# Chapter 4

## Index of Volatility for ASEAN

This chapter construct index of volatility for ASEAN by using three countries that have the highest level of volatility, namely, Indonesia, the Philippines, and Thailand because ASEAN countries do not have a volatility index that is a benchmark for stock market volatility. Index of volatility constructed by two ways are single index model consisting of univariate volatility model (ARCH, GARCH, GJR, EGARCH, and Riskmetrics$^{TM}$) of portfolio return and a portfolio model which use multivariate volatility model (CCC, VARMA-GARCH, VARMA-AGARCH, and DCC) to forecast variance and covariance to compute portfolio risk. Then compare various models indexes of volatility by using the predictive power of Value-at-Risk. Finally, this chapter finds out correlations of Value-at-Risk forecast calculated from various models. This chapter is a revised version from the original paper of Kunsuda Ninanussornkul, Chia-Lin Chang, Michael McAleer, and Songsak Sriboonchitta; presented at the Sixth International Conference on Business and Information 2009, Kuala Lumpur, Malaysia in Appendix B in 5 – 6 January 2009.

**Abstract**

Volatility forecasting is an important task in financial markets as the results become a key factor to many investment decisions and portfolio creations because investors and portfolio managers want to know certain levels of risk. Moreover, volatility is an important ingredient to calculate Value-at-Risk (VaR). Therefore, financial institutions would like to know about volatility because if a financial institution's VaR forecasts are violated more than can reasonably be expected, given the confidence level, the financial institution will hold a higher level of capital. However, ASEAN countries do not have a volatility index that is a benchmark for stock market volatility. Therefore, this paper constructs an index of volatility for ASEAN by using a single index model, or the covariance matrix of the portfolio to forecast the variance of a portfolio. This paper use three countries that have the highest level of volatility—namely, Indonesia, the Philippines, and Thailand—and estimates volatility by using univariate and multivariate conditional volatility models. A comparison of the index of volatility using the predictive power of Value-at-Risk will be made to determine the practical usefulness of these indices.

**Keywords:** Index of volatility, single index, portfolio model, Value-at-Risk

## 4.1 Introduction

Volatility forecasting has held the attention of academics and practitioners over the last two decades. Academics are interested in studying temporal patterns in expected returns and risk. For practitioners, volatility has an importance in investment, security valuation, and risk management. Volatility becomes a key factor to many investment decisions and portfolio creations because investors and portfolio managers want to be aware of certain levels of risk. (see Fleming, J., et al. (1995) and Poon, S. and Granger, C.W.J. (2003))

In addition, volatility is important ingredient to calculate Value-at-Risk (VaR). Therefore, financial institutions would like to know about volatility because if a financial institution's VaR forecasts are violated more than are reasonably to be expected, given the confidence level, the financial institution will hold a higher level of capital. (McAleer, M. (2008a))

In 1993, the Chicago Board Options Exchange (CBOE) introduced the CBOE volatility index, VIX, and it quickly became the benchmark for stock market volatility. (See, Jiang, G.J. and Tian, Y.S. (2005)) However, ASEAN does not have a volatility index to serve as the benchmark for stock market volatility. Most studies in the associated literature are about construction and prediction of the volatility index. (See Skiadopoulos, G.S. (2004) Moraux, F., et al. (1999) and Fernades, M. and Medeiros, M.C.)

This paper would like to construct an index of volatility by using conditional volatility models by: (1) fitting a univariate volatility model to the portfolio returns (hereafter called the single index model (see McAleer, M. and da Veiga, B. (2008a, 2008b)); and (2) using a multivariate volatility model to forecast the conditional variance of each asset in the portfolio, as well as the conditional correlations between all asset pairs in order to calculate the forecasted portfolio variance (hereafter called the portfolio model) for ASEAN by using the data of the three countries in ASEAN which have the highest volatilities—namely, Indonesia, the Philippines, and Thailand. Then, we compare the models of the index of volatility by using predictive power of Value-at-Risk.

The organization of the paper is as follows: section 4.2 presents the index of volatility, and section 4.3 shows the data and estimation. Empirical results, Value-at-Risk, and conclusion are in sections 4.4, 4.5, and 4.6, respectively.

## 4.2 Index of Volatility

This paper use stock price indices of Indonesia, the Philippines, and Thailand. Then we compute returns of each country follow:

$$R_{i,t} = 100 \times \log(P_{i,t} / P_{i,t-1}) \tag{4.1}$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing stock price index of country i (i = 1, 2, 3) at days t and t-1, Then we construct index of volatility with two models follows:



### 4.2.1 Single index model

This paper constructs the single index model with the following steps:

(1) Compute portfolio return by assuming that the portfolio weights are equal and constant over time, but these assumptions can be relaxed. Exchange rate risk is controlled by converting all prices to a common currency, namely the US Dollar.

(2) Estimate univariate volatility of portfolio return from first step by mean equation which has constant term and autoregressive term (AR(1)) in all models. The univariate volatility is the index of volatility. Moreover, this paper computes Riskmetrics™ by using the exponentially weighted moving average model (EWMA) of portfolio return.

