APPENDICES

APPENDIX A

Comparing the Volatility Index and Index of Volatility

for Europe and the USA

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Comparing the Volatility Index and Index of Volatility for Europe and the USA

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ABSTRACT

Volatility forecasting is an important task in financial markets. In 1993, the Chicago Board Options Exchange (CBOE) introduced the CBOE volatility index, VIX, and it quickly became the benchmark for stock market volatility. After 2003, the CBOE reported a new VIX, and changed the original VIX to VXO. The new VIX estimates reflect expected volatility from the prices of stock index options for a wide range of strike prices, not just at-the money strikes, as in the original VIX, so that the model-free implied volatility is more likely to be informationally efficient than the Black-Scholes implied volatility. However, the new VIX uses the model-free implied volatility, which is not based on a specific volatility model. This paper constructs an index of volatility for Europe and the USA by using a single index model or the covariance matrix of the portfolio forecast the variance of a portfolio. Using univariate and multivariate conditional volatility models. A comparison between the volatility index and the index of volatility using predictive power of Value-at-Risk will be made to determine the practical usefulness of these indexes.

1. Introduction

Volatility forecasting is an important task in financial markets, and it 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, risk management, and monetary policy making. Volatility is interpreted as uncertainty. It becomes a key factor to many investment decisions and portfolio creations because investors and portfolio managers want to know certain levels of risk.

Volatility is also the most important variable in the pricing of derivative securities. (see Fleming, J., Ostdiek, B. and Whaley, R.E.(1995) and Poon, S. and Granger, C.W.J.(2003))

Volatility has an effect on financial risk management exercise for many financial institutions around the world since the first Basle Accord was established in 1996. It is an important ingredient to calculate Value-at-Risk (VaR). Value-at-Risk may be defined as “a worst case scenario on a typical day”. If a financial institution’s VaR forecasts are violated more than can reasonably be

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expected, given the confidence level, the financial institution will hold a higher level of capital. (McAleer, M. (2008))

In 1993, the Chicago Board Options Exchange (CBOE) introduced the CBOE volatility index, VIX, and it quickly became the benchmark for stock market volatility. After 2003, the CBOE reported a new VIX, and changed the original VIX to VXO. The new VIX estimates reflect expected volatility from the prices of stock index options for a wide range of strike prices, not just at-the-money strikes, as in the original VIX. Therefore, the model-free implied volatility is more likely to be informationally efficient than the Black-Scholes implied volatility. However, the new VIX uses the model-free implied volatility, which is not based on a specific volatility model. (See, Jiang, G.J. and Tian, Y.S. (2005))

In Europe, there is also a volatility index. Its calculation method is the same method as CBOE's. One type of volatility indices in Europe is the VSTOXX volatility index, which was introduced on 20 April 2005. It has provided a key measure market expectations of near-term volatility based on the Dow Jones EURO STOXX 50 options prices.

Most studies in the literature about construction and prediction the volatility index. (See Skiadopoulos, G.S.(2004) Moraux, F., Navatte, P. and Villa, C. (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 the USA and Europe. Then, comparison between the index of volatility and the volatility index will be made by using the predictive power of Value-at-Risk.

The organization of the paper is as follows: section 2 presents the Index of Volatility and section 3 shows Volatility Index. The data and estimation are in Section 4. Empirical results, Value-at-Risk, and conclusion are in Section 5, 6, and 7, listed respectively.

2. Index of Volatility

This paper uses the price sector indices of S&P 500 for the USA and STOXX for Europe. There are 10 sector indices, however this paper aggregates price sector indices to be 3 sectors by using market capitalization as a weighted variable. For example, if we would like to aggregate sector *1, 2, 3* together, the model is as follows:

$$P_{123t} = \frac{MV_{1t} \times P_{1t} + MV_{2t} \times P_{2t} + MV_{3t} \times P_{3t}}{MV_{1t} + MV_{2t} + MV_{3t}} \quad (1)$$

where P_{123t} is the aggregate price sector index of sector *1,2,* and *3*, MV_{it} is market capitalization of sector i (i = 1, 2, 3), and P_{it} is price sector index of sector i (i = 1, 2, 3).

