APPENDICES

APPENDIX A

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

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Modelling the stock and bond returns and volatility in South-East Asia

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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 modelling The Philippines financial markets by using VARMA-GARCH is better than VARMA-AGARCH.

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 financial market. They are not investing only in their own country but also in the others countries because they may 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

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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. (1992) 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, The Philippines, Thailand, and Singapore) are tested by using univariate volatility and multivariate volatility.

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.

2.1 GARCH

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

$$h_t = \omega + \sum_{j=1}^{r} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{s} \beta_i h_{t-i} \quad (1)$$

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.

2.2 GJR

To accommodate differential impact on the conditional variance between positive and negative shocks, Glosten et al. (1992) proposed the following specification for h_t:

$$h_t = \omega + \sum_{j=1}^{r}\left(\alpha_j + \gamma_j I(\varepsilon_{t-j})\right)\varepsilon_{t-j}^2 + \sum_{i=1}^{s}\beta_i h_{t-i} \quad (2)$$

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, $\varpi > 0$, $\alpha_1 \geq 0$, $\alpha_1 + \gamma_1 \geq 0$, 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 $\alpha_1 + \gamma_1/2 + \beta_1$.

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:

$$\log h_t = \omega + \sum_{i=1}^{r}\alpha_i\left|\eta_{t-i}\right| + \sum_{i=1}^{r}\gamma_i\eta_{t-i} + \sum_{j=1}^{s}\beta_j \log h_{t-j} \quad (3)$$

In equation (3), $|\eta_{t-i}|$ 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) can allow asymmetric and leverage effect. As EGARCH also uses the logarithm of conditional volatility, there are no restrictions on the parameters in (3). As the standardized shocks have finite moments, the moment conditions of (3) are straightforward.

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

$$E(\log(\alpha_1\eta_t^2 + \beta_1)) < 0 \quad (4)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \quad (5)$$

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).

2.4 VARMA-GARCH

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

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \quad (6)$$

$$\varepsilon_t = D_t\eta_t \quad (7)$$

$$H_t = \omega + \sum_{k=1}^{r} A_k\vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \quad (8)$$

where $H_t = (h_{1t}, ..., h_{mt})'$, $\varpi = (\varpi_1, ..., \varpi_m)'$, $D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t}, ..., \eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2, ..., \varepsilon_{mt}^2)'$, A_k and B_l are $m \times m$ matrices with typical elements α_{ij} and β_{ij}, respectively, for $i,j = 1,\ldots,m$, $I(\eta_t) = diag(I(\eta_{it}))$ 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 $E(\eta_t\eta_t') = \Gamma$.

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

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \quad (9)$$

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

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

From equation (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.

2.6 CCC

If the model given by equation (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:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_i h_{i,t-l} \quad (10)$$

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 (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.

2.7 DCC

Engle (2002) proposed the Dynamic Conditional Correlation (DCC) model. The DCC model allows 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 it is used to estimate the parameters of DCC. The DCC model can be written as follows:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1,\ldots,T \quad (11)$$

$$Q_t = D_t \Gamma_t D_t, \quad (12)$$

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

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \quad (13)$$

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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}' + \phi_2 Q_{t-1} \quad (14)$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\} \quad (15)$$

Where S is the unconditional correlation matrix of the ε, equation (15) is used to standardize the matrix estimated in (14) to satisfy the definition of a correlation matrix.

3. Data and Estimation

3.1 Data

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, The 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 1.

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

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \qquad (16)$$

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.

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

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (17)$$

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 2. The plots of the daily returns for all series are shown in Figure 1. Figure 1 also shows that all returns have a constant mean, but a time-varying variance.