**Univariate Volatility**

**ARCH**

Engle, R.F. (1982) proposed the Autoregressive Conditional Heteroskedasticity of order p, or ARCH(p), follows:

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 \tag{4.2}$$

where $\omega > 0$ *and* $\alpha_j \geq 0$

**GARCH**

Bollerslev, T. (1986) generalized ARCH(p) to the GARCH(p,q), model as follows:

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \tag{4.3}$$

where $\omega > 0$, $\alpha_j \geq 0$ for $j$ = 1,…,$p$, and $\beta_i \geq 0$ for $i$ = 1,…,$q$, are sufficient to ensure that the conditional variance $h_t > 0$.

The model also assumes positive shock ( $\varepsilon_t > 0$ ) and negative shock ( $\varepsilon_t < 0$ ) of equal magnitude have the same impact on the conditional variance.

**GJR**

Glosten, L.R., et al. (1993) accommodate differential impacts on the conditional variance of positive and negative shocks of equal magnitude. The GJR(p,q) model is given by:

$$h_t = \omega + \sum_{j=1}^{p} \left( \alpha_j + \gamma_j I(\varepsilon_{t-j}) \right) \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad (4.4)$$

where the indicator variable, $I(\varepsilon_t)$, is defined as: $I(\varepsilon_t) = \begin{cases} 1, \varepsilon_t \le 0 \\ 0, \varepsilon_t > 0 \end{cases}$. If $p = q = 1$, $\omega > 0$, $\alpha_1 \ge 0$, $\alpha_1 + \gamma_1 \ge 0$, and $\beta_1 \ge 0$ 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, $\eta_t$, follow a symmetric distribution, the short run persistence is $\alpha_1 + \gamma_1 / 2$, and the contribution of shocks to long run persistence is $\alpha_1 + \gamma_1 / 2 + \beta_1$.

**EGARCH**

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

$$\log h_t = \omega + \sum_{j=1}^{p} \alpha_j \left| \eta_{t-j} \right| + \sum_{j=1}^{p} \gamma_j \eta_{t-j} \sum_{i=1}^{q} \beta_i \log h_{t-i} \qquad (4.5)$$

In equation (4.5), $|\eta_{t-j}|$ and $\eta_{t-j}$ capture the size and sign effects, respectively, of the standardized shocks. EGARCH in (4.5) uses the standardized residuals. As EGARCH uses the logarithm of conditional volatility, there are no restrictions on the parameters in (4.5). As the standardized shocks have finite moments, the moment conditions of (4.5) are entirely straightforward.

Lee, S.W. and Hansen, B.E. (1994) derived the log-moment condition for GARCH (1,1) as

$$E(\log(\alpha_1\eta_t^2 + \beta_1)) < 0 \tag{4.6}$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \tag{4.7}$$

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).



**Riskmetrics™**

Riskmetrics™ (1996) developed a model which estimates the conditional variances and covariances based on the exponentially weighted moving average (EWMA) method, which is, in effect, a restricted version of the ARCH($\infty$)

model. This approach forecasts the conditional variance at time $t$ as a linear combination of lagged conditional variance and the squared unconditional shock at time $t$-$1$. The Riskmetrics™ model estimate the conditional variances follows:

$$h_t = \lambda h_{t-1} + (1-\lambda)\varepsilon_{t-1}^2 \tag{4.8}$$

where $\lambda$ is a decay parameter. Riskmetrics™ (1996) suggests that $\lambda$ should be set at 0.94 for purposes of analyzing daily data.

**4.2.2 Portfolio model**

This paper constructs a portfolio model to follow these steps:

(1) Estimate multivariate volatility of three countries, namely, Indonesia, the Philippines, and Thailand, by mean equation, which has constant term and autoregressive term (AR(1)) in all models. Then compute variance and covariance matrix.

(2) Compute index of volatility by assuming the portfolio weights are equal and constant over time. This paper considers three countries so that we have the three conditional variances, and three covariances are estimated, it follows:

$$IVol_t = \lambda_1^2 h_{1t} + \lambda_2^2 h_{2t} + \lambda_3^2 h_{3t} + 2\lambda_1\lambda_2 h_{12t} + 2\lambda_1\lambda_3 h_{13t} + 2\lambda_2\lambda_3 h_{23t} \tag{4.9}$$

where $IVol_t$ is index of volatility, $h_{it}$ is conditional variances of country $i$ ($i$=1,2,3), $h_{ijt}$ is covariance between country $i$ and country $j$ ($i,j$ = 1,2,3), and $\lambda_1 = \lambda_2 = \lambda_3 = \frac{1}{3}$.