Then we compute returns of each sector as follows:

$$R_{i,t} = 100 \times \log(P_{i,t} / P_{i,t-1}) \quad (2)$$

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of sector i (i = 1, 2, 3) at days t and $t-1$, Then we construct Index of Volatility by two model follows:

2.1 Single index model

This paper constructs a single index model following these steps:

(1) Compute portfolio returns by using market capitalization at the first day as a weighted variable, as follows:

$$Port_t = \frac{MV_1 \times r_{1t} + MV_2 \times r_{2t} + MV_3 \times r_{3t}}{MV_1 + MV_2 + MV_3} \quad (3)$$

where $Port_t$ is portfolio returns, MV_i is market capitalization of sector i (i = 1, 2, 3), and r_{it} is returns of sector i (i = 1, 2, 3).

(2) Estimating univariate volatility of portfolio returns from the first step by mean equation have constant term and autoregressive term (AR(1)) in all models. The univariate volatility is the Index of Volatility. Moreover, this paper computes Riskmetrics[TM] by using the exponentially weighted moving average model (EWMA) of portfolio returns.

Univariate Volatility

ARCH

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

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 \qquad (4)$$

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

GARCH

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

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad (5)$$

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. (1992) accommodate differential impact on the conditional variance of positive and negative shocks of equal magnitude. The GJR(p,q) model is given by:

$$h_t = \omega + \sum_{j=1}^{p} \left(\alpha_j + \gamma_j I(\varepsilon_{t-j})\right) \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad (6)$$

where the indicator variable, $I(\varepsilon_t)$, is defined as: $I(\varepsilon_t) = \begin{cases} 1, \varepsilon_t \leq 0 \\ 0, \varepsilon_t > 0 \end{cases}$. If p = q = 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 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:

$$\log h_t = \omega + \sum_{i=1}^{p} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{p} \gamma_i \eta_{t-i} \sum_{j=1}^{q} \beta_j \log h_{t-j} \qquad (7)$$

In equation (7), $\left|\eta_{t-i}\right|$ and η_{t-i} capture the size and sign effects, respectively, of the standardized shocks. EGARCH in (7) uses the standardized residuals. As EGARCH uses the logarithm of conditional volatility, there are no restrictions on the parameters in (7). As the standardized shocks have finite moments, the moment conditions of (7) are straightforward.

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

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \qquad (8)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \qquad (9)$$

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(∞) 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:

$$h_t = \lambda h_{t-1} + (1-\lambda)\varepsilon_{t-1}^2 \qquad (10)$$

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

2.2 Portfolio model

This paper constructs the portfolio model by following these steps:

(1) Estimate multivariate volatility of three sectors for Europe and the USA by mean equation so that they have constant term and autoregressive term (AR(1)) in all models. Then compute variance and covariance matrix.

(2) Compute Index of Volatility by using market capitalization at the first observation is a weighted variable. This paper has three sectors so that we have the three conditional variances and three covariance estimated. It follows that:

$$IVol_t = \lambda_1^2 h_{1t} + \lambda_2^2 h_{2t} + \lambda_3^2 h_{3t} + 2\lambda_1\lambda_2 h_{12t} + 2\lambda_1\lambda_3 h_{13t} + 2\lambda_2\lambda_3 h_{23t} \qquad (11)$$

where $IVol_t$ is Index of Volatility, h_{it} is conditional variances of sector i (i=1,2,3), h_{ijt} is covariance of sector i (i=1,2,3), and

$$\lambda_1 = \frac{MV_1}{MV_1 + MV_2 + MV_3},$$

$$\lambda_2 = \frac{MV_2}{MV_1 + MV_2 + MV_3},$$

and $\lambda_3 = \dfrac{MV_3}{MV_1 + MV_2 + MV_3}$.