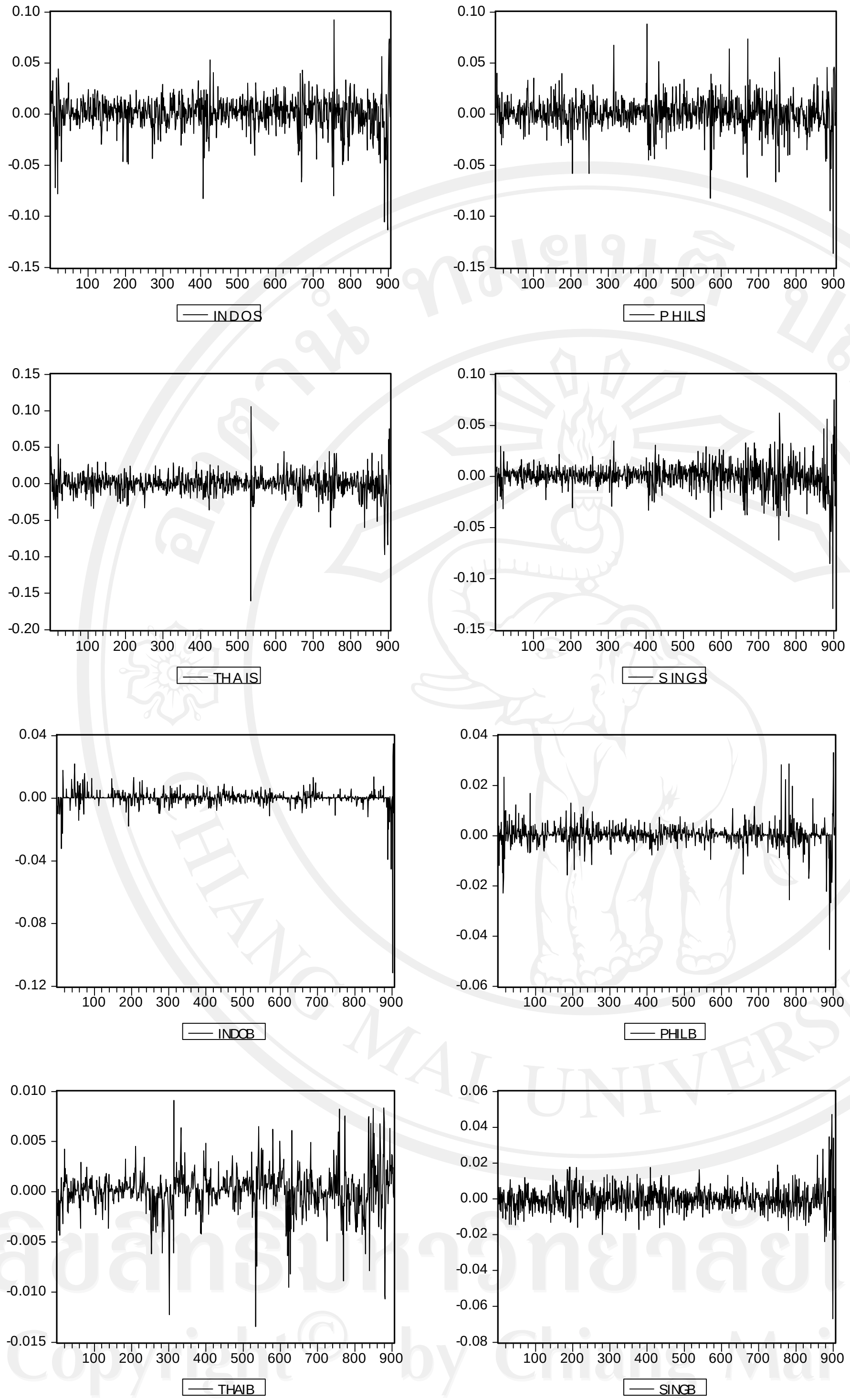
Table 1: Summary of Variable Names

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 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

Figure 1: Daily Returns for All series



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 Table 3a-3c. From the Table 3a-3c, 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.

We can see multivariate volatility with CCC-GARCH (1,1) in Table 4. 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 available upon request. We can summarize the number of volatility spillovers and number of asymmetric effects in VARMA-GARCH and VARMA-AGARCH models as shown in table 5. 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 The 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 The 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 5 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 6. 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. Furthermore, the short-run and long-run persistence of shocks to conditional correlations is statistically significant.

Table 3a: 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 3a: Univariate GARCH (1,1) (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 3b: 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 3b: Univariate GJR (1,1) (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 3c: Univariate EGARCH (1,1)

	Mean equation			Variance equation				AIC	SC
	C	AR(1)	MA(1)	ω	α	γ	β		
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 3c: Univariate EGARCH (1,1) (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 4: 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 5: 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 6: 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.

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5. Conclusion

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. This means that we should adjust portfolios over time to obtain efficient portfolios.