The number of covariance increases dramatically with m, the number of assets in the portfolio. Thus, for $m$ = 2, 3, 4, 5, 10, 20, the number of covariance is 1, 3, 6, 10, 45, and 190, respectively. This increases the computation burden significantly. (see details in McAleer, M. (2008a))

**Multivariate volatility**

**VARMA-GARCH**

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

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{4.10}$$

$$\varepsilon_t = D_t \eta_t \tag{4.11}$$

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \tag{4.12}$$

where $H_t = (h_{1t}, ..., h_{mt})'$, $\omega = (\omega_1, ..., \omega_m)'$, $D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t}, ..., \eta_{mt})'$, $\vec{\varepsilon}_t = (\varepsilon_{1t}^2, ..., \varepsilon_{mt}^2)'$, $A_k$ and $B_l$ are $m \times m$ matrices with typical elements $\alpha_{ij}$ and $\beta_{ij}$, respectively, for $i,j$=1,…,$m$, 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 $E(\eta_t \eta_t') = \Gamma$.

**VARMA-AGARCH**

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

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{p} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \tag{4.13}$$

where $C_k$ are $m \times m$ matrices for $k$ = 1,…,$p$ and I($\eta_t$)=diag(I($\eta_{it}$)) is an $m \times m$ matrix, so that $I = \begin{cases} 0, \varepsilon_{k,t} > 0 \\ 1, \varepsilon_{k,t} \leq 0 \end{cases}$. VARMA-AGARCH reduces to VARMA-GARCH when $C_k$ =0 for all $k$.

**CCC**

If the model given by equation (4.13) 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:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_i h_{i,t-l} \tag{4.14}$$

Which is the constant conditional correlation (CCC) model of Bollerslev, T. (1990), for which the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$. As given in equation (4.14), 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.

**DCC**

Engle, R.F. (2002) proposed the Dynamic Conditional Correlation (DCC) model. The DCC model can be written as follows:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, \ldots, T \tag{4.15}$$

$$Q_t = D_t \Gamma_t D_t, \tag{4.16}$$

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

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{i,l} h_{i,t-l} \tag{4.17}$$

When the univarate 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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta'_{t-1} + \phi_2 Q_{t-1} \tag{4.18}$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\}, \tag{4.19}$$

where S is the unconditional correlation matrix of the returns shocks, and equation (4.19) is used to standardize the matrix estimated in (4.18) to satisfy the definition of a correlation matrix. For details regarding the regularity conditional and statistical properties of DCC and the more general GARCC model, see McAleer, M., et at. (2008).

## 4.3 Data and Estimation

### 4.3.1 Data

The data used in the paper are the daily closing stock price indices of Indonesia, the Philippines, and Thailand. All the data is obtained from the DataStream and the sample ranges from 5/1/1988 up to 13/3/2009 with 4,916 observations.

The summaries of variables are in Table 4.1. Two characteristics of the data, namely normality and stationarity, will be investigated before estimating univariate and multivariate analyses. Normality is an important issue in estimation since it is typically assumed in the maximum likelihood estimation (MLE) method; otherwise, the quasi-MLE (QMLE) method should be used. The normality of the variables and the descriptive statistics for the returns of the three indices are given in Table 4.2. All series have similar means and medians (which are close to zero), minima that range between -43.081 and -10.942, and maxima which vary between 18.100 and 44.515. The three standard deviations vary between 1.759 and 2.786. The skewness is similar for all series, and the kurtosis range between 12.517 and 43.254. These are high degrees of kurtosis so it would seem to indicate the existence of extreme observations. The Jarque-Bera test strongly rejects the null hypothesis of normally distributed returns.

Stationarity is an important characteristic for time series data. If data is nonstationary, differencing data will be necessary before estimation, because if no differencing of data is done, the result will be spurious regression. To test stationarity of data, this paper uses the Augmented Dicky Fuller (ADF) test. The test is given as follows:

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{4.20}$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{4.21}$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{4.22}$$

where equation (4.20) has no intercept or trend, equation (4.21) has intercept but no trend, and equation (4.22) has intercept and trend. The null hypothesis in equation (4.20), (4.21) and (4.22) is $\theta = 0$, which means that $y_t$ is nonstationary (Dickey and Fuller, 1979). However, the ADF test accommodates serial correlation by explicitly modeling the structure of serial correlation, but not heteroscedasticity, while the Phillips-Perron (PP) tests accommodates both serial correlation and heteroscedasticity using non-parametric techniques. The PP test has also been shown to have higher power in finite samples than the ADF test (Phillips and Perron, 1988).

The PP test estimates as follows:

$$\Delta y_t = \theta y_{t-1} + x_t' \delta + \varepsilon_t \tag{4.23}$$

the test is evaluated using a modified t-ratio of the form:

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{1/2} - \frac{T\left(f_0 - \gamma_0\right)\left(se(\hat{\alpha})\right)}{2 f_0^{1/2} s}$$

where $\hat{\alpha}$ is the estimate, $t_\alpha$ is the t-ratio of $\hat{\alpha}$, $se(\hat{\alpha})$ is the standard error of $\hat{\alpha}$, and $s$ is the standard error of the regression. In addition, $\gamma_0$ is a consistent estimate of the error variance in (4.23). The remaining $f_0$ is an estimator of the residual spectrum at frequency zero. The PP test is known as the non-augmented Dickey-Fuller test. The results of test stationary by using ADF test and PP test for ASEAN in Table 4.3 show that all the returns are stationary at the 1% level.

