Chapter 3

Modelling the Stock and Bond Returns and Volatility in South-East Asia

The risk plays an important role in portfolio and risk management, especially with modern financial theory. Therefore, volatility has become a necessary tool for financial institutions, government agencies, and investors to use while making decisions for investments. Moreover, volatility information is also used to determine the overall risk of a portfolio, to identify hedging strategies that make the portfolio neutral with respect to market moves, and also used in derivatives trading and valuation. Investors tend to move their funds from the markets that have high volatility to the markets that have low volatility to reduce or diversify their portfolio risk, while speculators do the opposite. Therefore, this chapter investigates the volatility linkages or volatility spillovers between the markets and across the countries because they are important for a variety of investment and risk management decisions.

This chapter is a revised version from the original paper presented at the Second Conference of The Thailand Econometric Society, Chiang Mai, Thailand in Appendix A.

Abstract

International investment is important for risk diversification and portfolio management, especially in stock and bond markets. The paper investigates the relationship of volatility across stock and bond markets in South-East Asia because there are emerging markets in which investments are made. However, stock and bond markets exist not only in emerging markets, but also in developed markets. Therefore, an examination of the volatility spillovers in this region, namely Indonesia, Philippines, Thailand, and Singapore, is important. The data from 1 April 2004 to 5 November 2008 is used to model the volatility. Univariate volatility, namely GARCH, GJR, and EGARCH, and multivariate volatility, namely CCC, VARMA-GARCH, VARMA-AGARCH and DCC are employed. The paper found that volatility and asymmetric effects coefficients in variance equations are all significant only in the long run, but some in the short run in univariate volatility models and GJR and EGRACH are not superior to GARCH. For multivariate volatility, CCC shows the constant conditional correlation in all series except Thai bond market and other countries stock market whereas DCC shows the statistically significant time-varying conditional correlations. The evidence of volatility spillovers and asymmetric effects from VARMA-GARCH and VARMA-AGARCH models found that there are volatility spillovers and asymmetric effects across South-East Asia financial markets around 40% and 60% of pair of assets, respectively. The result also suggests that modeling The Philippines financial markets by using VARMA-GARCH is better than VARMA-AGARCH.

3.1 Introduction

In portfolio management, the returns and risk are used as a tool in investment strategies not only in stock markets, but also in bond markets. Many financial institutions, government agencies, or investors are investing in the financial market. They are not investing only in their own country, but also in other countries because they may wish to decrease their portfolio volatility or diversify their portfolio risk. However, investment across the markets and countries can increase or decrease portfolio volatility depending on correlation or covariance, which is a key point in portfolio and risk management.

The efficient portfolio relies on the correlation or covariance of a pair of assets that may change over time. Therefore, much research in economics and finance is trying to model the variance, covariance, and correlation of assets to construct an efficient portfolio and adjust it over time if correlations change.

Many models have been developed to assess the characteristic of volatility. Engle (1982) introduced the Autoregressive Conditional Heterscedasticity (ARCH) to model the character of volatility. In 1986, Bollerslev generalized ARCH to the Generalized Autoregressive Conditional Heterscedasticity (GARCH). However, both of them assume that positive and negative shocks have the same impact on the conditional variance. To accommodate differential impact on the conditional variance between positive and negative shocks, Glosten et al. (1993) proposed the GJR model. The EGARCH model, invented by Nelson (1991), separates the size and the sign effects to capture asymmetric effect.

Multivariate volatility models are common in modelling the volatility. The CCC model of Bollerslev (1990) assumes the conditional correlation coefficients of the returns are time invariant and restricted for volatility spillovers between different returns. Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model to allow correlation varying over time, but still not allow volatility spillovers. The VARMA-GARCH model of Ling and McAleer (2003) and the VARMA-AGARCH model of McAleer et al. (2009) are extended to capture the volatility spillovers, but constant conditional correlation is maintained.

Many papers have investigated volatility, especially volatility spillovers and correlations across countries or markets, such as Fleming, Kirby, and Ostdiek (1998), Izquierdo and Lafuente (2004), Gannon (2005), Steeley (2006), and da Veiga, Chan, and McAleer (2008). In most cases, the authors of these papers found volatility spillover across countries or markets.

This paper aims to investigate the volatility linkages and spillovers across intra- and international bond and stock markets. The volatility spillovers, asymmetric effects, and correlations in four countries (Indonesia, Philippines, Thailand, and Singapore) are tested by using univariate volatility and multivariate volatility.

3.2 Model Specifications

A wide range of conditional volatility models are used to estimate the volatility and volatility spillovers with symmetric and asymmetric effects in financial markets. The 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 characteristic of the volatility on financial market in South-East Asia. In 1982, Engle introduced the Autoregressive Conditional Heteroskedasticity (ARCH) that volatility is affected by positive shock and negative shock in the previous period in the same impact. After that many models are developed and extended continuously.