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, 190, respectively. This increases the computation burden significantly. (See details in McAleer, M. (2008))

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* (≥ 2) financial assets be given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (12)$$

$$\varepsilon_t = D_t \eta_t \qquad (13)$$

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \qquad (14)$$

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

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:

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{p} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \quad (15)$$

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

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

VARMA-AGARCH reduces to VARMA-GARCH when $C_k = 0$ for all k.

CCC

If the model given by equation (15) 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:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_i h_{i,t-l} \quad (16)$$

Which is the constant conditional correlation (CCC) model of Bolerslev, T. (1990), for which the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$. As given in equation (16), 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:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1,\ldots,T \quad (17)$$

$$Q_t = D_t \Gamma_t D_t, \quad (18)$$

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

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{i,l} h_{i,t-l} \quad (19)$$

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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}' + \phi_2 Q_{t-1} \quad (20)$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\}, \quad (21)$$

where S is the unconditional correlation matrix of the returns shocks, and equation (21) is used to standardize the matrix estimated in (20) 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).

3. Volatility Index

This paper uses the Chicago Board Options Exchange (CBOE) volatility index (VIX) to represent the Volatility Index for the USA, and uses The Dow Jones EURO STOXX 50 volatility index (VSTOXX) to represent the Volatility Index for Europe. It provides a key measure of market expectations of near-term volatility based on the Dow Jones EURO STOXX 50 options prices. The Dow Jones EURO STOXX 50 index is a Blue-chip representation of sector leaders in the Euro zone. The index covers Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, and Spain.

The method to calculate Volatility Index follows:

Step 1: Calculate σ_1^2 and σ_2^2 (1= the near term options, 2 = the next term options[1])

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1 The new VIX generally uses put and call options in the two nearest-term expiration months in order to bracket a 30-day calendar period. However, with 8 days left to expiration, the new VIX ”rolls” to the second and third contract months in order to

$$\sigma_i^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

Where

σ is VIX/100

T Time to expiration

F Forward index level derived from index option prices

(Note: F = Strike price+ e^{RT} x (Call price – Put price)

K_i Strike price of i^{th} out-of-the-money options; a call if $K_i > F$ and a put if $K_i < F$

ΔK_i Interval between strike prices-half the distance between the strike on either side of K_i: $\Delta K_i = (K_{i+1} - K_{i-1})/2$

(Note: ΔK for the lowest strike is simply the difference between the lowest strike and the next higher strike. Likewise, ΔK for the highest strike is the difference between the highest strike and the next lower strike.)

K_0 First strike below the forward index level, F

R Risk-free interest rate to expiration

$Q(K_i)$ The midpoint of the bid-ask spread for each option with strike K_i.

Step 2: Interpolate σ_1^2 and σ_2^2 to arrive at a single value with a constant maturity of 30 days to expiration. Then take the square root of that value.

$$\sigma = \sqrt{\left\{T_1\sigma_1^2\left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}}\right] + T_2\sigma_2^2\left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}}\right]\right\} \times \frac{N_{365}}{N_{30}}}$$

Where

N_{T_1} = Number of minutes to expiration of the near term options

N_{T_2} = Number of minutes to expiration of the next term options

N_{30} = Number of minutes in 30 days

N_{365} = Number of minutes in a 365-day year

Step 3: multiply by 100 to get VIX.

$$VIX = 100 \times \sigma$$

minimize pricing anomalies that might occur close to expiration.

4. Data and Estimation

4.1 Data

The data used in the paper is the daily closing price sector indices of the S&P 500 and STOXX for the USA and Europe, respectively. The price sector indices of the S&P 500 and STOXX have 10 sectors, as shown in Table 1. However, this paper aggregates the price sector index by grouping sectors 1, 2, and 3 together, grouping sectors 4, 5, and 6 together, and grouping sectors 7, 8, 9, and 10 together. All the data is obtained from DataStream. The sample ranges from 23 January 1995 through 6 November 2008 with 3,476 observations for the USA, and 1 January 1992 through 6 November 2008 with 4,333 observations for Europe.