### 4.3.2 Estimation

The parameters in models (4.2), (4.3), (4.4), (4.5), (4.12), (4.13), (4.14), and (4.17) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, as follows:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{2} \sum_{t=1}^{n} (\log|Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t) \tag{4.24}$$

where $\theta$ denotes the vector of parameters to be estimated in the conditional log-likelihood function, $|Q_t|$ denotes the determinant of $Q_t$, the conditional covariance matrix. When $\eta_t$ does not follow a joint normal distribution, equation (4.24) is defined as the Quasi-MLE (QMLE).

## 4.4 Empirical Results

This paper uses ARCH(1), GARCH(1,1), GJR(1,1), and EGARCH(1,1) models to estimate the single index model, and we assume that mean equations of all models have autoregressive terms (AR(1)). The results are shown in Table 4.4. The two entries for each parameter are the parameter estimate and Bollerslev-Wooldridge (1992) robust t-ratios. The variables in mean equations are significant differences from zero, except constant terms in the ARCH(1) model. In variance equations, all variables are significant except asymmetric terms in both GJR(1,1) and EGARCH(1,1). Therefore, ASEAN volatility has no asymmetry and also leverage from EGARCH(1,1).

The portfolio model estimated by using multivariate volatility is given in Tables 4.5 to 4.8. The multivariate volatilities used in this paper are CCC, DCC, VARMA-GARCH, and VARMA-AGARCH. The results of VARMA-GARCH for ASEAN in Table 4.5 show volatility spillover from THA to PHI and negative effect of shock or news from PHI to THA. The results VARMA-AGARCH for ASEAN are given in Table 4.6. Asymmetric effects are not significant in any of the countries.

Conditional correlations between the standardized residuals, of IND and PHI for the CCC, VARMA-GARCH, and VARMA-AGARCH in Table 4.7 are identical at 0.237. Conditional correlations between the standardized residuals, of IND and THA for the three models above are identical at 0.265. PHI and THA have conditional correlations between the standardized residuals, for the three models, which are identical at 0.227. In Table 4.8, we can see that estimated coefficient is significantly different from zero, which means that the conditional correlations of the overall returns are dynamic.

## 4.5 Value-at-Risk

Value-at-Risk (VaR) needs to be provided to the appropriate regulatory authority at the beginning of the day, and is then compared with the actual returns at the end of the day. (see McAleer, M. (2008a))

For the purposes of the Basel II Accord penalty structure for violations arising from excessive risk taking, a violation is penalized according to its cumulative frequency of occurrence in 250 working days, which is shown in Table 4.9.

A violation occurs when $VaR_t$ > negative returns at time t. Suppose that interest lies in modeling the random variable $Y_t$, which can be decomposed as follows (see McAleer, M. and da Veiga, B. (2008a):

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (4.25)$$

This decomposition suggests that $Y_t$ is comprised of a predictable component, $E(Y_t \mid F_{t-1})$, which is the conditional mean, and a random component, $\varepsilon_t$. The variability of $Y_t$, and hence its distribution, is determined entirely by the variability of $\varepsilon_t$. If it is assumed that $\varepsilon_t$ follows a distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t) \qquad (4.26)$$

where $\mu_t$ and $\sigma_t$ are the unconditional mean and standard deviation of $\varepsilon_t$, respectively, the VaR threshold for $Y_t$ can be calculated as:

$$VaR_t = E(Y_t \mid F_{t-1}) - \alpha\sigma_t$$

where $\alpha$ is the critical value from the distribution of $\varepsilon_t$ to obtain the appropriate confidence level. Alternatively, $\sigma_t$ can be replaced by alternative estimates of the conditional variance to obtain an appropriate VaR (see Section 4.2).

The Basel II encourages the optimization problem with the number of violations and forecasts of risk as endogenous choice variables, which are as follows:

$$\underset{\{k, VaR_t\}}{Minimize} \quad DCC_t = \max\left\{-(3+k)\overline{VaR}_{60}, -VaR_{t-1}\right\} \tag{4.27}$$

where DCC is daily capital charges, $k$ is a violation penalty ($0 \le k \le 1$) (see Table 4.9), $\overline{VaR}_{60}$ is mean VaR over the previous 60 working days, and $VAR_t$ is Value-at-Risk for day $t$.

In order to simplify the analysis, we assumed that the portfolio returns are equal weights and constant over time. $E(Y_t \mid F_{t-1})$ is expected returns for all models, and $\alpha$ is the critical value from the distribution of $\varepsilon_t$ to obtain the appropriate confidence level of 1%.

Figures 4.1– 4.2 show the VaR forecasts and realized returns of each single index model and portfolio model for ASEAN, respectively.

Table 4.10 shows the mean daily capital charge for ASEAN. In the single index models, ARCH(1) model has the highest value at 22.422%, while EGARCH(1,1) model has the lowest value at 20.550%. ARCH(1) model has the least number of violations at 37 , and the highest mean of absolute deviation of the violation from the VaR forecast at 2.149%. Riskmetrics$^{TM}$ has the greatest number of violations at 49. GJR(1,1) and EGARCH(1,1) have the lowest mean of absolute deviation of the violation from the VaR forecast at 1.173%.