3.2.1 GARCH

Bollerslev (1986) generalized ARCH (r) to the GARCH (r,s), model as follows:

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \qquad (3.1)$$

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 α_i represent the ARCH effects and β_j represent the GARCH effects.

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

3.2.2 GJR

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

$$h_t = \omega + \sum_{i=1}^{r} \left(\alpha_i + \gamma_i I(\varepsilon_{t-i})\right) \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \qquad (3.2)$$

where $I(\varepsilon_{t-i})$ is an indicator function that takes value 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. The impact of positive shocks and negative shocks on conditional variance is allowing asymmetric impact. The expected value of γ_i is greater than zero that means the negative shocks give higher impact than the positive shocks, $\alpha_j + \gamma_j > \alpha_j$. However, 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 $\beta_1 \geq 0$ then it has sufficient conditions to ensure that the conditional variance $h_t > 0$. The short-run persistence of positive (negative) shocks is given by $\alpha_1 \left(\alpha_1 + \gamma_1\right)$. When the conditional shocks, η_t, follow a symmetric distribution, the expected short-run persistence is $\alpha_1 + \gamma_1 / 2$, and the contribution of shocks to expected long-run persistence is $\alpha_1 + \gamma_1 / 2 + \beta_1$.

3.2.3 EGARCH

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

$$\log h_t = \omega + \sum_{i=1}^{r} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{r} \gamma_i \eta_{t-i} + \sum_{j=1}^{s} \beta_j \log h_{t-j} \qquad (3.3)$$

In equation (3.3), $\left|\eta_{t-i}\right|$ and η_{t-i} capture the size and sign effects of the standardized shocks respectively. The expected value of γ_i is less than zero. Therefore, the positive shock provides less volatility than the negative shock. This mean (3.3) can allow asymmetric and leverage effects. As EGARCH also uses the logarithm of conditional volatility, there are no restrictions on the parameters in (3.3). As the standardized shocks have finite moments, the moment conditions of (3.3) are straightforward.

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

$$E(\log(\alpha_1\eta_t^2 + \beta_1)) < 0 \qquad (3.4)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \qquad (3.5)$$

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).

3.2.4 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 (≥ 2) financial assets be given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (3.6)$$

$$\varepsilon_t = D_t \eta_t \tag{3.7}$$

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{3.8}$$

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 α_{ij} and β_{ij}, respectively, for i,j = 1,…,m, I(η_t) = diag(I(η_{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 $E(\eta_t \eta_t') = \Gamma$.

3.2.5 VARMA-AGARCH

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

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{3.9}$$

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

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

From equation (3.9) if m = 1, the model reduces to the asymmetric univariate GARCH or GJR. If C_k = 0 for all k it reduces to VARMA-GARCH.

3.2.6 CCC

If the model given by equation (3.9) is restricted so that C_k = 0 for all k, with A_k and B_l being diagonal matrics for all k,l, then VARMA-AGARCH reduces to:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_i h_{i,t-l} \tag{3.10}$$

which is the constant conditional correlation (CCC) model of Bolerslev (1990). The CCC model also assumes that the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$. As given in equation (3.10), the CCC model does not have volatility spillover effects across different financial assets. Moreover, CCC also does not allow conditional correlation coefficients of the returns to vary over time.

3.2.7 DCC

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

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, ..., T \tag{3.11}$$

$$Q_t = D_t \Gamma_t D_t, \tag{3.12}$$

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

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \tag{3.13}$$

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:

$$Q_t = (1-\phi_1-\phi_2)S + \phi_1 \eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1} \tag{3.14}$$

$$\Gamma_t = \left\{(diag(Q_t)^{-1/2}\right\} Q_t \left\{(diag(Q_t)^{-1/2}\right\}, \tag{3.15}$$

where S is the unconditional correlation matrix of the ε and equation (3.15) is used to standardize the matrix estimated in (3.14) to satisfy the definition of a correlation matrix.

3.3 Data and Estimation

The data that is used to estimate for univariate and multivariate GARCH models is the daily returns of stock and bond indexes of four countries in Southeast Asia, namely Indonesia, Philippines, Thailand, and Singapore. The sample ranges from 1 April 2004 to 5 November 2008 with 905 observations. All data is obtained from DataStream, Reuters, and the Thai Bond Market Association. The stock and bond returns and their variable names are summarized in Table 3.1.

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

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \tag{3.16}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of market *i* at days *t* and *t-1*, respectively. Each stock and bond price index is denominated in the local currency.

