Chapter 4

Modelling Stock Volatility in South-East Asia

An efficient portfolio relies on the correlation or covariance of a pair of assets that may change over time. Investors can make decisions and manage their portfolios to weigh between the expected returns and risks. In recent years emerging stock markets have been of considerable interest to investors who have been attracted by the opportunities for further international portfolio diversification and the high expected rates of return offered. Stock markets in South-East Asia are attractive for international investors in many reasons such as the increasing in market capitalization and higher average returns.

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 B.

Abstract

Stock returns and volatility are important for investment decision making and risk management. This paper evaluates the volatility linkages and spillovers across stock markets because investors tend to move their funds across markets to adjust portfolio risk and returns. The volatility spillovers in six countries, namely Indonesia, The Philippines, Thailand, and Singapore, are examined using daily returns of stock indices from 31 July 2000 to 12 November 2008. The univariate volatility models suggest that Indonesia and Singapore markets have asymmetric effects in that positive and negative shocks have the same impact on conditional volatility. The multivariate volatility is used to determine the conditional correlation and spillover effects. CCC model found the constant conditional correlation, except in the correlation between Vietnam and Indonesia, and between Vietnam and Thailand. VARMA-GARCH and VARMA-AGARCH models show that the volatility spillovers are evident in 8 of 15 for both models. Moreover, the numbers of cases that have significant and insignificant asymmetric effect do not differ much. Therefore, VARMA-AGARCH is not clearly superior to VARMA-GARCH. In addition, DCC shows significant time-varying correlations.

4.1 Introduction

Volatility is the key for portfolio and risk management, especially with modern financial theory. It has become an important tool for fund managers and investors to use while making decisions for investments. Fund managers and investors tend to move their funds from the markets that have high volatility to the markets that have low volatility. For example, they can move funds from one stock market to other stock markets if the volatility in the first stock market has increased.

This behavior of fund managers and investors leads to increases or decreases in the volatility across the countries. Another cause that changes the volatility is the information that affects all markets and all countries simultaneously, such as the Asian financial crisis in 1997. This means there are volatility linkages and spillovers across the countries. Therefore, fund managers and investors can make decisions and manage their portfolio to weigh between the expected return and risk.

Consequently, many models have been developed to capture the characteristic of volatility. Engle (1982) introduced the Autoregressive Conditional Heterscedasticity (ARCH) to model the character of volatility. In 1986, Bollerslev generalized ARCH to become Generalize 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 impacts on the conditional variance between positive and negative shocks, Glosten et al. (1993) proposed the GJR model. The EGARCH model of Nelson (1991) can also capture asymmetric volatility.

The multivariate volatility models are common in modelling volatility. The CCC model of Bollerslev (1990) assumes that the conditional correlation coefficients of the returns are time invariant and restricted for volatility spillovers among different returns. Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model to allow correlation variance over time, but it still does 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.

This paper aims to examine the characteristic of volatility, the asymmetric effect of positive and negative shocks, and volatility spillovers across Southeast Asian stock markets to manage the portfolio risk and returns.

4.2 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.

4.2.1 GARCH

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

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{4.1}$$

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.

4.2.2 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:

$$h_t = \omega + \sum_{i=1}^{r} \left(\alpha_i + \gamma_i I(\varepsilon_{t-i}) \right) \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{4.2}$$

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, $\alpha_j + \gamma_j > \alpha_j$.

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 $\alpha_1(\alpha_1 + \gamma_1)$. 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 $\alpha_1 + \gamma_1 / 2 + \beta_1$.

4.2.3 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:

$$\log h_t = \omega + \sum_{i=1}^{r} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{r} \gamma_i \eta_{t-i} + \sum_{j=1}^{s} \beta_j \log h_{t-j} \qquad (4.3)$$

In equation (4.3), $\left|\eta_{t-i}\right|$ 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 (4.3) can allow asymmetric and leverage effects. As EGARCH also uses the logarithm of conditional volatility, there are no restrictions on the parameters in (4.3). As the standardized shocks have finite moments, the moment conditions of (4.3) are straightforward.