In the portfolio models, the mean daily capital charge of the VARMA-AGARCH model has the lowest value at 20.417%, while the DCC model has the highest value at 21.651%. The DCC model has the highest number of violations at 45 times for all observations, while VARMA-GARCH and VARMA-AGARCH have the lowest number of violations at 42 times for all observations. Moreover, VARMA-GARCH and VARMA-AGARCH have the highest mean of absolute deviation of the violation from the VaR forecast at 3.760%, while CCC model has the lowest at 2.918%.

Moreover, the correlations of Value-at-Risk forecast calculated from various models for ASEAN is shown in Table 4.11. It shows that the correlations between the GARCH (1,1) model and the GJR(1,1) model are high correlated because in single index model has no asymmetric effect and the correlations between the VARMA-GARCH model and the VARMA-AGARCH model are also high correlated because asymmetric effects are not significant.

## 4.6 Conclusion

Knowing more about volatility would help investors, risk managers, and financial institutions. Therefore, volatility forecasting is an important task in the financial world. In 1993, CBOE constructed the benchmark for stock market volatility: the CBOE volatility index, VIX. However, ASEAN does not have a volatility index, so this paper constructs an index of volatility to serve as the benchmark for stock market volatility.

Conditional volatility models construct an index of volatility by: (1) fitting a univariate volatility model to the portfolio returns (see McAleer, M. and da Veiga, B.(2008a,2008b)), and (2) using a multivariate volatility model to forecast the conditional variance and the conditional correlations, in order to calculate the forecasted portfolio variance for ASEAN by using the three most volatile stock markets—namely, Indonesia, the Philippines, and Thailand. Finally, we compared the index of volatility by using the predictive power of Value-at-Risk.

The univariate volatility models used in this paper are ARCH(1), GARCH(1,1), GJR(1,1), and EGARCH(1,1), which means the equations have constant terms and autoregressive terms (AR(1)), and we also compute Riskmetrics$^{TM}$. For the multivariate volatility model, we used CCC, DCC, VARMA-GARCH, VARMA-AGARCH, which means the equations have constant terms and autoregressive terms (AR(1)), the same as the univariate volatility model.

If we consider the mean daily capital charge, the results show that the EGARCH(1,1) model dominates the other models in the single index model, while in portfolio model the VARMA-AGARCH model dominates the other models. However, overall the VARMA-AGARCH model dominates the other models in both the single index model and the portfolio model because the mean daily capital charge is lowest. Meanwhile, ARCH(1) has the highest mean daily capital charge, and it also has the minimum number of violations for all observations.

Moreover, the correlations of Value-at-Risk forecast for ASEAN calculated from the GARCH (1,1) model and the GJR(1,1) model and from the VARMA-GARCH model and the VARMA-AGARCH model are high correlated because asymmetric effects are not significant.

Table 4.1 Summary of Variable Names

| Variables | Index Names |
|---|---|
| IND | Jakarta Stock Exchange Index |
| PHI | Philippine SE Comp. Index |
| THA | Stock Exchange of Thailand Index |
| PORT | Portfolio of three countries above |

Table 4.2 Descriptive Statistic for Returns

| Statistics | IND | PHI | THA |
|---|---|---|---|
| Mean | 0.017 | 0.003 | -0.017 |
| Median | 0.041 | 0.012 | -0.022 |
| Maximum | 44.515 | 21.972 | 18.100 |
| Minimum | -43.081 | -10.942 | -18.085 |
| Std. Dev. | 2.786 | 1.759 | 2.113 |
| Skewness | 0.080 | 0.512 | 0.400 |
| Kurtosis | 43.254 | 13.502 | 12.517 |
| Jarque-Bera | 331912.0 | 22805.55 | 18682.52 |

Table 4.3 Unit Root Test of Returns for ASEAN

| Variables | Trend and intercept | Intercept | None |
|---|---|---|---|
| Augmented Dickey-Fuller test | | | |
| IND | **-24.237** | **-24.216** | **-24.215** |
| PHI | **-59.312** | **-59.304** | **-59.309** |
| THA | **-60.163** | **-60.160** | **-60.163** |
| PORT | **-54.150** | **-54.137** | **-54.142** |
| Phillips-Perron Test | | | |
| IND | **-58.192** | **-58.342** | **-58.346** |
| PHI | **-58.979** | **-58.989** | **-58.996** |
| THA | **-60.147** | **-60.126** | **-60.129** |
| PORT | **-54.058** | **-54.226** | **-54.232** |

Note: Entries in bold are significant at the 99% level.

Table 4.4 Single Index Model for ASEAN

| Model | Mean equation | | Variance equation | | | |
|---|---|---|---|---|---|---|
| | C | AR(1) | ϖ | α | γ | β |
| ARCH(1) | -0.001 | **0.180** | **1.455** | **0.484** | | |
| | -0.045 | **4.125** | **15.404** | **7.906** | | |
| GARCH(1,1) | **0.054** | **0.231** | **0.034** | **0.141** | | **0.855** |
| | **2.788** | **12.950** | **4.986** | **8.517** | | **62.439** |
| GJR(1,1) | **0.038** | **0.231** | **0.039** | **0.119** | 0.048 | **0.850** |
| | **2.037** | **12.919** | **5.369** | **4.182** | 1.390 | **56.046** |
| EGARCH(1,1) | **0.042** | **0.224** | **-0.190** | **0.272** | -0.021 | **0.977** |
| | **2.148** | **12.577** | **-7.998** | **7.967** | -0.976 | **195.250** |

Notes: (1) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.