Stationarity of the data will be tested by using the Augmented Dickey-Fuller (ADF) test. The test is given as follows:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{3.17}$$

The null hypothesis is $\theta = 0$, if the null hypothesis is rejected, it means that the series y_t is stationary. The estimated values of θ and t-statistic of all returns are significant less than zero at 1% level, as shown in Table 3.2. The plots of the daily returns for all series are shown in Figure 3.1. Figure 3.1 also shows that all returns have a constant mean, but a time-varying variance.

3.4 Empirical Results

The univariate GARCH(1,1), GJR(1,1), and EGARCH(1,1) are estimated to determine the coefficient of conditional mean equations and conditional variance equations, with three types of conditional mean equations. The results are given in Tables 3.3–3.5. From Tables 3.3–3.5, coefficients in variance equations are all significant in the long run, but some are also significant in the short run. The GJR and EGARCH models show that about half of them, especially in stock markets, have asymmetric effects of positive and negative shocks on conditional variance. Moreover, many empirical evidences suggest that the changes in volatility are correlated with the variation in the term structure of interest.

We can see multivariate volatility with CCC-GARCH (1,1) in Table 3.6. As shown, the estimated correlation yields the constant conditional correlation (range from -0.1775 to 0.5634), except correlation between the Thai government bond market and other countries' stock markets. Therefore, Thai government bonds should be an asset in the portfolio to reduce the portfolio risk because they have no correlation with other assets. Moreover, the correlation between the Singapore government bond market and other financial markets, except the Thai bond market, are all negative. This means that including the Singapore government bonds in a portfolio can diversify portfolio risk efficiently.

The results of VARMA-GARCH and VARMA-AGARCH for each pair of assets are estimated. We can summarize the number of volatility spillovers and number of asymmetric effects in VARMA-GARCH and VARMA-AGARCH models as shown in Table 3.7. The results show the volatility spillovers are evident in 12 of 28 and 10 of 28 cases for VARMA-GARCH and VARMA-AGARCH, respectively. Asymmetric effects are significant in 17 of 28 cases and the most insignificant coefficients (8 of 11 cases) are the pair of Philippines financial markets and the others markets. This suggests that the VARMA-GARCH model is better than the VARMA-AGARCH model in investigating the volatility of Philippines' financial markets.

Based on pairs of stock market assets, VARMA-AGARCH shows that there are no volatility spillovers between the Indonesian stock market and the others stock markets. However, two out of three pairs show asymmetric effects.

According to pairs of assets in the bond market, the results suggest that they have no volatility spillovers for the Thai bond market based on VARMA-GARCH and VARMA-AGARCH models. This means that the volatility of the Thai bond market neither affects the volatility of other bond markets, nor is affected by the volatility of other bond markets.

Table 3.7 also reports that, for VARMA-GARCH, the Thai stock market and the other bond markets have volatility spillovers to each other, whereas VARMA-AGARCH gives the results contradictorily. However, the parameters of asymmetric effects, three of four pairs of assets, are not significant. The results of VARMA-AGARCH for Thailand are quite similar to the results of VARMA-GARCH for the Indonesian stock market, which reports no volatility spillovers between the Indonesian stock market and the other countries' bond markets.

The DCC-GARCH(1,1), allowing correlation varying overtime, are shown in Table 3.8. The value of parameter $\hat{\phi}_1$ and $\hat{\phi}_2$ are significantly different from zero, which clearly means that the conditional correlations vary over time, or constant condition correlations do not hold. However, 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.

3.5 Concluding Remarks

The paper estimated three models for univariate volatility, namely GARCH(1,1), GJR(1,1), and EGARCH(1,1), on stock and bond markets in Southeast Asian countries. The evidence of volatility and asymmetric effects shows that coefficients in variance equations are all significant in the long run, but some are also significant in the short run. GJR and EGARCH are not clearly superior to GARCH.

For multivariate volatility, CCC, VARMA-GARCH, VARMA-AGARCH and DCC are employed to capture the characteristic of volatility. CCC suggests that including Thai government bonds in portfolios is likely preferable to other assets, except Singaporean government bonds, which can diversify portfolio risk efficiently. The evidence of volatility spillovers and asymmetric effects from VARMA-GARCH and VARMA-AGARCH models shows that there are volatility spillovers and asymmetric effects across Southeast Asian financial markets around 40% and 60% of pairs of assets, respectively. The result suggests that the VARMA-GARCH model is better than the VARMA-AGARCH model for modelling the volatility of Philippine financial markets. It also shows that they have no volatility spillovers for the Indonesian stock market and the other stock markets as the Thai bond market and the other bond markets. The DCC model shows the statistically significant overall time-varying conditional correlations. However, the conditional correlations are very tiny change over time, which means that consideration in time-varying conditional correlation is not necessary in practice.