Two characteristics of the data, namely normality and stationarity, will be investigated before estimate 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. Stationarity is an important characteristic for time series data. If data is nonstationary, it will be necessary to difference the data before estimation because if not, the result will be spurious regression.

The normality of the variables can be seen from the Jarque-Bera (J-B) Lagrange multiplier test statistics in Table 2. As the probability associated with the J-B statistics is zero, it can be seen that the returns data is not normally distributed.

Table 1: Summary of Variable Names

USA	Price Sector Index Names	Variable Names
	S&P500 CONSUMER DISCRETIONARY S&P500 CONSUMER STAPLES S&P500 ENERGY	sp53cce
	S&P500 FINANCIALS S&P500 HEALTH CARE S&P500 INDUSTRIALS	sp53fhi
	S&P500 INFORMATION TECHNOLOGY S&P500 MATERIALS S&P500 TELECOMMUNICATION SERVICES S&P500 UTILITIES	sp53imtu
Europe	DJ EURO STOXX AUTOMOBILES & PARTS DJ EURO STOXX BANKS DJ EURO STOXX BASIC RESOURCES	stabb
	DJ EURO STOXX CHEMICALS DJ EURO STOXX CONSTRUCTION & MATERIALS DJ EURO STOXX FINANCIAL SERVICES	stccf
	DJ EURO STOXX FOOD & BEVERAGE DJ EURO STOXX INDUSTRIAL GOODS & SERVICES DJ EURO STOXX INSURANCE DJ EURO STOXX MEDIA	stfiim

Source: DataStream.

Table 2: Jarque-Bera Test of Normality and Probability for Returns

Country	Returns	Jarque-Bera	Probability
USA	RPORTSP53	8789.624	0.000
	RSP53CCE	39039.39	0.000
	RSP53FHI	6186.943	0.000
	RSP53IMTU	3676.259	0.000
Europe	RPORTST3	12404.28	0.000
	RSTABB	227469.0	0.000
	RSTCCF	12175.59	0.000
	RSTFIIM	8260.200	0.000

For the stationarity of data, this paper uses the Augmented Dicky Fuller (ADF) test. The test is given as follows:

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (22)$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (23)$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \qquad (24)$$

where equation (22) has no intercept and trend, equation (23) has intercept but no trend, and equation (24) has intercept and trend. The null hypothesis in equations (22), (23) and (24) are $\theta = 0$, which means that y_t is nonstationary. The test results for the 17 series show that θ for all the returns are significantly less than zero at the 1% level, so that the returns are stationary.

4.2 Estimation

The parameters in models (4), (5), (6), (7), (14), (15), (16), and (19) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, as follows:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{2}\sum_{t=1}^{n}(\log|Q_t| + \varepsilon_t' Q_t^{-1}\varepsilon_t) \quad (25)$$

where θ denotes the vector of parameters to be estimated in the conditional log-likelihood function, and $|Q_t|$ denotes the determinant of Q_t, the conditional covariance matrix. When η_t does not follow a joint normal distribution, equation (26) is defined as the Quasi-MLE (QMLE).

5. Empirical Results

This paper use ARCH(1), GARCH(1,1), GJR(1,1), and EGARCH(1,1) models to estimate the Single Index Model, and we assume that mean equation of all models have autoregressive terms (AR(1)). The results are shown in Table 3. The two entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios. In the USA, mean equation is significant only in constant terms. Variance equation estimates are significant for all models except for ARCH effect in GJR model. For Europe, mean equation is significant in both constant terms and AR(1) terms, except the ARCH(1) model and all models in variance equation are significant. GJR dominates GARCH and ARCH. So, there is asymmetry, while EGARCH shows there is asymmetry but not leverage in Europe and the USA.