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

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \tag{4.4}$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \tag{4.5}$$

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).

4.2.4 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:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{4.6}$$

$$\varepsilon_t = D_t \eta_t \tag{4.7}$$

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{4.8}$$

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 $E(\eta_t \eta_t') = \Gamma$.

4.2.5 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

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (4.9)$$

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

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

From equation (4.9) 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.

4.2.6 CCC

If the model given by equation (4.9) 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:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_i h_{i,t-l} \qquad (4.10)$$

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 (4.10), 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.

4.2.7 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:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, \ldots, T \qquad (4.11)$$

$$Q_t = D_t \Gamma_t D_t, \qquad (4.12)$$

where $D_t = diag(h_{1t}^{1/2}, \ldots, h_{mt}^{1/2})$ 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:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \qquad (4.13)$$

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:

$$Q_t = (1-\phi_1-\phi_2)S + \phi_1\eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1} \qquad (4.14)$$

$$\Gamma_t = \left\{(diag(Q_t)^{-1/2}\right\} Q_t \left\{(diag(Q_t)^{-1/2}\right\}, \qquad (4.15)$$

where S is the unconditional correlation matrix of the ε and equation (4.15) is used to standardize the matrix estimated in (4.14) to satisfy the definition of a correlation matrix.

4.3 Data and Estimation

The data used to estimate univariate and multivariate GARCH models is the daily returns of stock indices of six countries in Southeast Asia, namely Indonesia, Malaysia, The Philippines, Thailand, Singapore, and Vietnam. The sample ranges from 31 July 2000 to 12 November 2008 with 1,529 observations. All data was obtained from Reuters. The stock returns and their variable names are summarized in Table 4.1.

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

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \qquad (4.16)$$

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 price index is denominated in the local currency. The plots of the daily returns for all series are shown in Figure 4.1. Figure 4.1 shows that all returns have constant mean, but the time-varying variance.

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

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (4.17)$$

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 if less than zero at 1% level, as shown in Table 4.2.

4.4 Empirical Results

The univariate methods (namely, GARCH (1,1), GJR (1,1), and EGARCH (1,1)) are estimated to determine the coefficient of conditional mean equations and condition variance equations, with three types of conditional mean equations. The results are given in Tables 4.3-4.5. As shown in Table 4.3, coefficients in variance equations are all significant in the short and long runs. Asymmetric effects of positive and negative shocks on conditional volatility in GJR and EGARCH are significant only in Indonesia and Singapore, while the rest are insignificant. Therefore, asymmetric models of univariate volatility are preferred to GARCH in the cases of Indonesia and Singapore.

As CCC-GARCH (1,1) shows in Table 4.6 for multivariate volatility, we can see that the estimated correlation yields the constant conditional correlation, except with correlation between Vietnam and Indonesia, and between Vietnam and Thailand. Moreover, the correlation between Vietnam and Malaysia is negative. This means a portfolio which is constructed from the assets in Vietnamese and Malaysian stock markets 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 asymmetric effects of positive and negative shocks. The results of VARMA-GARCH and VARMA-AGARCH for each pair of assets are estimated. Then, we summarize the number of volatility spillovers and number of asymmetric effects in VARMA-GARCH and VARMA-AGARCH models in Table 4.7. The results show the volatility spillovers are evident in 8 of 15 for both models. Asymmetric effects are not significant in 6 of 15 cases, which mean that positive and negative shocks have the same impact on conditional volatility. However, 60% of cases are statistically significant. We can conclude that overall VARMA-AGARCH is not clearly superior to VARMA-GARCH. For the Indonesian market, the results of VARMA-GARCH found that there is no volatility spillover between the Indonesian market and the other markets. On the other hand, VARMA-AGARCH gives better results to show that volatility spillovers and asymmetric effects exist in most cases for Indonesia. Therefore, the VARMA-AGARCH is superior to VARMA-GARCH even though overall it does not seem to be.