Table 3.1 Summary of Variable Names

Variables	**Index Names**
indos	Jakarta Stock Exchange Index
phils	Philippine SE Comp. Index
thais	Stock Exchange of Thailand Index
sings	FTSE STI
indob	Citigroup Indonesia Government Bond Total Return Index
philb	Citigroup Philippines Government Bond Total Return Index
thaib	Thailand Government Bond Total Return Index
singb	JP Morgan Singapore Government Bond Total Return Index

Table 3.2 ADF test of a Unit Root in the Returns

Returns	Coefficient	t-statistic
indos	-0.8209	-19.9447
phils	-0.9322	-20.3689
thais	-0.8653	-19.4268
sings	-0.9851	-21.2993
indob	-1.1143	-23.5271
philb	-0.9094	-19.6288
thaib	-0.6396	-17.0120
singb	-0.9460	-20.7826

Table 3.3 Univariate GARCH (1,1)

	Mean equation			Variance equation			AIC	SC
	C	AR(1)	MA(1)	ω	α	β		
indos	**0.00159**			8.75E-06	**0.1407**	**0.8412**	-5.5462	-5.5249
	3.2166			1.9516	**4.4415**	**22.4578**		
	0.00162	**0.1763**		8.33E-06	**0.1393**	**0.8424**	-5.5693	-5.5428
	2.7596	**4.6470**		1.9114	**4.3267**	**21.6090**		
	0.00163	0.0312	0.1497	**8.19E-06**	**0.1394**	**0.8431**	-5.5677	-5.5358
	2.8283	0.1533	0.7479	**1.9076**	**4.3308**	**21.7705**		
phils	**0.00105**			**3.84E-05**	**0.2025**	**0.6724**	-5.4952	-5.4739
	2.2604			**2.3849**	**2.8702**	**7.6035**		
	0.00104	0.0598		**3.96E-05**	**0.2037**	**0.6655**	-5.4959	-5.4693
	2.1123	1.5308		**2.4334**	**2.9079**	**7.4884**		
	0.00098	**0.6735**	**-0.6323**	**3.87E-05**	**0.2036**	**0.6696**	-5.4953	5.4634
	1.8710	**2.8813**	**-2.5812**	**2.3741**	**2.8675**	**7.4596**		
thais	0.00068			3.61E-05	**0.1173**	**0.7345**	-5.6052	-5.5839
	1.6360			0.9799	**2.4142**	**5.5438**		
	0.00067	**0.15186**		3.80E-05	**0.1301**	**0.7135**	-5.6208	-5.5942
	1.3599	**3.4804**		0.9773	**2.9008**	**4.9375**		
	0.00067	0.1489	0.0030	3.79E-05	**0.1302**	**0.7136**	-5.6186	-5.5867
	1.3552	0.7393	0.0144	0.9726	**2.9016**	**4.9077**		
sings	**0.00096**			2.44E-06	**0.1328**	**0.8623**	-6.2196	-6.1984
	3.1588			1.8406	**5.1753**	**35.4656**		
	0.00097	-0.0317		2.43E-06	**0.1329**	**0.8622**	-6.2185	-6.1919
	3.3416	-0.8736		1.8440	**5.1219**	**35.5601**		
	0.00100	**0.8533**	**-0.8817**	**2.43E-06**	**0.1325**	**0.8623**	-6.2190	-6.1871
	4.1952	**6.3959**	**-7.3624**	**2.4760**	**5.0906**	**37.8438**		

Table 3.3 (Continued)

	Mean equation			Variance equation			AIC	SC
	C	AR(1)	MA(1)	ω	α	β		
indob	**0.00048**			**6.26E-07**	**0.1178**	**0.8741**	-8.2848	-8.2635
	5.0560			**2.0237**	**2.0990**	**31.4239**		
	0.00045	**0.1180**		**5.58E-07**	0.1107	**0.8824**	-8.2930	-8.2664
	4.4070	**2.1785**		**2.2494**	1.9097	**35.6374**		
	.00045	-0.0604	0.1803	**5.57E-07**	0.1097	**0.8830**	-8.2914	-8.2595
	4.4938	-0.1592	0.4975	**3.4240**	1.9552	**32.6421**		
philb	**0.00062**			**4.77E-07**	**0.1301**	**0.8682**	-8.2521	-8.2309
	4.8064			**2.2097**	**2.7292**	**31.7528**		
	0.00062	**0.0857**		4.78E-07	**0.1288**	**0.8680**	-8.2562	-8.2296
	4.5259	**2.0435**		1.9574	**2.6043**	**39.7056**		
	0.00062	0.2971	-0.2094	**4.76E-07**	**0.1283**	**0.8684**	-8.2546	-8.2227
	4.4645	0.6924	-0.4786	**2.2779**	**2.6728**	**31.0896**		
thaib	**0.00024**			2.61E-07	**0.3182**	**0.6796**	-9.7493	-9.7280
	5.5157			1.6127	**3.9047**	**13.1649**		
	0.00025	**0.4084**		1.74E-07	**0.2352**	**0.7531**	-9.8770	-9.8504
	3.1662	**9.5046**		1.3478	**3.8007**	**15.6648**		
	0.00024	**0.4856**	-0.0947	1.69E-07	**0.2288**	**0.7595**	-9.8754	-9.8435
	2.9821	**5.2058**	-0.9978	1.3701	**3.8397**	**17.9382**		
singb	-0.00031			7.74E-07	**0.0828**	**0.9053**	-7.3361	-7.3149
	-1.6568			1.8030	**3.5560**	**33.0925**		
	-0.00030	0.0413		7.44E-07	**0.0817**	**0.9068**	-7.3343	-7.3077
	-1.5416	1.1951		1.6915	**3.5376**	**33.3517**		
	-0.00030	-0.0672	0.1072	7.44E-07	**0.0818**	**0.9068**	-7.3322	-7.3003
	-1.5531	-0.1241	0.1976	1.6617	**3.5367**	**33.0944**		