Table 3: Single Index Model for the USA and Europe

Variable	Model	Mean equation		Variance equation			
		C	AR(1)	ϖ	α	γ	β
RPORTSP53	ARCH(1)	**0.0414**	-0.137	**1.174**	**0.301**		
		2.263	-1.9156	**16.357**	**5.487**		
	GARCH(1,1)	**0.066**	-0.026	**0.008**	**0.070**		**0.928**
		4.572	-1.52	**2.433**	**6.121**		**89.919**
	GJR(1,1)	**0.035**	-0.012	**0.011**	-0.009	**0.125**	**0.938**
		2.400	-0.735	**4.452**	-0.875	**6.618**	**106.635**
	EGARCH(1,1)	**0.030**	-0.014	**-0.088**	**0.117**	**-0.103**	**0.982**
		2.021	0.017	**-6.257**	**6.505**	**-6.659**	**297.543**
RPORTST3	ARCH(1)	**0.049**	0.082	**1.017**	**0.419**		
		2.404	1.075	**15.582**	**7.826**		
	GARCH(1,1)	**0.053**	**0.045**	**0.015**	**0.098**		**0.894**
		4.113	**2.750**	**3.871**	**7.467**		**73.446**
	GJR(1,1)	**0.031**	**0.047**	**0.017**	**0.035**	**0.098**	**0.902**
		2.332	**2.960**	**4.730**	**2.507**	**5.026**	**84.428**
	EGARCH(1,1)	**0.0298**	**0.040**	**-0.130**	**0.170**	**-0.071**	**0.983**
		2.204	**2.450**	**-7.859**	**7.825**	**-5.023**	**282.238**

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.

The Portfolio Model is estimated by using multivariate volatility as given in Tables 4 to 11. The multivariate volatility used in this paper is CCC, DCC, VARMA-GARCH, and VARMA-AGARCH. The results of VARMA-GARCH for the USA and Europe in Table 4 and 5, respectively, show that the ARCH effect for RSP53CCE (RSP53FHI) sector returns is significant in the conditional volatility model for RSP53FHI (RSP53CCE) sector returns. Therefore, RSP53CCE sector and RSP53FHI sector are significant interdependences in the conditional volatilities. In RSP53IMTU (RSP53FHI) sector, the ARCH and GARCH effects are significant in the conditional volatility model for RSP53FHI (RSP53IMTU) returns. It is clear that there is significant interdependence in the conditional volatilities between the RSP53IMTU sector and RSP53FHI sector.

Table 4: Portfolio Models for the USA: VARMA-GARCH

Sectors	ϖ	α_{CCE}	β_{CCE}	α_{FHI}	β_{FHI}	α_{IMTU}	β_{IMTU}
RSP53CCE	0.005 1.753	**0.124** **6.604**	**0.836** **13.157**	**-0.062** **-2.185**	0.144 1.718	-0.014 -0.816	-0.024 -0.554
RSP53FHI	0.004 1.062	**-0.071** **-4.437**	0.141 1.622	**0.126** **4.662**	**0.797** **9.540**	-0.033 -1.938	0.092 1.694
RSP53IMTU	0.003 0.696	-0.006 -1.006	-0.013 -0.670	**-0.032** **-3.686**	**0.046** **2.034**	**0.076** **7.265**	**0.915** **70.325**

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.

VARMA-GARCH for Europe is given in Table 5. The results show that RSTABB sector and RSTFIIM sector have significant interdependence in the conditional volatilities because the ARCH and GARCH effects in RSTABB (RSTFIIM) sector returns are significant in the conditional volatility model for RSTFIIM (RSTABB) sector returns. The ARCH effects of RSTFIIM sector are significant for RSTCCF sector returns, while the GARCH effects of RSTCCF sector are significant for RSTFIIM sector returns.

The results VARMA-AGARCH for the USA and Europe are given in Tables 6 and 7. Asymmetric effects are significant only for RSP53CCE sector returns for the USA and RSTABB sector returns for Europe.