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

Table 4.5 Portfolio Models for ASEAN: VARMA-GARCH

| Countries | $\omega$ | $\alpha_{IND}$ | $\beta_{IND}$ | $\alpha_{PHI}$ | $\beta_{PHI}$ | $\alpha_{THA}$ | $\beta_{THA}$ |
|---|---|---|---|---|---|---|---|
| IND | -0.049 | **0.288** | **0.622** | 0.033 | 0.689 | -0.008 | 0.191 |
| | -1.122 | **5.656** | **8.514** | 0.730 | 1.502 | -0.228 | 1.082 |
| PHI | **0.199** | 0.022 | 0.130 | **0.169** | **0.536** | 0.016 | **0.690** |
| | **2.514** | 0.574 | 0.780 | **5.420** | **3.883** | 0.610 | **2.266** |
| THA | 0.074 | -0.007 | 0.095 | **-0.051** | 0.470 | **0.148** | **0.737** |
| | 1.276 | -0.410 | 1.131 | **-2.337** | 1.348 | **2.271** | **5.829** |

Notes: (1) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.

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

Table 4.6  Portfolio Models for ASEAN: VARMA-AGARCH

| Countries | $\omega$ | $\alpha_{IND}$ | $\beta_{IND}$ | $\alpha_{PHI}$ | $\beta_{PHI}$ | $\alpha_{THA}$ | $\beta_{THA}$ | $\gamma$ |
|---|---|---|---|---|---|---|---|---|
| IND | -0.053 | **0.278** | **0.612** | 0.030 | 0.719 | -0.012 | 0.208 | 0.027 |
| | -1.245 | **5.328** | **9.472** | 0.799 | 1.682 | -0.399 | 1.306 | 0.606 |
| PHI | **0.218** | 0.020 | 0.169 | **0.167** | **0.517** | 0.017 | **0.671** | 0.119 |
| | **3.076** | 0.547 | 1.016 | **3.966** | **3.754** | 0.688 | **2.339** | 0.000 |
| THA | 0.070 | -0.013 | 0.087 | **-0.042** | 0.486 | **0.100** | **0.743** | -0.145 |
| | 1.129 | -0.719 | 0.840 | **-3.035** | 1.713 | **2.589** | **6.774** | 0.000 |

Notes: (1) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.

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

Table 4.7 Constant Conditional Correlations between countries for ASEAN

| Model | $\rho_{IND,PHI}$ | $\rho_{IND, THA}$ | $\rho_{PHI,THA}$ |
|---|---|---|---|
| CCC | **0.239** | **0.263** | **0.230** |
| | **17.037** | **18.998** | **16.496** |
| VARMA-GARCH(1,1) | **0.237** | **0.265** | **0.227** |
| | **17.344** | **17.810** | **15.237** |
| VARMA-GARCH(1,1) | **0.237** | **0.265** | **0.227** |
| | **19.442** | **21.853** | **17.081** |

Notes: (1) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.

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

Table 4.8 DCC-GARCH(1,1) Estimates for ASEAN

| Model | $\phi_1$ | $\phi_2$ |
|---|---|---|
| $Q_t = (1-\phi_1-\phi_2)S + \phi_1\eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1}$ | **0.015**<br>**3.989** | **0.981**<br>**190.958** |

Notes: (1) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.

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

Table 4.9  Basel Accord Penalty Zones

| Zone | Number of Violations | Increase in k |
|---|---|---|
| Green | 0 to 4 | 0.00 |
| Yellow | 5 | 0.40 |
| | 6 | 0.50 |
| | 7 | 0.65 |
| | 8 | 0.75 |
| | 9 | 0.85 |
| Red | 10+ | 1.00 |

Note: The number of violations is given for 250 business days.

Table 4.10 Mean Daily Capital Charge and AD of Violations for ASEAN

| Model | Number of Violations | | Mean Daily Capital Charge | AD of Violations | |
|---|---|---|---|---|---|
| | All observation | 250 trading day | | Maximum | Mean |
| ARCH | 37 | 2 | 22.422 | 8.458 | 2.149 |
| GARCH | 42 | 2 | 20.859 | 3.782 | 1.784 |
| GJR | 44 | 2 | 20.819 | 2.027 | 1.173 |
| EGARCH | 44 | 2 | 20.550 | 2.027 | 1.173 |
| Riskmetrics$^{TM}$ | 49 | 2 | 20.617 | 0.000 | 0.000 |
| CCC | 44 | 2 | 20.825 | 1.570 | 2.918 |
| DCC | 45 | 2 | 21.651 | 1.585 | 3.169 |
| VARMA-GARCH | 42 | 2 | 20.462 | 1.758 | 3.760 |
| VARMA-AGARCH | 42 | 2 | 20.417 | 1.758 | 3.760 |

Note: (1) Number of Violations are a greater number of violations than would reasonably be expected given the specified confidence level of 1%.