The DCC-GARCH(1,1) estimate and t-ratio are shown in Table 4.8. The value of parameter $\hat{\phi}_1$ and $\hat{\phi}_2$ is significantly different from zero, which clearly means that the conditional correlations in overall are time-varying, or that constant condition correlations do not hold. Furthermore, the short-run and long-run persistence of shocks to conditional correlations is statistically significant. 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.

4.5 Concluding Remarks

The paper estimates the conditional volatility of Southeast Asian countries (Indonesia, Malaysia, The Philippines, Thailand, Singapore, and Vietnam) using univariate and multivariate volatility models. The univariate volatility models suggest that negative shocks in Indonesia and Singapore make that stock market more volatile than positive shock.

For multivariate volatility, CCC provided the constant conditional correlation, except correlation between Vietnam and Indonesia, and Vietnam and Thailand. Correlation between Vietnam and Malaysia is only negative. This means that portfolio managers can diversify risk efficiently if they invest in Vietnamese and Malaysian stock. The VARMA-GARCH and VARMA-AGARCH models show that the volatility spillovers are evident in 8 of 15 for both models. Asymmetric effects are insignificant in 6 of 15 cases, which means that positive and negative shocks have the same impact on conditional volatility. However, the numbers of cases that are significant or insignificant are not very different, so VARMA-AGARCH is not clearly superior to VARMA-GARCH. The evidence of the DCC model shows the statistically significant time-varying conditional correlations.

Table 4.1 Summary of Variable Names

Variables	**Index Names**
indos	Jakarta Stock Exchange Index
malas	Kuala Lumpur Comp. Price Index
phils	Philippine SE Comp. Index
thais	Stock Exchange of Thailand Index
sings	FTSE STI
viets	Vietnam Stock Exchange Index

Table 4.2 ADF Test of a Unit Root in the Returns

Returns	Coefficient	t-statistic
indos	-0.8435	-25.6478
malas	-0.8572	-25.2510
phils	-0.9341	-26.5831
sings	-0.9388	-26.2514
thais	-0.8801	-25.7109
viets	-0.7467	-24.1369

Table 4.3 Univariate GARCH (1,1)

	Mean equation			Variance equation			AIC	SC
	C	AR(1)	MA(1)	ω	α	β		
indos	**0.0014**			**1.81E-06**	**0.1296**	**0.8134**	-5.4558	-5.4507
	3.8427			**2.6543**	**3.8135**	**17.3384**		
	0.0015	**0.1430**		**1.69E-06**	**0.1249**	**0.8205**	-5.4705	-5.4640
	3.3335	**4.8499**		**2.6716**	**3.9559**	**18.3939**		
	0.0014	0.1808	-0.0386	**1.69E-05**	**0.1249**	**0.8204**	-5.4692	-5.4483
	3.3121	0.9630	0.2045	**2.6798**	**3.9660**	**18.4340**		
malas	**0.0004**			**6.54E-07**	**0.1163**	**0.8935**	-6.5223	-6.5084
	2.5132			**2.2647**	**6.2337**	**68.3310**		
	0.0004	**0.139**		4.47E-07	**0.0925**	**0.9141**	-6.5365	-6.5191
	1.9538	**3.9705**		1.7428	**6.2644**	**73.7371**		
	0.0003	**0.4778**	-0.3526	**4.00E-07**	**0.0858**	**0.9199**	-6.5376	-6.5166
	1.7322	**2.6853**	-1.8609	**2.2067**	**5.9967**	**88.8074**		
phils	0.0003			**2.93E-05**	**0.2061**	**0.7129**	-5.4926	-5.4786
	1.0193			**3.2261**	**3.8770**	**13.7358**		
	0.0004	**0.0795**		**3.01E-05**	**0.2074**	**0.7080**	-5.4954	-5.4779
	0.9915	**2.5959**		**3.3581**	**3.9051**	**13.8951**		
	0.0003	0.4888	-0.4065	**3.14E-05**	**0.2159**	**0.6959**	-5.4954	-5.4745
	0.8266	1.7726	-1.4412	**3.5461**	**3.8799**	**13.7583**		
thais	**0.0010**			2.72E-05	**0.1112**	**0.7929**	-5.4715	-5.4576
	2.7028			1.3314	**2.7011**	**13.1301**		
	0.0010	**0.1283**		2.82E-05	**0.1167**	**0.7827**	-5.4833	-5.4658
	2.4370	**3.7622**		1.3910	**2.7499**	**12.9605**		
	0.0010	0.0858	**0.0427**	2.79E-05	**0.1162**	**0.7840**	-5.4820	-5.4610
	2.4598	0.4193	**0.2040**	1.3896	**2.7607**	**13.1086**		