Table 5: Portfolio Models for Europe: VARMA-GARCH

Sectors	ϖ	α_{ABB}	β_{ABB}	α_{CCF}	β_{CCF}	α_{FIIM}	β_{FIIM}
RSTABB	-0.005 -0.437	**0.218** **5.297**	0.332 1.955	-0.051 -1.119	0.129 0.852	**-0.113** **-5.500**	**0.425** **5.975**
RSTCCF	**0.028** **3.589**	-0.047 -1.369	0.162 0.836	**0.128** **3.161**	**0.597** **5.860**	**-0.057** **-2.235**	0.051 0.421
RSTFIIM	0.006 0.704	**-0.134** **-4.140**	**0.559** **3.986**	-0.020 -0.652	**0.215** **2.047**	**0.212** **8.871**	**0.519** **3.478**

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 6: Portfolio Models for the USA: VARMA-AGARCH

Sectors	ϖ	α_{CCE}	β_{CCE}	α_{FHI}	β_{FHI}	α_{IMTU}	β_{IMTU}	γ
RSP53CCE	0.006 1.907	**0.076** **4.494**	**0.847** **16.810**	**-0.068** **-3.245**	0.106 1.824	-0.006 -0.367	-0.054 -1.133	**0.061** **5.030**
RSP53FHI	**0.007** **2.238**	**-0.067** **-5.087**	**0.144** **2.092**	**0.089** **4.563**	**0.840** **13.920**	**-0.048** **-2.802**	**0.132** **2.291**	-4.811 0.000
RSP53IMTU	0.007 1.726	-0.006 -1.109	-0.0156 -1.010	**-0.030** **-5.273**	**0.036** **2.073**	**0.049** **4.894**	**0.910** **67.129**	0.027 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 7: Portfolio Models for Europe: VARMA-AGARCH

Sectors	ϖ	α_{ABB}	β_{ABB}	α_{CCF}	β_{CCF}	α_{FIIM}	β_{FIIM}	γ
RSTABB	-0.006 -0.255	**0.192** **3.77**	0.310 0.762	-0.058 -1.067	0.156 0.541	**-0.115** **-2.493**	0.462 1.295	**0.051** **3.191**
RSTCCF	**0.029** **2.014**	-0.042 -1.404	0.191 0.701	**0.118** **3.905**	**0.578** **4.801**	-0.072 -1.330	0.119 0.330	-0.006 0.000
RSTFIIM	0.004 0.160	**-0.149** **-3.264**	0.568 1.928	-0.038 -0.576	0.221 0.984	**0.209** **6.621**	**0.436** **5.208**	-6.912 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.

In the USA, constant conditional correlations between the conditional volatilities of RSP53CCE sector and RSP53FHI sector for the CCC, VARMA-GARCH, and VARMA-AGARCH in Table 8 are identical at 0.789. Constant conditional correlations between the conditional volatilities of RSP53CCE sector and RSP53IMTU sector for the three models above are identical at 0.639. RSP53CCE sector and RSP53IMTU sector have constant conditional correlations between the conditional volatilities for the three models which are identical at 0.689.

Constant conditional correlations between the conditional volatilities of RSTABB sector and RSTCCF sector, RSTABB sector and RSTFIIM sector, and RSTCCF sector and RSTFIIM sector for the CCC, VARMA-GARCH, and VARMA-AGARCH in Table 9 are identical at 0.86, 0.88, and 0.84, respectively, in Europe.

From Tables 10 and 11, we can see that estimated coefficient is significant in both the USA and Europe market. Therefore the conditional correlations of the overall returns are dynamic.

Table 8: Constant Conditional Correlations between Sectors Returns for the USA

Model	$\rho_{CCE, FHI}$	$\rho_{CCE, IMTU}$	$\rho_{FHI, IMTU}$
CCC	**0.764** **118.173**	**0.623** **66.102**	**0.678** **76.010**
VARMA-GARCH(1,1)	**0.789** **95.676**	**0.639** **54.975**	**0.689** **69.040**
VARMA-GARCH(1,1)	**0.789** **95.677**	**0.639** **54.975**	**0.689** **69.040**

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 9: Constant Conditional Correlations between Sectors Returns for Europe