(2) AD is the absolute deviation of the violations from the VaR forecast.

Table 4.11 Correlations of Value-at-Risk forecasts for ASEAN

| | ARCH | GARCH | GJR | EGARCH | RISKMETRICS$^{TM}$ | CCC | DCC | VARMA_GARCH | VARMA_AGARCH |
|---|---|---|---|---|---|---|---|---|---|
| ARCH | 1 | 0.640 | 0.647 | 0.637 | 0.551 | 0.663 | 0.657 | 0.674 | 0.676 |
| GARCH | 0.640 | 1 | **0.997** | 0.990 | **0.951** | 0.964 | 0.982 | 0.964 | 0.962 |
| GJR | 0.647 | **0.997** | 1 | **0.992** | 0.943 | 0.962 | 0.980 | 0.963 | 0.964 |
| EGARCH | 0.637 | 0.990 | 0.992 | 1 | 0.943 | 0.950 | 0.970 | 0.955 | 0.956 |
| RISKMETRICS$^{TM}$ | 0.551 | 0.951 | 0.943 | 0.943 | 1 | 0.898 | 0.931 | 0.902 | 0.898 |
| CCC | 0.663 | 0.964 | 0.962 | 0.950 | 0.898 | 1 | **0.991** | 0.996 | 0.995 |
| DCC | 0.657 | 0.982 | 0.980 | 0.970 | 0.931 | 0.991 | 1 | 0.990 | 0.988 |
| VARMA_GARCH | 0.674 | 0.964 | 0.963 | 0.955 | 0.902 | **0.996** | 0.990 | 1 | **0.998** |
| VARMA_AGARCH | **0.676** | 0.962 | 0.964 | 0.956 | 0.898 | 0.995 | 0.988 | **0.998** | 1 |