Table 4.3 (Continued)

	Mean equation			Variance equation			AIC	SC
	C	AR(1)	MA(1)	ω	α	β		
sings	**0.0007**			2.34E-06	**0.1196**	**0.8803**	-5.9478	-5.9338
	2.7517			1.9354	**4.0187**	**34.0953**		
	0.0007	-0.0190		2.31E-06	**0.1188**	**0.8809**	-5.9472	-5.9298
	2.8099	-0.6842		1.9290	**3.9582**	**33.9351**		
	0.0007	-0.1676	0.1489	2.31E-06	**0.1187**	**0.8811**	-5.9460	-5.9250
	2.7951	-0.1151	0.1018	1.9264	**3.9577**	**33.9443**		
viets	5.91E-05			**3.80E-06**	**0.4298**	**0.6871**	-5.5085	-5.4945
	0.2281			**2.8483**	**5.4381**	**16.3879**		
	9.28E-05	**0.2831**		**4.10E-06**	**0.4003**	**0.7021**	-5.5674	-5.5499
	0.2444	**7.8533**		**3.0184**	**6.0897**	**20.1821**		
	9.27E-05	**0.2774**	0.0063	**4.10E-06**	**0.4002**	**0.7021**	-5.5661	-5.5451
	0.2445	**2.5729**	0.0512	**3.0182**	**6.1451**	**20.1756**		

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 4.4 Univariate GJR (1,1)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
indos	**0.0012**			**4.50E-05**	0.0295	**0.2172**	**0.6907**	-5.4722	-5.4547
	3.1681			**4.0283**	0.9356	**3.2513**	**10.7198**		
	0.0010	**0.1519**		**3.14E-05**	0.0250	**0.1815**	**0.7637**	-5.4881	-5.4672
	2.2358	**5.1435**		**3.1101**	0.7874	**2.7809**	**12.3098**		
	0.0009	0.3069	-0.1591	**3.12E-05**	0.0238	**0.1841**	**0.7645**	-5.4872	-5.4628
	2.0573	1.7806	-0.8939	**3.1429**	0.7367	**2.7976**	**12.4962**		
malas	0.0003			**1.03E-06**	**0.0969**	0.0814	**0.8716**	-6.5305	-6.5130
	1.6160			**3.2141**	**3.5141**	1.4761	**59.7811**		
	0.0003	**0.1290**		**9.37E-07**	**0.0904**	0.0825	**0.8773**	-6.5437	-6.5227
	1.2046	**3.8024**		**3.0964**	**3.2849**	1.4478	**65.8644**		
	0.0002	**0.4882**	**-0.3659**	**8.87E-07**	**0.0840**	0.0833	**0.8824**	-6.5447	-6.5202
	0.9479	**2.8315**	**-1.9774**	**2.6283**	**3.0516**	1.4564	**67.8420**		
phils	0.0001			**2.64E-05**	**0.1054**	0.1319	**0.7509**	-5.4997	-5.4822
	0.4147			**2.5674**	**2.2301**	1.8712	**11.9633**		
	0.0001	**0.0790**		**2.64E-05**	**0.0997**	0.1380	**0.7528**	-5.5027	-5.4818
	0.3175	**2.4466**		**2.5588**	**2.1850**	1.8867	**12.0069**		
	8.36E-05	0.3774	-0.2954	**2.67E-05**	**0.1014**	0.1414	**0.7492**	-5.5024	-5.4779
	0.2008	1.1608	-0.9069	**2.5979**	**2.2148**	1.8807	**11.9564**		
thais	**0.0008**			3.88E-05	0.0559	0.2091	**0.7069**	-5.4877	-5.4702
	2.2146			1.6201	1.0457	1.7758	**7.4489**		
	0.0006	**0.1345**		3.80E-05	0.0472	0.2242	**0.7097**	-5.5008	-5.4799
	1.5051	**4.0079**		1.6364	0.9166	1.8120	**7.6814**		
	3.36E-05	0.0896	0.0103	**0.0001**	-0.0468	**0.3111**	**0.5254**	-5.4122	-5.3877
	0.0743	0.2292	0.0228	**2.8622**	-0.9251	**2.0651**	**3.3195**		