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APPENDIX B

Modelling Stock Volatility in South-East Asia

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Modelling stock volatility in South-East Asia

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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.

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.

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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. (1992) 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.

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.

2.1 GARCH

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

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

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 ($\varepsilon_t < 0$) has the same impact on the conditional variance.

2.2 GJR

To accommodate differential impact on the conditional variance between positive and negative shocks, Glosten et al. (1992) proposed the following specification for h_t:

$$h_t = \omega + \sum_{j=1}^{r} \left(\alpha_j + \gamma_j I(\varepsilon_{t-j}) \right) \varepsilon_{t-j}^2 + \sum_{i=1}^{s} \beta_i h_{t-i} \qquad (2)$$

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

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:

$$\log h_t = \omega + \sum_{i=1}^{r} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{r} \gamma_i \eta_{t-i} + \sum_{j=1}^{s} \beta_j \log h_{t-j} \qquad (3)$$

In equation (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) can allow asymmetric and leverage effect. As EGARCH also uses the logarithm of conditional volatility, there are no restrictions on the parameters in (3). As the standardized shocks have finite moments, the moment conditions of (3) are straightforward.

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

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \qquad (4)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \qquad (5)$$

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).

2.4 VARMA-GARCH

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

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (6)$$

$$\varepsilon_t = D_t \eta_t \qquad (7)$$

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (8)$$

where $H_t = (h_{1t},...,h_{mt})'$, $\varpi = (\varpi_1,...,\varpi_m)'$, $D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)'$, 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 $E(\eta_t \eta_t') = \Gamma$.

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

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (9)$$

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 (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.

2.6 CCC

If the model given by equation (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:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_i h_{i,t-l} \qquad (10)$$

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.

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:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, \ldots, T \qquad (11)$$

$$Q_t = D_t \Gamma_t D_t, \qquad (12)$$

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

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \qquad (13)$$

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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}' + \phi_2 Q_{t-1} \qquad (14)$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\} \qquad (15)$$

where S is the unconditional correlation matrix of the ε, equation (15) is used to standardize the matrix estimated in (14) to satisfy the definition of a correlation matrix.

3. Data and Estimation

3.1 Data

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 1.

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

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \qquad (16)$$

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 1. Figure 1 shows that all returns have constant mean but the time-varying variance.

