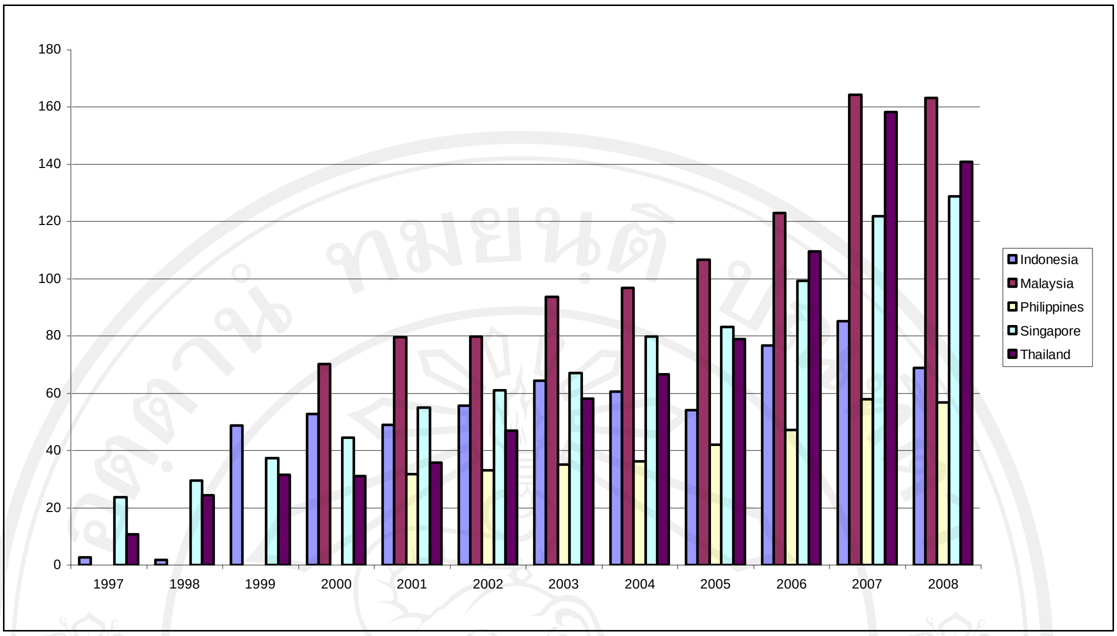


Figure 5.1 Market Size of Bond Markets (USD Billions)

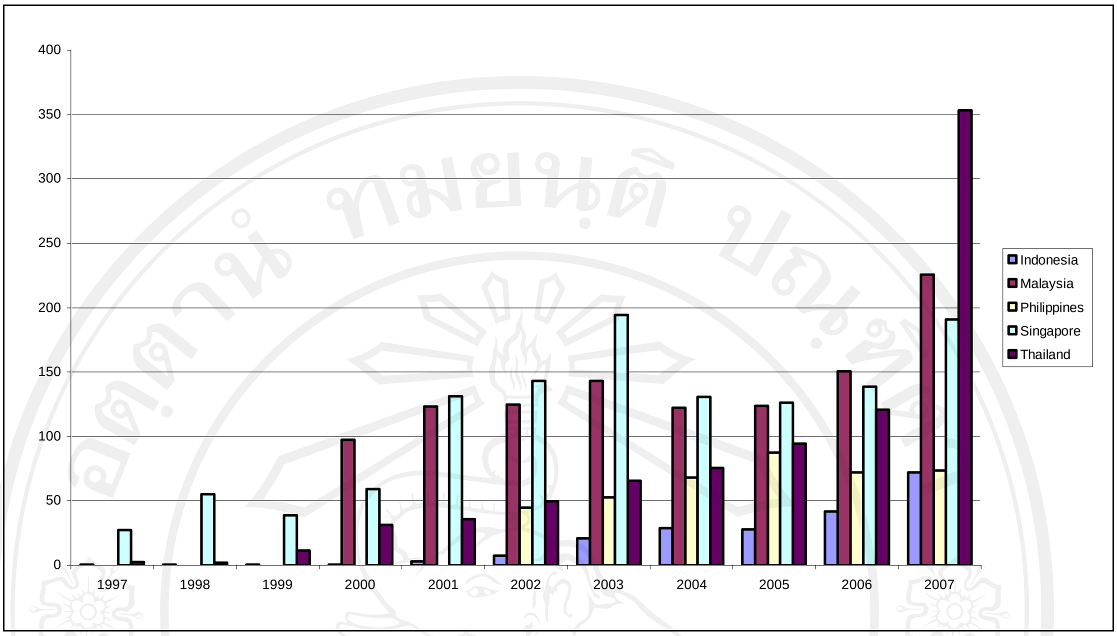


Figure 5.2 Trade Volume of Bond Markets (USD Billions)