Table 4.4 (Continued)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
sings	0.0003			**2.90E-06**	0.0170	**0.1414**	**0.9020**	-5.9748	-5.9573
	1.1357			**2.2613**	0.9478	**3.5644**	**35.1220**		
	0.0003	-0.0080		**2.88E-06**	0.0162	**0.1419**	**0.9023**	-5.9749	-5.9539
	1.1829	-0.3009		**2.2611**	0.8962	**3.5958**	**34.9504**		
	0.0003	**-0.9885**	**0.9975**	**2.89E-06**	0.0150	**0.1428**	**0.9033**	-5.9771	-5.9527
	1.1487	**-169.2199**	**286.1736**	**2.5822**	0.8422	**3.6608**	**38.2496**		
viets	9.17E-05			**3.89E-06**	**0.4431**	-0.0282	**0.6863**	-5.5074	-5.4899
	0.3870			**2.9384**	**4.5974**	-0.2784	**16.5202**		
	0.0001	**0.2832**		**4.16E-06**	**0.4115**	-0.0219	**0.7011**	-5.5662	-5.5453
	0.3918	**7.8555**		**3.1135**	**4.5192**	-0.1831	**20.3239**		
	0.0001	**0.2836**	-0.0005	**4.16E-06**	**0.4115**	-0.0220	**0.7011**	-5.5649	-5.5405
	0.3938	**2.6636**	-0.0044	**3.1159**	**4.5783**	-0.1835	**20.3205**		

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 4.5 Univariate EGARCH (1,1)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
indos	**0.0012**			**-0.9633**	**0.2200**	**-0.1010**	**0.9037**	-5.4732	-5.4557
	3.1649			**-3.7808**	**4.2967**	**-2.8893**	**32.1669**		
	0.0009	**0.1552**		**-0.9160**	**0.2042**	**-0.1147**	**0.9082**	-5.4921	-5.4711
	1.9061	**5.3051**		**-3.6909**	**4.0325**	**-2.9584**	**33.4730**		
	0.0008	0.2693	-0.1164	**-0.9161**	**0.2041**	**-0.1164**	**0.9082**	-5.4910	-5.4666
	1.7507	1.6346	-0.6933	**-3.6997**	**4.0382**	**-2.9294**	**33.5499**		
malas	0.0003			**-0.3260**	**0.2371**	-0.0567	**0.9837**	-6.5438	-6.5264
	1.4362			**-4.1404**	**8.5934**	-1.8253	**126.5452**		
	0.0002	**0.1356**		**-0.3168**	**0.2292**	-0.0622	**0.9842**	-6.5615	-6.5405
	1.0933	**4.3042**		**-4.2073**	**8.5955**	-1.9114	**131.3602**		
	0.0002	**0.5155**	**-0.3859**	**-0.3084**	**0.2247**	-0.0655	**0.9848**	-6.5631	-6.5386
	0.8569	**3.2903**	**-2.2952**	**-4.2356**	**8.6135**	-1.9177	**134.8770**		
phils	3.79E-05			**-1.0352**	**0.3219**	-0.0798	**0.9032**	-5.5000	-5.4826
	0.1053			**-2.0571**	**3.7712**	-1.7496	**16.2402**		
	-7.86E-05	**0.0962**		**-1.0958**	**0.3322**	-0.0897	**0.8970**	-5.5043	-5.4834
	-0.1965	**2.9033**		**-2.1933**	**3.8948**	-1.6877	**16.2805**		
	-0.0002	0.3020	-0.2036	**-1.1057**	**0.3359**	-0.0924	**0.8961**	-5.5036	-5.4792
	-0.3869	0.9585	-0.6435	**-2.2060**	**3.9097**	-1.6835	**16.2366**		
thais	**0.0009**			**-1.3493**	**0.2558**	-0.1423	**0.8606**	-5.4922	-5.4747
	2.4606			**-2.1323**	**3.0695**	-1.7579	**11.2990**		
	0.0007	**0.1298**		**-1.3478**	**0.2441**	-0.1538	**0.8600**	-5.5054	-5.4844
	1.6268	**3.9985**		**-2.1349**	**3.1527**	-1.7414	**11.2392**		
	0.0007	0.1073	0.0233	**-1.3501**	**0.2445**	-0.1539	**0.8598**	-5.5041	-5.4796
	1.6115	0.4374	0.0939	**-2.1258**	**3.1696**	-1.7666	**11.1812**		