Note: Entries in bold are highest correlation

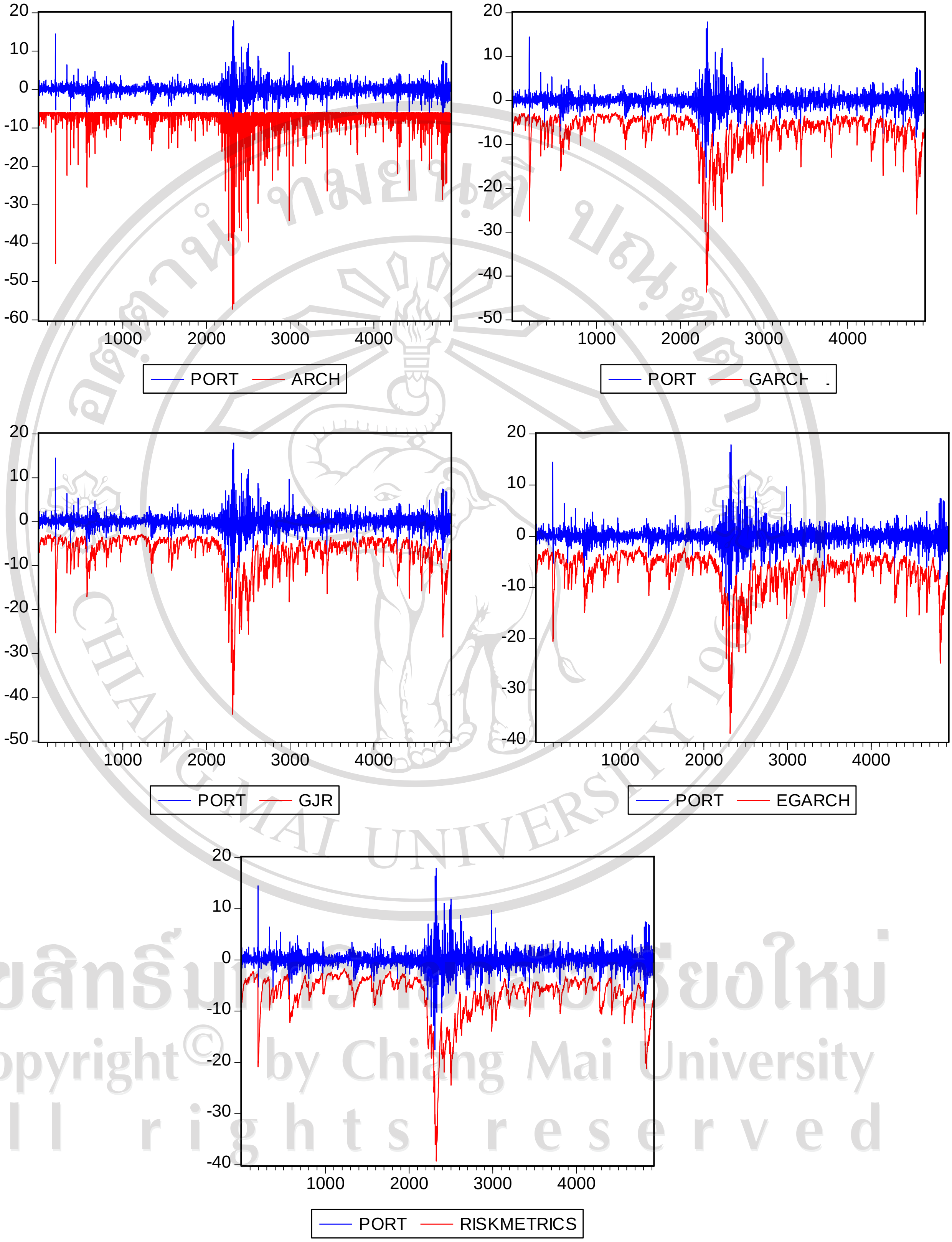


Figure 4.1 Single Index Models and Realized Returns VaR Forecasts for ASEAN

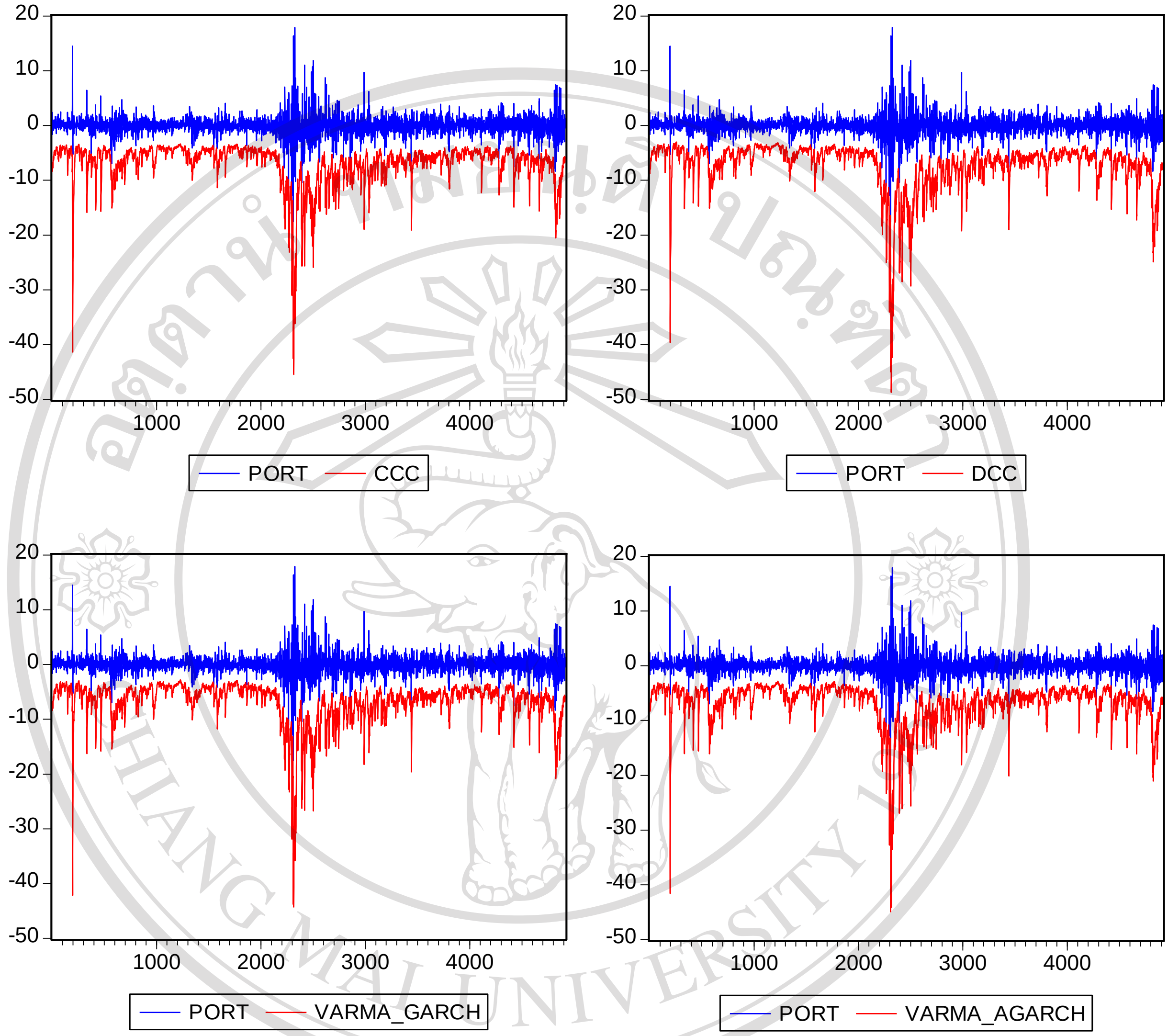
20
10
0
-10
-20
-30
-40
-50
1000
2000
3000
4000
PORT
CCC
PORT
DCC
PORT
VARMA_GARCH
PORT
VARMA_AGARCH

Figure 4.2 Portfolio Models and Realized Returns VaR Forecasts for ASEAN