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 3.4 Univariate GJR (1,1)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
indos	0.00160			**6.13E-05**	**-0.1008**	**0.4848**	**0.5858**	-5.5736	-5.5471
	3.9596			**51.7774**	**-5.7712**	**5.2675**	**11.8346**		
	0.00079	0.1636		**5.27E-05**	**-0.1174**	**0.4963**	**0.6544**	-5.5966	-5.5647
	1.5234	12.2672		**347.5637**	**-4.9839**	**6.4511**	**16.2607**		
	0.00075	0.2767	-0.1164	**5.27E-05**	**-0.1166**	**0.4985**	**0.6582**	-5.5943	-5.5571
	1.3450	1.3212	-0.5642	**328.0517**	**-5.2213**	**6.1371**	**16.6691**		
phils	0.00074			**4.03E-05**	0.0846	0.1765	**0.6835**	-5.5055	-5.4789
	1.6155			**2.5271**	1.0845	1.6876	**7.2836**		
	0.00064	**0.0764**		**4.26E-05**	0.0753	0.1982	**0.6721**	-5.5081	-5.4762
	1.2847	**1.9989**		**2.5706**	1.0045	1.7818	**6.9558**		
	0.00057	0.4482	-0.3717	**4.16E-05**	0.0745	0.2001	**0.6765**	-5.5073	-5.4701
	1.0761	1.5918	-1.2902	**2.5212**	1.0075	1.7755	**6.9594**		
thais	0.00027			**3.47E-05**	-0.0294	**0.2333**	**0.7551**	-5.6432	-5.6166
	0.6650			1.7447	-0.3541	**2.3890**	**11.6881**		
	6.02E-05	**0.1288**		3.53E-05	-0.0217	0.2436	**0.7423**	-5.6554	-5.6235
	0.1285	**3.1938**		1.5544	-0.2218	1.8372	**9.7420**		
	7.75E-05	0.0401	0.0931	3.55E-05	-0.0215	0.2472	**0.7393**	-5.6534	-5.6161
	0.1685	0.1543	0.3452	1.5212	-0.2197	1.8347	**9.3234**		
sings	0.00061			**3.65E-06**	0.0386	**0.1566**	**0.8610**	-6.2311	-6.2046
	2.0204			**2.6803**	1.3748	**3.6668**	**33.2861**		
	0.00064	-0.0291		**3.66E-06**	0.0401	**0.1557**	**0.8594**	-6.2300	-6.1981
	2.2152	-0.7904		**2.6855**	1.4218	**3.5787**	**32.8635**		
	0.00067	0.3876	-0.4236	**3.65E-06**	0.0416	**0.1512**	**0.8598**	-6.2282	-6.1910
	2.3440	0.5303	-0.5886	**2.6792**	1.4778	**3.5360**	**32.8415**		