Table 4.5 (Continued)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
sings	0.0003			**-0.3388**	**0.1793**	**-0.0894**	**0.9767**	-5.9789	-5.9615
	1.0602			**-2.9299**	**5.3785**	**-2.8563**	**87.9317**		
	0.0003	-0.0214		**-0.3411**	**0.1805**	**-0.0889**	**0.9766**	-5.9790	-5.9580
	1.2306	-0.8216		**-2.9471**	**5.3260**	**-2.8633**	**88.0682**		
	0.0007	**0.9972**	**-0.9973**	**-0.3185**	**0.1792**	**-0.0888**	**0.9790**	-5.9790	-5.9545
	1.0234	**359.5283**	**-370.7887**	**-2.8963**	**5.4987**	**-2.8762**	**92.4021**		
viets	0.0003			**-0.8749**	**0.5701**	0.0125	**0.9448**	-5.5285	-5.5111
	1.3025			**-5.5206**	**7.8097**	0.3436	**68.0807**		
	0.0004	**0.2749**		**-0.8246**	**0.5348**	0.0061	**0.9474**	-5.5837	-5.5628
	1.2152	**8.2818**		**-5.5000**	**7.7074**	0.1404	**71.7807**		
	0.0005	**0.8200**	**-0.6376**	**-0.8513**	**0.5409**	0.0029	**0.9441**	-5.5823	-5.5578
	0.9275	**16.3590**	**-7.9423**	**-5.3444**	**7.3438**	0.0647	**66.0766**		

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

Returns	indos	malas	phils	thais	sings
malas	**0.3634**				
	15.3114				
phils	**0.3296**	**0.3241**			
	13.8315	**11.2059**			
thais	**0.3790**	**0.3800**	**0.2842**		
	21.1724	**19.5228**	**13.1261**		
sings	**0.4564**	**0.4561**	**0.3495**	**0.4422**	
	19.3563	**24.3327**	**13.5171**	**20.8740**	
viets	0.0287	-0.0152	**0.0674**	0.0184	0.0649
	1.0280	-0.4632	**2.4731**	0.6034	2.1610

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 4.7 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	
indos_malas	0	1	1
indos_phils	0	1	1
indos_thais	0	0	1
indos_sings	0	1	0
indos_viets	0	0	1
malas_phils	1	2	1
malas_thais	0	0	0
malas_sings	1	2	0
malas_viets	1	0	0
phils_thais	2	0	0
phils_sings	1	2	1
phils_viets	1	0	0
thais_sings	1	1	1
thais_viets	2	2	1
sings_viets	0	0	1

Table 4.8 DCC-GARCH(1,1) Estimates

Parameter Estimates	Estimates in the Q_t Equation
$\hat{\phi}_1$	0.0119
	6.7891
$\hat{\phi}_2$	0.9716
	195.4114