Table 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

Figure 1: Daily Returns for All series

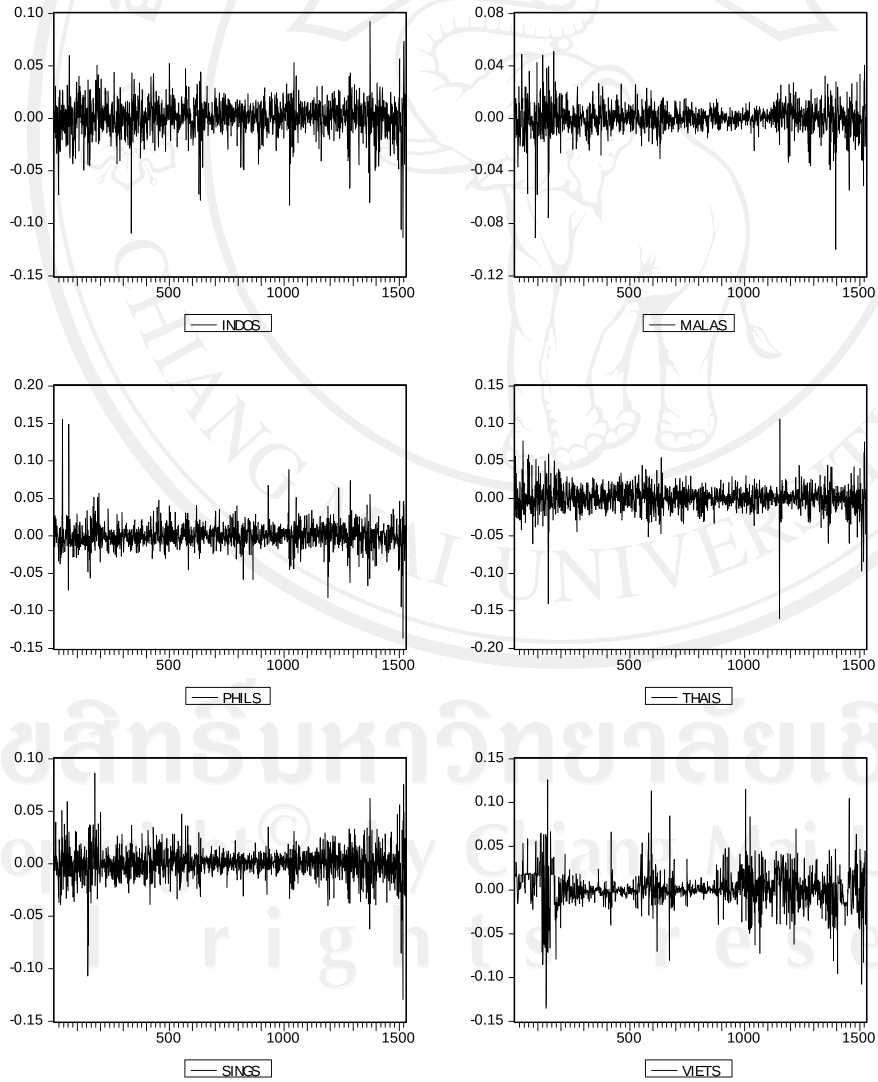

Table 2: ADF Test of a Unit Root in the Returns

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

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

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (17)$$

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 that shows in table 2.

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 table 3a-3c. From the table 3a, 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 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.

VARMA-GARCH and VARMA-AGARCH models are used to determine the linkage 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 available upon request. From those results, we can summarize the number of volatility spillovers and number of asymmetric effects in VARMA-GARCH and VARMA-AGARCH models in table 5. 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.

Table 3a: 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 3a: Univariate GARCH (1,1) (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 3b: 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 3b: Univariate GJR (1,1) (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 3c: 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 3c: Univariate EGARCH (1,1) (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: 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 5: 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 6: 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 robust t-ratios.

The DCC-GARCH (1,1) estimate and t-ratio are shown in table 6. 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.

5. Conclusion

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.

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APPENDIX C

Modelling the Volatility in Bond Returns in South-East Asia

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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.

Keywords: Bond price volatility, univariate models, multivariate models, spillovers, asymmetry, constant conditional correlations, dynamic conditional correlations.

JEL Classifications: C22, C32, G17, G32

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 1 and 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. (1992) 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 2, data are discussed in Section 3, empirical results are analysed in Section 4, and some concluding remarks are presented in Section 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.

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:

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

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 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.

2.2 GJR

In order to accommodate differential impacts on the conditional variance of positive and negative shocks of equal magnitude, Glosten et al. (1992) proposed the following specification for h_t:

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

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 γ_i is positive, such that negative shocks have a higher impact on volatility than do positive shocks of equal magnitude.

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 α_1 $(\alpha_1 + \gamma_1)$. When the conditional shocks, η_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 $\alpha_1 + \gamma_1 / 2 + \beta_1$.

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:

$$\log h_t = \omega + \sum_{i=1}^{r}\alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{r}\gamma_i \eta_{t-i} + \sum_{j=1}^{s}\beta_j \log h_{t-j} \qquad (3)$$

In equation (3), $\left|\eta_{t-i}\right|$ and η_{t-i} capture the size and sign effects, respectively, of the standardized shocks. If γ_i is less than zero, positive shocks will have a smaller effect on volatility than will negative shocks of equal magnitude. Moreover, (3) can allow for asymmetric and leverage effects. As EGARCH uses the logarithm of conditional volatility, there are no restrictions on the parameters in (3). As the standardized shocks are assumed to have finite moments, the moment conditions of (3) are entirely straightforward.

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

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \qquad (4)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \tag{5}$$

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).

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:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{6}$$

$$\varepsilon_t = D_t \eta_t \tag{7}$$

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{8}$$

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

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

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{r} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \tag{9}$$

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 (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.

2.6 CCC

If the model given by equation (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

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_i h_{i,t-l} \tag{10}$$

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 (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.