Model	ρ ABB, CCF	ρ ABB, CCF	ρ CCF, FIIM
CCC	**0.848** **146.682**	**0.865** **111.551**	**0.831** **114.528**
VARMA-GARCH(1,1)	**0.862** **142.523**	**0.880** **179.222**	**0.848** **155.775**
VARMA-GARCH(1,1)	**0.860** **122.988**	**0.879** **127.783**	**0.846** **117.031**

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 10: DCC-GARCH(1,1) Estimates for the USA

Model	ϕ_1	ϕ_2
$Q_t = (1-\phi_1-\phi_2)S + \phi_1\eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1}$	**0.034** **10.070**	**0.963** **245.762**

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 11: DCC-GARCH(1,1) Estimates for Europe

Model	ϕ_1	ϕ_2
$Q_t = (1-\phi_1-\phi_2)S + \phi_1\eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1}$	**0.030** **5.758**	**0.970** **182.163**

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

6. 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. (2008))

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 12.

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):

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (26)$$

Table 12: Basel Accord Penalty Zones

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

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

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, ε_t. The variability of Y_t, and hence its distribution, is determined entirely by the variability of ε_t. If it is assumed that ε_t follows a distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t) \qquad (27)$$

where μ_t and σ_t are the unconditional mean and standard deviation of ε_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 α is the critical value from the distribution of ε_t to obtain the appropriate confidence level. Alternatively, σ_t can be replaced by alternative estimates of the conditional variance to obtain an appropriate VaR. (see Section 2 and 3)

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

$$\underset{\{k, VaR\}}{Minimize}\; DCC_t = \max\left\{-(3+k)\overline{VaR}_{60}, -VaR_{t-1}\right\} \quad (28)$$

where DCC is daily capital charges, k is a violation penalty ($0 \le k \le 1$) (see Table 12), $\overline{VaR}_{60}$ is mean VaR over the previous 60 working days, and VAR_t is Value-at-Risk for day t.

This paper calculates VaR from the period of 4 January 1999 up to 6 November 2008 for Europe because VSTOXX has data starting from 4 January 1999. In the USA, we calculate VaR from the period of 24 January 1995 up to 6 November 2008. In order to simplify the analysis, we assumed that the portfolio returns are constant weights by using market capitalization at the first daily data. $E(Y_t \mid F_{t-1})$ is the expected returns for all models, and α is the critical value from the distribution of ε_t to obtain the appropriate confidence level of 1%.

Figures 1–4 show the VaR forecasts and realized returns of each Single Index Models and Portfolio Models for the USA and Europe, respectively.

Table 13 shows the mean daily capital charge for the USA, in the Single Index Models, ARCH(1) model has the highest at 12.353% and EGARCH(1,1) model has the lowest at 11.053% if compared with other ARCH-type models. However, the Riskmetrics™ model has the lowest at 10.855% in the Single Index Models. ARCH(1) model has minimum number of violations at 21 times, and the lowest mean of absolute deviation of the violation from the VaR forecast at 1.736%. The Riskmetrics™ model has maximum number of violations at 33 times, and the EGARCH(1,1) model has the highest mean of absolute deviation of the violation from the VaR forecast at 2.257%. GJR(1,1) has maximum number of violations at 25 times, which compares with the ARCH-type model. In the Portfolio Models, DCC model has the lowest mean daily capital charge at 9.383%, the lowest the mean of absolute deviation of the violations from the VaR forecast at 1.563%, and the minimum number of violations at 16 times for all observations. VARMA-GARCH model has the highest mean daily capital charge at 9.599% and the highest the mean of absolute deviation of the violations from the VaR forecast at 1.867%. The CCC model has the maximum number of violations at 20 times for all observations. Table 13 also shows the model which uses VIX to calculate VaR has meant the daily capital charge is 10.091%, and the number of violations is 23 times for all observations.