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

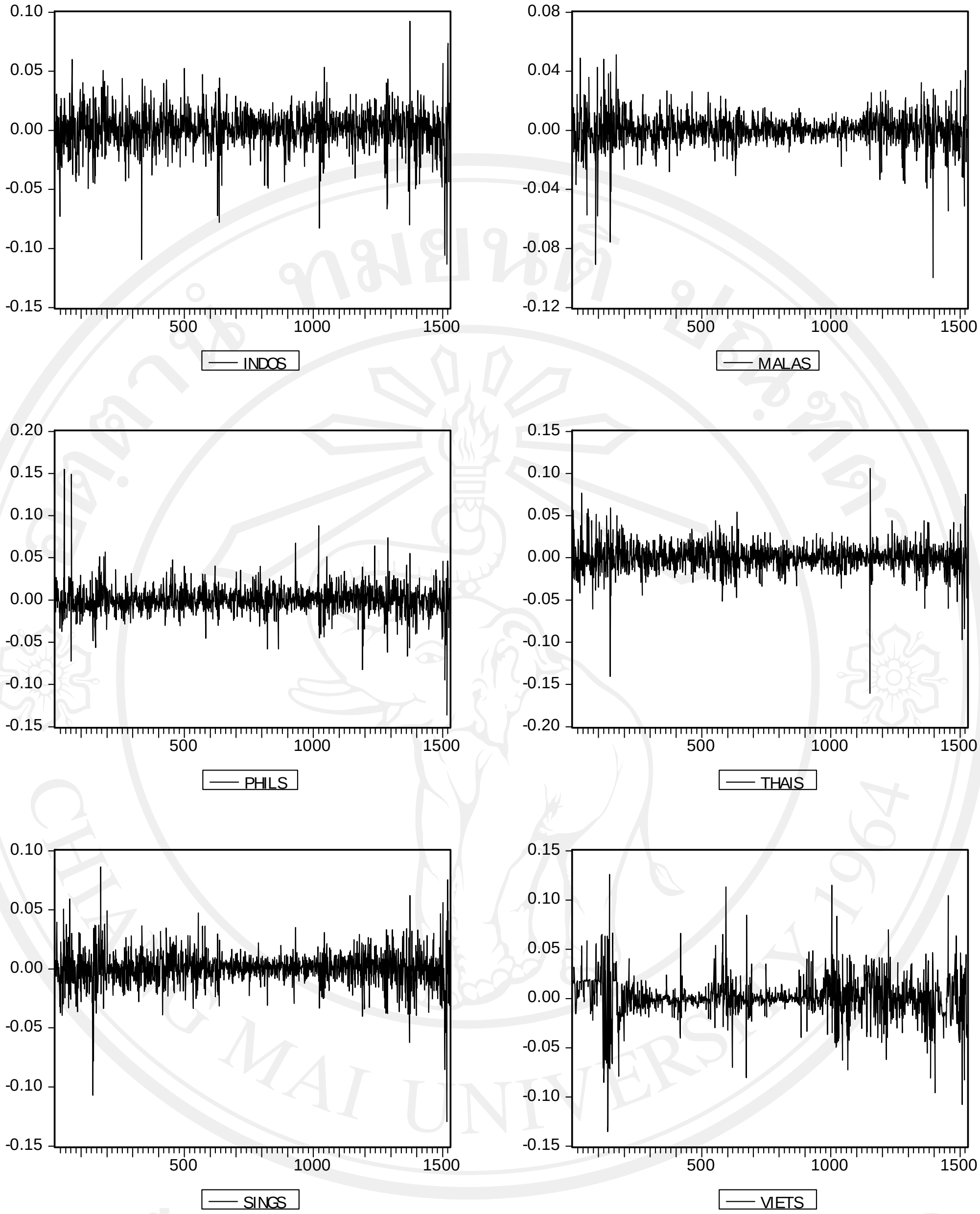

Figure 4.1 Daily Returns for All series