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:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1,\dots,T, \tag{11}$$

$$Q_t = D_t \Gamma_t D_t, \tag{12}$$

where D_t = diag(h_{1t},…,h_{mt}) 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:

$$h_{it} = \omega_i + \sum_{k=1}^{r} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{s} \beta_{i,l} h_{i,t-l} \tag{13}$$

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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}' + \phi_2 Q_{t-1} \tag{14}$$

$$\Gamma_t = \left\{ (diag(Q_t))^{-1/2} \right\} Q_t \left\{ (diag(Q_t))^{-1/2} \right\}, \tag{15}$$

where S is the unconditional correlation matrix of the returns shocks, and equation (15) is used to standardize the matrix estimated in (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).

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 1.

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

$$R_{i,t} = \log(P_{i,t} / P_{i,t-1}) \tag{16}$$

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 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:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{17}$$

The null hypothesis is $\theta = 0$ which, if rejected, means that the series y_t is stationary. The estimated values of θ and the t-statistics of all the returns are significantly less than zero at the 1% level, as given in Table 2, which shows that all series are stationary.

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 3a-3c. From Table 3a, 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, 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.

For multivariate volatility, the results for CCC in Table 4 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 5-6, for which the number of volatility spillovers and asymmetric effects are summarized in Table 7. The results show that volatility spillovers are evident in both models. Table 5 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 6, 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-AGRACH models. The rolling window size is set at 1,000 for all pair of assets, and the results are shown in Figures 4 and 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 8. The value of $\hat{\phi}_2$ is significantly different from zero, 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.

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.

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Table 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 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 3a: 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**		

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 3b: 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**		

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 3c: 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**		

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 4: 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: Estimates for VARMA-GARCH(1,1)

Returns	ω	α_{indob}	α_{philb}	α_{singb}	α_{thaib}	β_{indob}	β_{philb}	β_{singb}	β_{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**

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 6: Estimates for VARMA-AGARCH(1,1)

Returns	ω	α_{indob}	α_{philb}	α_{singb}	α_{thaib}	γ	β_{indob}	β_{philb}	β_{singb}	β_{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**

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 7: 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 8: 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 1: Market Size of Bond Markets (USD Billions)

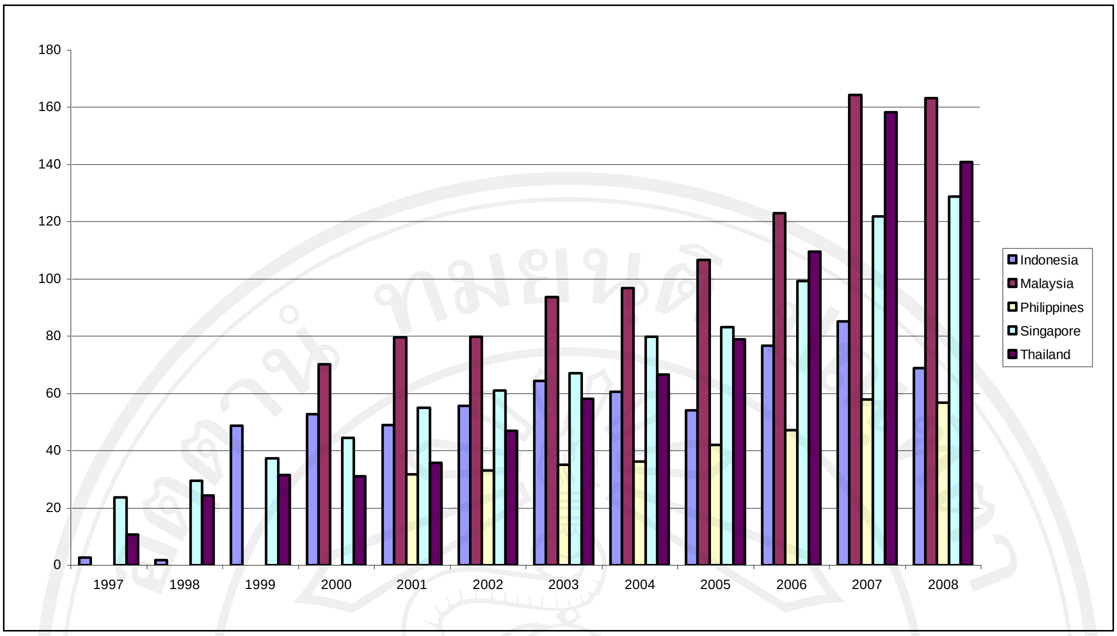


Figure 2: Trade Volume of Bond Markets (USD Billions)