Table 3.4 (Continued)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
indob	**0.00031**			**5.73E-07**	0.0175	0.1856	**0.8839**	-8.3442	-8.3176
	3.2236			**3.7314**	0.6645	1.7019	**41.1949**		
	0.00025	**0.1341**		**5.28E-07**	0.0105	0.1847	**0.8919**	-8.3550	-8.3231
	2.1734	**2.2415**		**2.3655**	0.4335	1.5594	**41.8992**		
	0.00025	0.1789	-0.0447	**5.30E-07**	0.0105	0.1866	**0.8914**	-8.3529	-8.3156
	2.0138	0.5481	-0.1398	**1.9692**	0.4234	1.7700	**32.8010**		
philb	**0.00043**			**8.02E-07**	0.0347	0.1791	**0.8491**	-8.2843	-8.2577
	3.5832			**4.8247**	0.9249	1.4422	**23.9217**		
	0.00042	0.0579		**7.83E-07**	0.0386	0.1742	**0.8488**	-8.2858	8.2538
	3.0301	1.4101		**2.1483**	0.8696	1.4945	**28.2659**		
	0.00041	0.3565	-0.2947	7.78E-07	0.0385	0.1743	**0.8493**	-8.2842	-8.2470
	3.3027	0.6740	-0.5472	0.9364	0.8481	1.1681	**11.5565**		
thaib	**0.00023**			**2.64E-07**	**0.2480**	0.1033	**0.6877**	-9.7518	-9.7252
	5.0874			**2.0320**	**3.8518**	0.9835	**13.4129**		
	0.00019	**0.4051**		1.75E-07	**0.1676**	0.1126	**0.7583**	-9.8819	-9.8500
	2.6451	**8.7827**		1.4430	**2.4909**	0.9943	**20.1370**		
	0.00019	**0.4583**	-0.0651	1.72E-07	**0.1656**	0.1093	**0.7622**	-9.8801	-9.8428
	2.5446	**4.6168**	-0.6744	1.5164	**2.4418**	0.9517	**19.0666**		
singb	-0.00026			**1.14E-06**	**0.1070**	-0.0473	**0.8938**	-7.3365	-7.3100
	-1.3529			**2.0731**	**3.1530**	-1.3771	**29.8199**		
	-0.00025	0.0406		1.10E-06	**0.1060**	-0.0471	**0.8955**	-7.3346	-7.3027
	-1.2321	1.1869		1.8896	**3.1930**	-1.3750	**29.9882**		
	-0.00025	-0.0671	0.1061	**1.10E-06**	**0.1060**	-0.0468	**0.8953**	-7.3324	-7.2952
	-1.2498	-0.1225	0.1933	1.8954	**3.1806**	-1.3624	**30.0174**		

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 3.5 Univariate EGARCH (1,1)

	Mean equation			Variance equation					
	C	AR(1)	MA(1)	ω	α	γ	β	AIC	SC
indos	**0.00120**			**-0.8018**	**0.2452**	**-0.1109**	**0.9260**	-5.5610	-5.5345
	2.7516			**-3.0615**	**3.3850**	**-2.2150**	**33.4643**		
	0.00077	**0.2021**		**-0.9073**	**0.2217**	**-0.1618**	**0.9118**	-5.5924	-5.5605
	1.2810	**5.5047**		**-3.1912**	**2.8047**	**-2.8331**	**30.9296**		
	0.00076	0.2291	-0.0279	**-0.9073**	**0.2212**	**-0.1627**	**0.9118**	-5.5902	-5.5530
	1.2342	1.3433	-0.1621	**-3.1832**	**2.8017**	**-2.8176**	**30.8660**		
thais	0.00024			**-1.1519**	0.0913	**-0.2094**	**0.8727**	-5.6659	-5.6393
	0.5684			**-2.7823**	0.9382	**-1.9726**	**15.6802**		
	-2.61E-05	**0.1202**		**-1.1411**	0.0796	-0.2221	**0.8731**	-5.6779	-5.6460
	-0.0552	**2.9889**		**-2.7070**	0.7420	-1.8286	**15.3463**		
	-1.21E-05	0.0675	0.0552	**-1.1475**	0.0812	-0.2224	**0.8724**	-5.6758	-5.6385
	-0.0258	0.2576	0.2045	**-2.6322**	0.7626	-1.8342	**14.8891**		
sings	0.00057			-0.4369	0.2008	**-0.1125**	**0.9684**	-6.2357	-6.2091
	1.9702			-3.7979	4.6541	**-3.8029**	**87.5987**		
	0.00061	-0.0345		-0.4416	0.2041	**-0.1104**	**0.9682**	-6.2347	-6.2027
	2.1804	-0.9891		-3.8271	4.7035	**-3.7500**	**87.1849**		
	0.00063	**-0.8563**	**0.838586**	-0.4431	0.2032	**-0.1120**	**0.9680**	-6.2336	-6.1963
	2.2287	**-3.3402**	**3.088216**	-3.8131	4.6617	**-3.7874**	**86.3531**		
phils	0.00064			-1.7398	0.3629	-0.1278	**0.8231**	-5.5075	-5.4809
	1.4782			-2.7310	3.0552	-1.8129	**11.5848**		
	0.00055	0.0726		**-1.7671**	**0.3635**	-0.1360	**0.8201**	-5.5102	-5.4783
	1.1386	1.8619		**-2.8155**	**3.1256**	-1.8389	**11.7343**		
	0.00044	**0.9976**	**-0.9974**	-1.3457	0.1040	-0.0406	**0.8481**	-5.4441	-5.4069
	0.1542	**77.2508**	**-79.9912**	-0.9303	0.9390	-0.5513	**5.0605**		