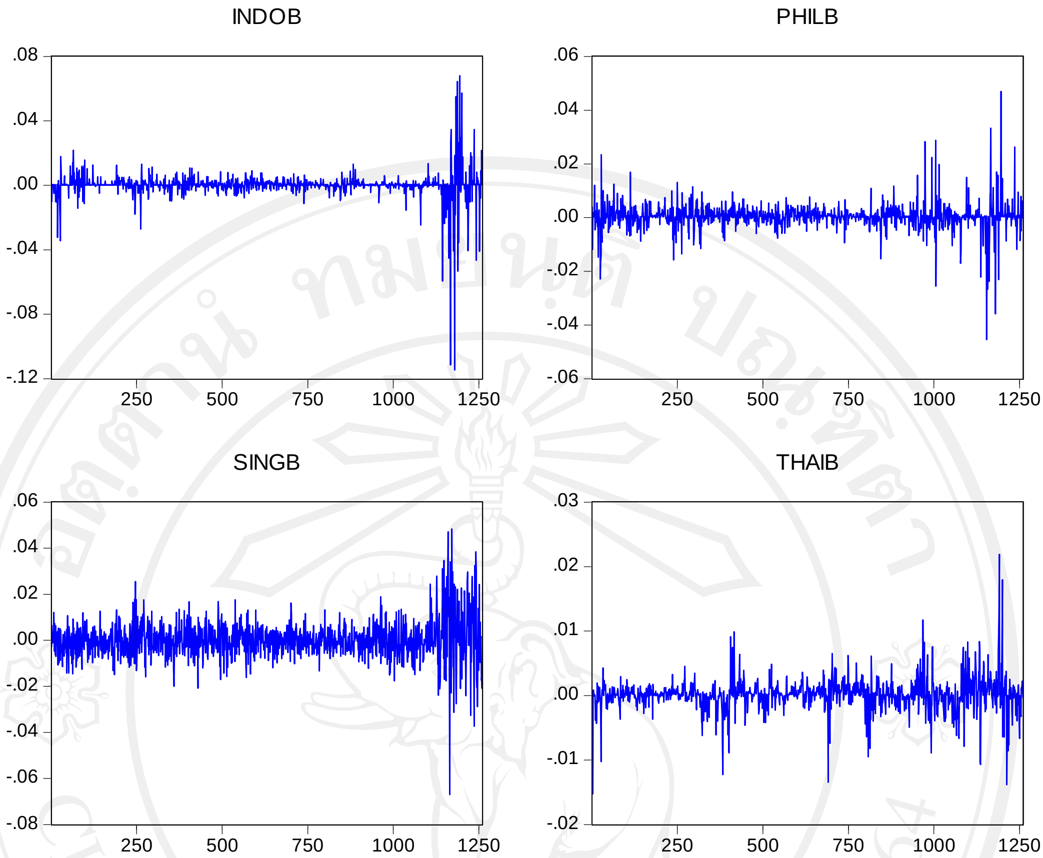


Figure 5.3 Daily Returns for All Series

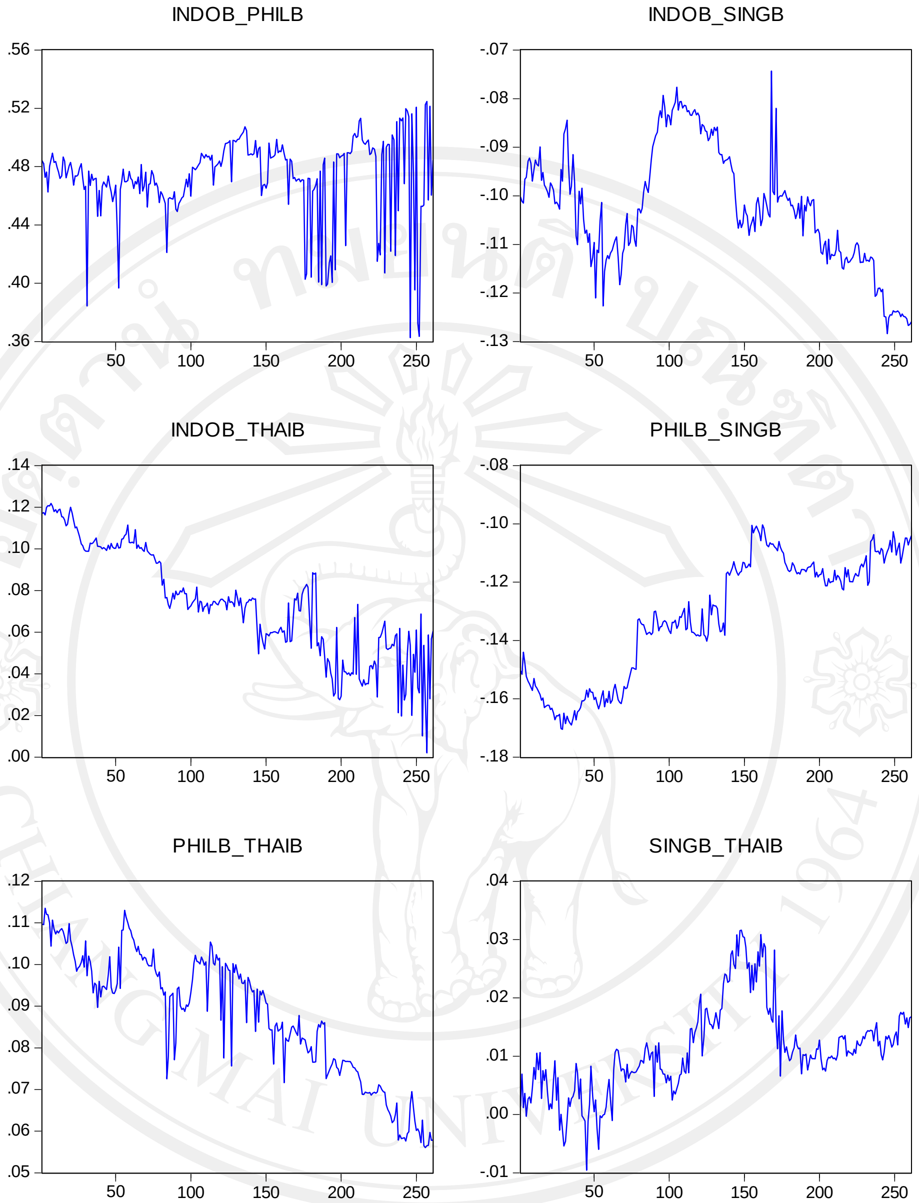


Figure 5.4 Dynamic Paths of Conditional