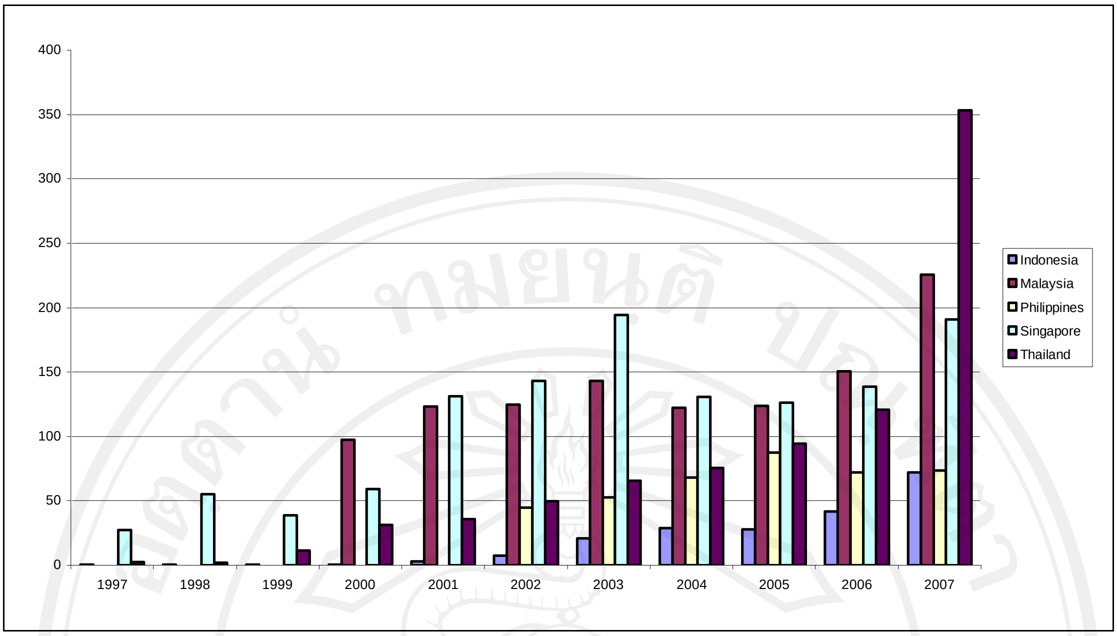


Figure 3: Daily Returns for All Series

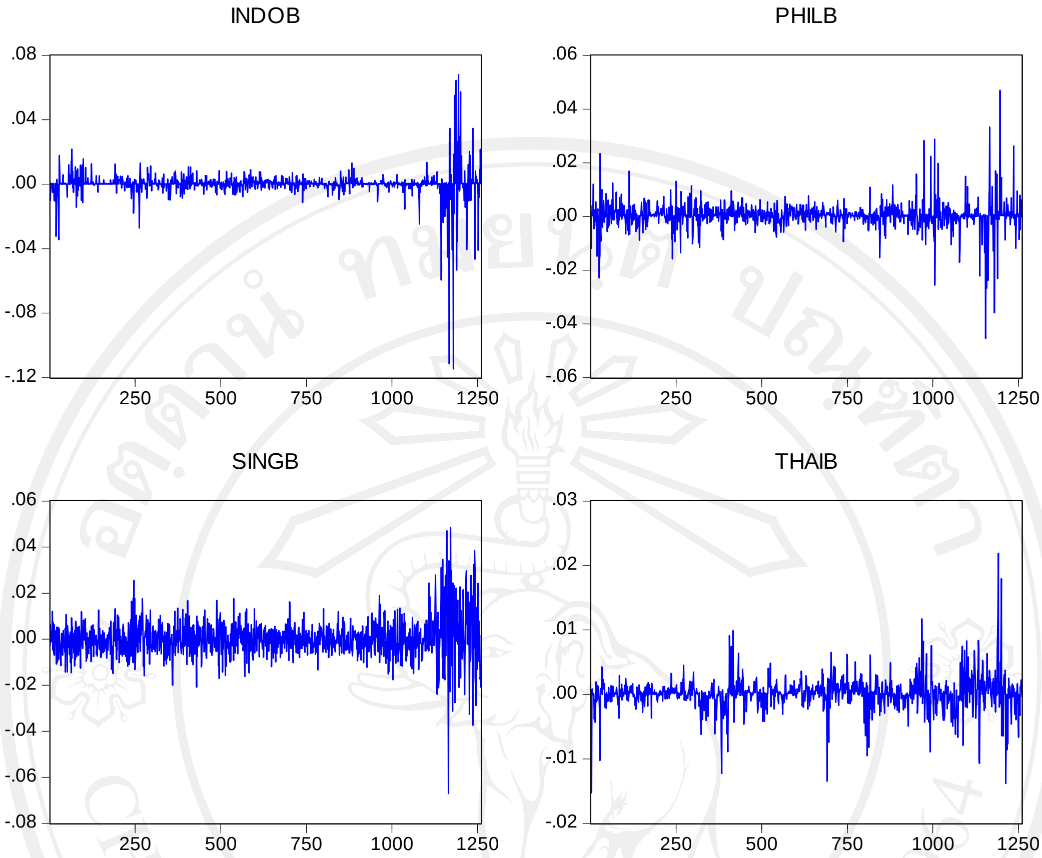


Figure 4: Dynamic Paths of Conditional Correlations of Pairs of Assets for VARMA-GARCH