Table 3.5 (Continued)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
indob	**0.00078**			-0.4458	0.2026	-0.1347	**0.9715**	-8.2896	-8.2631
	4.1634			-1.0816	2.4350	-1.8443	**27.8703**		
	0.00072	**0.1265**		-0.4034	0.1708	-0.1493	**0.9735**	-8.2964	-8.2645
	3.6520	**2.2845**		-1.0414	2.7406	-1.8861	**29.0994**		
	0.00060	-0.2290	0.3853	-0.4270	0.1664	-0.1448	**0.9708**	-8.2974	-8.2602
	3.2353	-0.8817	1.3614	-1.0827	2.8885	-1.8850	**28.0739**		
philb	**0.00056**			**-0.6098**	**0.1670**	**-0.1554**	**0.9549**	-8.2786	-8.2520
	3.6421			**-3.5869**	**2.0413**	**-2.3139**	**65.4667**		
	0.00060	0.0594		**-0.5976**	**0.1750**	**-0.1562**	**0.9567**	-8.2802	-8.2483
	3.1648	1.0011		**-3.6806**	**2.2054**	**-2.2415**	**67.8028**		
	0.00058	0.5586	-0.4843	**-0.5970**	**0.1790**	**-0.1642**	**0.9570**	-8.2808	-8.2436
	2.9046	1.7535	-1.5084	**-3.5299**	**2.3661**	**-2.2114**	**64.8746**		
thaib	**0.00024**			**-1.6188**	**0.5224**	-0.0464	**0.9006**	-9.7718	-9.7453
	4.9891			**-4.2943**	**5.9168**	-0.9016	**33.7635**		
	0.00019	**0.3842**		**-1.1472**	**0.3960**	-0.0549	**0.9317**	-9.8643	-9.8840
	2.6652	**8.3494**		**-3.5151**	**4.7755**	-0.9044	**41.2655**		
	0.00019	**0.3906**	-0.0077	**-1.1545**	**0.3978**	-0.0547	**0.9312**	-9.8940	-9.8568
	2.6802	**3.4190**	-0.0704	**-3.5293**	**4.7818**	-0.8912	**41.1367**		
singb	-0.00027			**-0.4127**	**0.1911**	0.0403	**0.9737**	-7.3276	-7.3011
	-1.3900			**-2.1468**	**4.4041**	1.6484	**55.1679**		
	-0.00026	0.0379		**-0.3988**	**0.1881**	0.0398	**0.9749**	-7.3252	-7.2933
	-1.2541	1.0837		**-2.1027**	**4.3902**	1.6044	**55.9244**		
	-0.00029	0.6442	-0.6357	**-0.4098**	**0.1905**	0.0407	**0.9740**	-7.3226	-7.2853
	-1.4350	0.7430	-0.7284	**-2.1336**	**4.3860**	1.6282	**55.2070**		

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 3.6 Constant Conditional Correlation between Returns in CCC-GARCH(1,1)

Returns	indos	phils	thais	sings	indob	philb	thaib
phils	**0.3916**						
	11.7978						
thais	**0.4641**	**0.3254**					
	18.0797	**10.1285**					
sings	**0.5634**	**0.3963**	**0.4674**				
	18.7840	**12.2588**	**16.9134**				
indob	**0.1134**	**0.1407**	**0.1352**	**0.1219**			
	3.4451	**4.2084**	**4.0705**	**4.2852**			
philb	**0.1327**	**0.1631**	**0.1561**	**0.1371**	**0.4485**		
	2.8370	**3.7403**	**4.3675**	**3.1652**	**12.0181**		
thaib	0.0131	0.0560	**0.1505**	0.0626	**0.0821**	**0.0882**	
	0.3393	1.3539	**2.1052**	1.5581	**2.3388**	**2.2775**	
singb	**-0.1775**	**-0.0749**	**-0.1502**	**-0.1934**	**-0.0991**	**-0.1195**	-0.0094
	-5.2379	**-2.4717**	**-4.5711**	**-6.2245**	**-3.1282**	**-3.4832**	0.2593

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 3.7 Summary of Volatility Spillovers and Asymmetric Effect of Negative and Positive Shocks