Correlations of Pairs of Assets for VARMA-GARCH

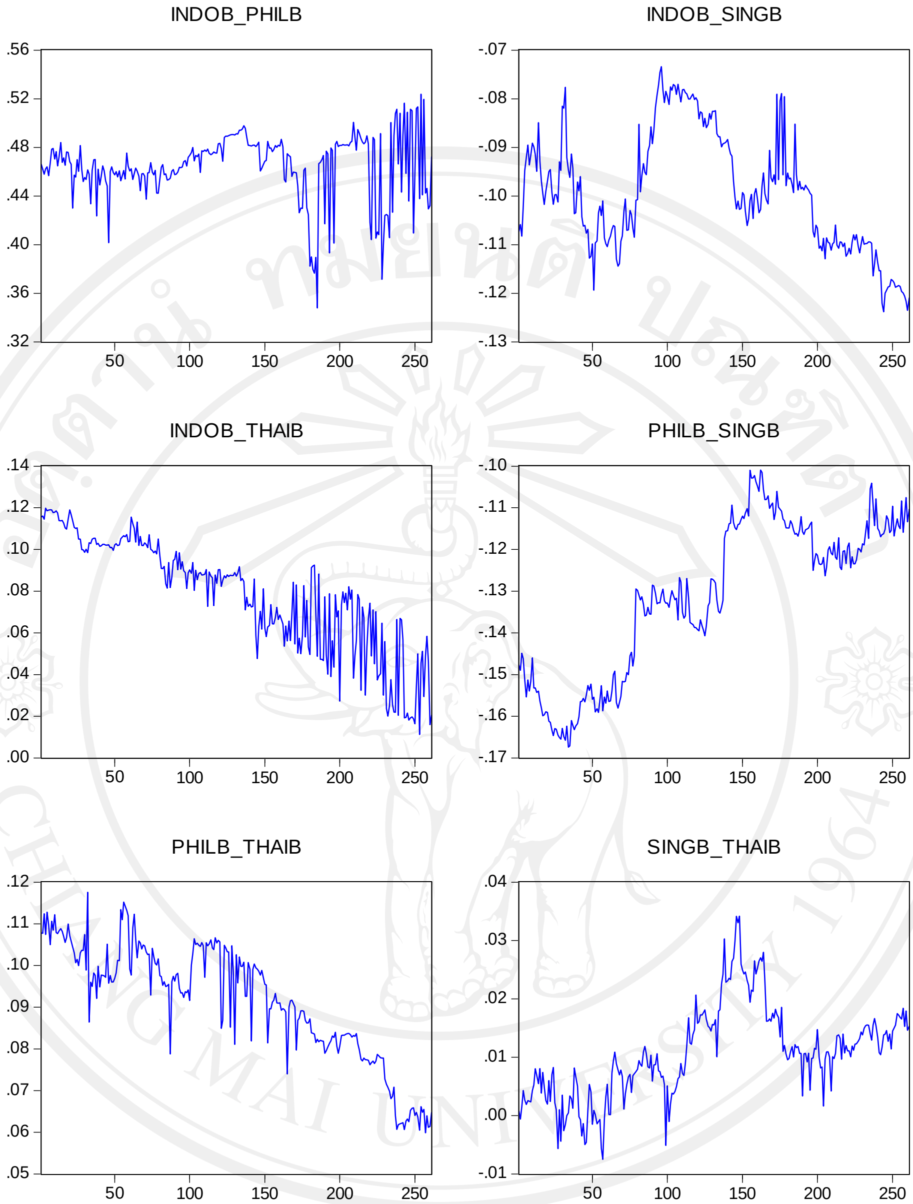


Figure 5.5 Dynamic Paths of Conditional Correlations of Pairs of Assets for VARMA-AGARCH