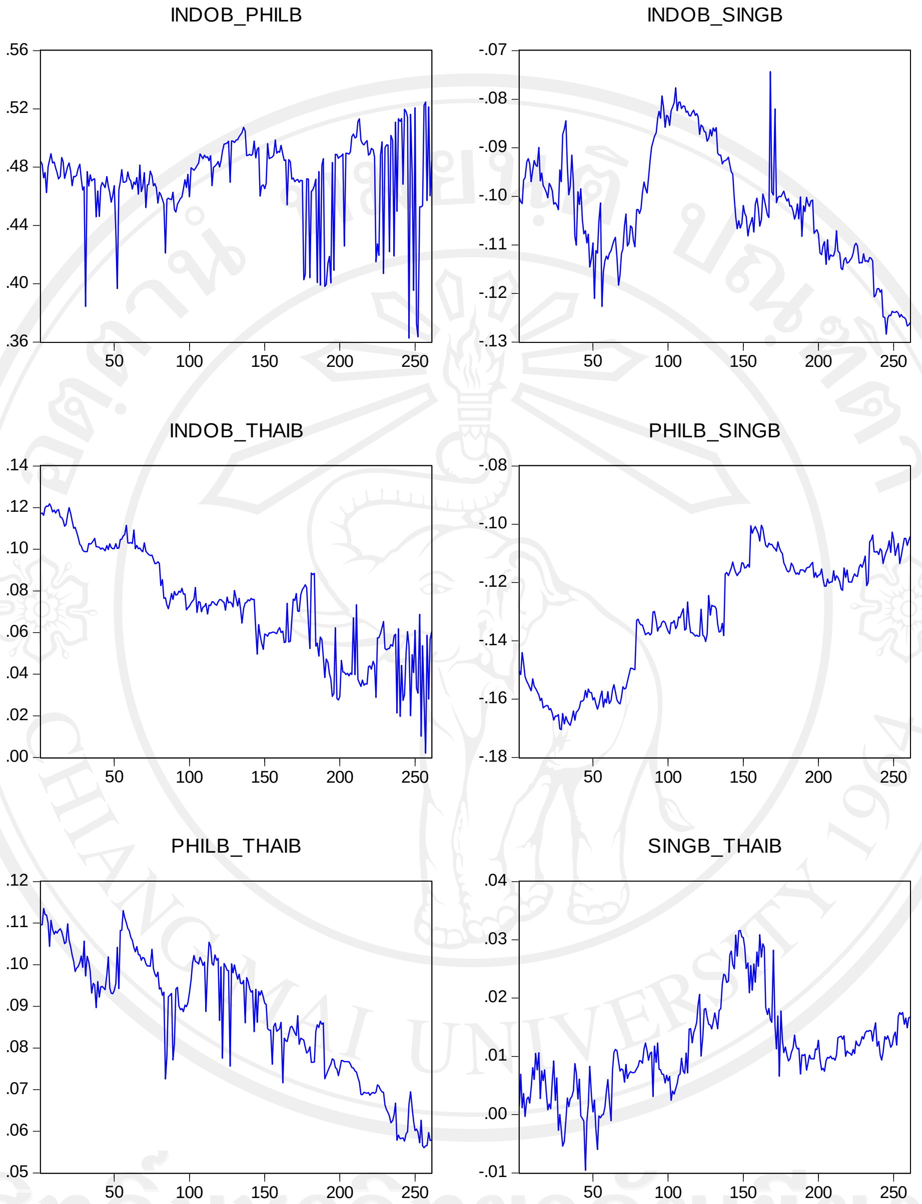
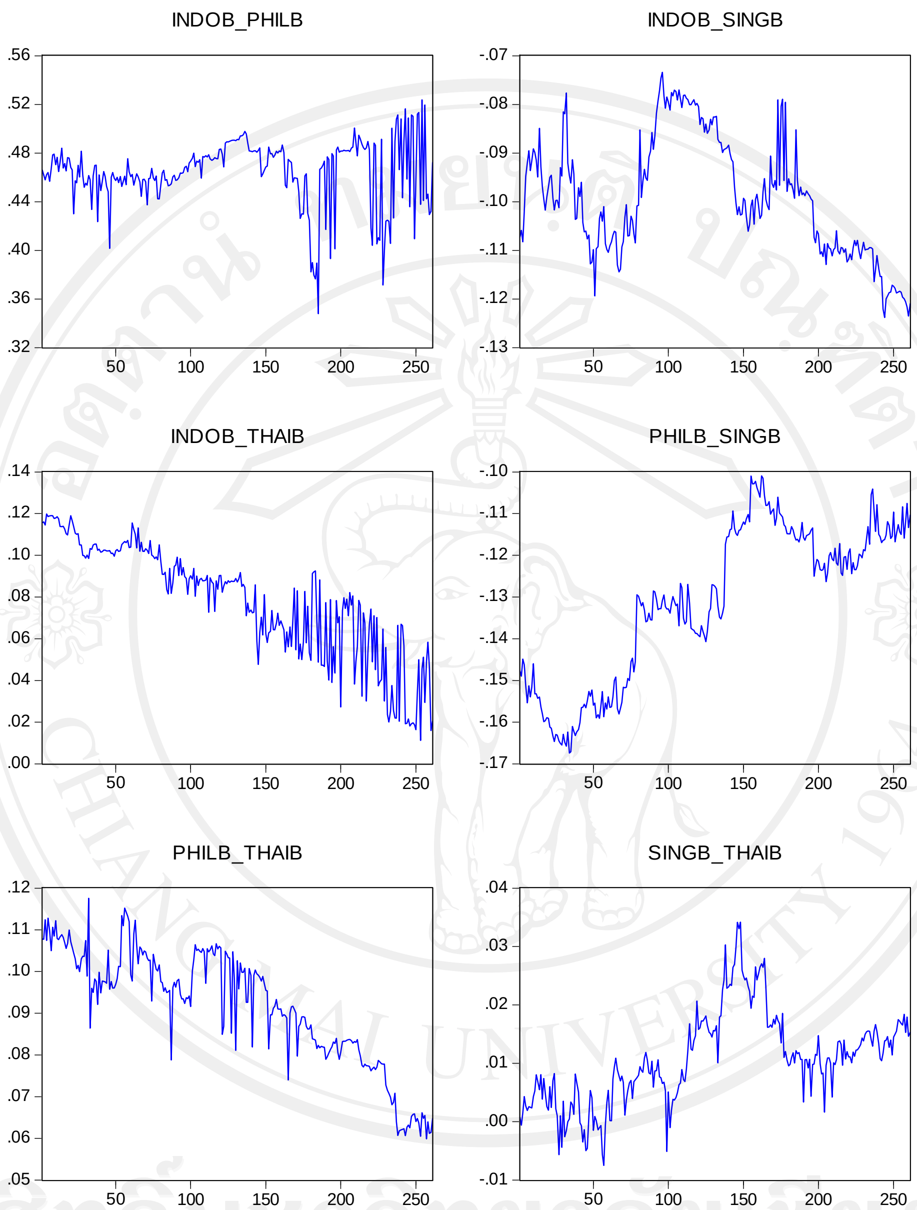


Figure 5: Dynamic Paths of Conditional Correlations of Pairs of Assets for VARMA-AGARCH



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