Pairs of assets	Number of volatility spillovers		Number of asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
Stock-Stock			
indos_phils	1	0	1
indos_thais	1	0	1
indos_sings	0	0	0
phils_thais	0	2	1
phils_sings	2	0	0
thais_sings	2	1	1
Stock-Bond			
indos_indob	1	0	1
indos_philb	0	0	0
indos_thaib	0	0	1
indos_singb	0	2	1
phils_indob	0	1	1
phils_philb	0	0	0
phils_thaib	1	1	0
phils_singb	0	0	0
thais_indob	2	0	1
thais_philb	2	0	0
thais_thaib	2	0	0
thais_singb	2	0	0
sings_indob	1	1	1
sings_philb	0	1	0
sings_thaib	0	0	1
sings_singb	0	0	1
Bond-Bond			
indob_philb	0	2	1
indob_thaib	0	0	1
indob_singb	0	2	1
philb_thaib	0	0	0
philb_singb	2	1	1
thaib_singb	0	0	1

Table 3.8 DCC-GARCH(1,1) Estimates

Parameter Estimates	Estimates in the Q_t Equation
$\hat{\phi}_1$	0.0033
	4.2238
$\hat{\phi}_2$	0.9846
	223.7337

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

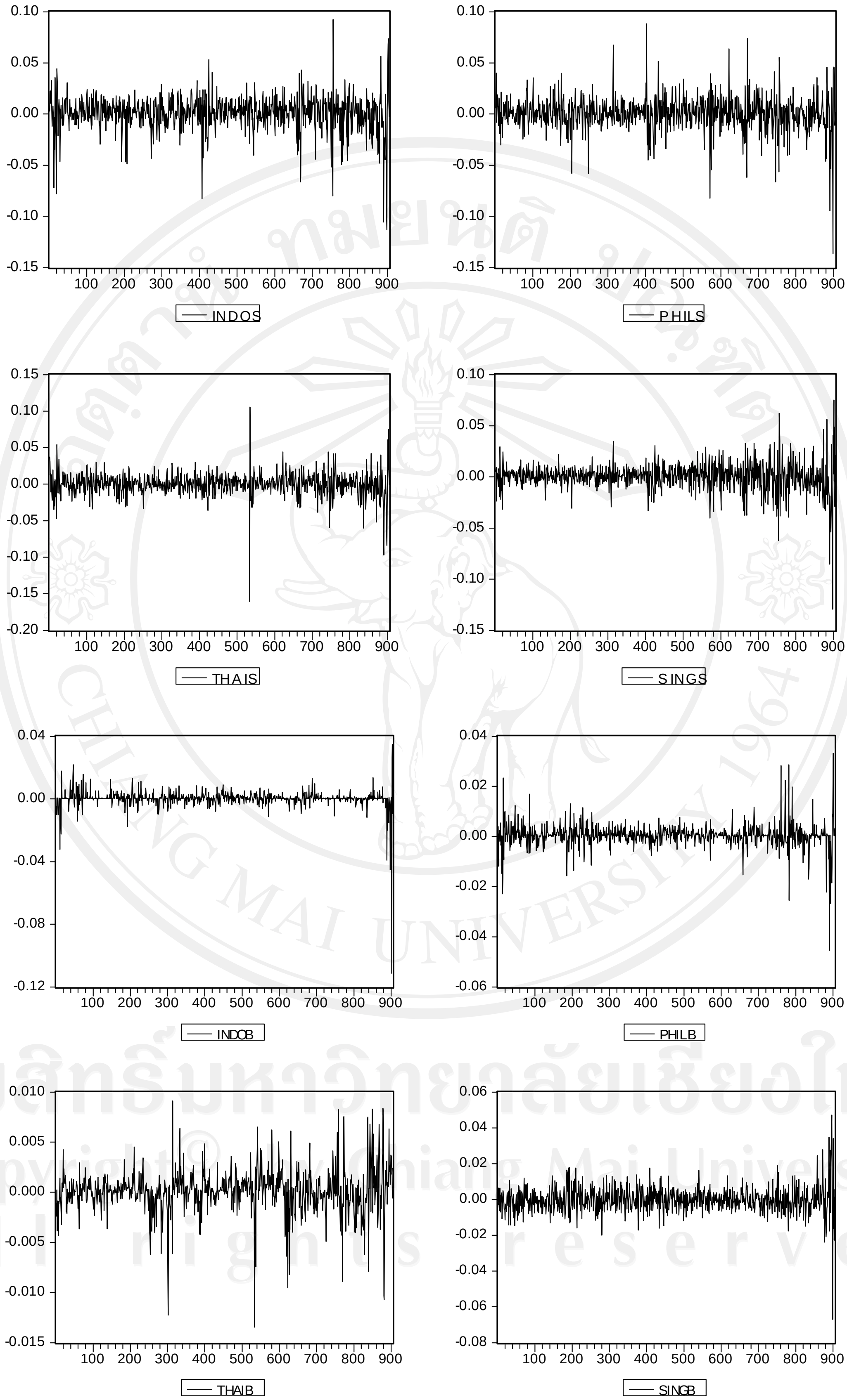

Figure 3.1 Daily Returns for All series