The mean daily capital charge for Europe is shown in Table 14, in the Single Index Models, ARCH(1) model has the highest at 15.437%, and minimum number of violations at 12 times. GJR(1,1) model has the lowest mean daily capital charge at 14.443% if compared with the ARCH-type model. However, the Riskmetrics™ model has the lowest mean daily capital charge at 14.353% of all Single Index Models. The EGARCH(1,1) model has the maximum number of violations at 23 times in ARCH-type model, and the highest mean of absolute deviation of the violation from the VaR forecast at 2.410%. However, the Riskmetrics™ model has the maximum number of violations at 25 times. In the Portfolio Models, The mean daily capital charge of the CCC model has the lowest at 11.991%. VARMA-GARCH model has the highest mean daily capital charge at 12.514%. The DCC model has the highest mean of absolute deviation of the violations from the VaR forecast at 1.968%, and the minimum number of violations at 18 times for all observations. The VARMA-AGARCH model has the highest mean of absolute deviation of the violation from the VaR forecast at 1.772%, and the maximum number of violations at 21 times for all observations. Table 14 also shows the model which uses VSTOXX to calculate VaR, and the mean daily capital charge is 13.714%.

7. Conclusion

Volatility forecasting is an important task in financial markets. In 1993, the Chicago Board Options Exchange (CBOE) introduced the CBOE volatility index, VIX, and it quickly became the benchmark for stock market volatility. In Europe there is also a volatility index, which is calculated by the same method of CBOE. The volatility index in Europe is the VSTOXX volatility index, which was introduced on 20 April 2005. However, the Volatility index uses the model-free implied volatility, which is not based on a specific volatility model.

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 and de Veiga (2008a,2008b)); or (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 the USA and Europe. Then the index of volatility is compared with the volatility index and RiskmetricsTM 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 term and autoregressive term (AR(1)). For the multivariate volatility model, we used CCC, DCC, VARMA-GARCH, VARMA-AGARCH models, which means the equations have constant term and autoregressive term (AR(1)), the same as the univariate volatility model.

If we consider the mean daily capital charge, the results show that the RiskmetricsTM model dominates the other models in the Single Index Model for the USA and Europe. However, if we compare between ARCH-type, the EGARCH(1,1) model dominates the other models for the USA. However, the GJR(1,1) model dominates the other models in Europe. In Portfolio Model, the DCC model dominates the other models for the USA. Immediate CCC model dominates the other models for Europe. If we compare the mean daily capital charge of the Index of Volatility, which uses the Single Index Model and Volatility Index (i.e. VIX and VSTOXX), the results show that the VIX and VSTOXX are dominate for the Single Index Model. However, if we compare the Index of Volatility, which uses the Portfolio Models with Volatility Index (VIX or VSTOXX), the results show that the Portfolio Models dominate the Volatility Index because the Portfolio Models have a lower mean daily capital charge compared to the Volatility Index. The higher daily capital charge has an effect on the profitability of the financial institution.

Table 13: Mean Daily Capital Charge and AD of Violations for the USA

Model	Number of Violations		Mean Daily Capital Charge	AD of Violations	
	All observation	250 trading day		Maximum	Mean
ARCH	21	2	12.353	3.706	1.736
GARCH	24	2	11.234	4.448	1.938
GJR	25	2	11.084	4.590	2.245
EGARCH	24	2	11.053	4.886	2.257
Riskmetrics^{TM}	33	2	10.855	1.827	1.827
CCC	20	1	9.471	4.972	1.749
DCC	16	1	9.383	5.199	1.563
VARMA-GARCH	17	1	9.599	5.085	1.867
VARMA-AGARCH	17	1	9.515	5.326	1.646
VIX	23	2	10.091	3.319	3.319

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 14: Mean Daily Capital Charge and AD of Violations for Europe

Model	Number of Violations		Mean Daily Capital Charge	AD of Violations	
	All observation	250 trading day		Maximum	Mean
ARCH	12	1	15.437	2.148	1.001
GARCH	22	2	14.510	2.860	1.906
GJR	22	2	14.443	2.860	1.906
EGARCH	23	2	14.519	2.410	2.410
Riskmetrics^{TM}	25	2	14.353	0.000	0.000
CCC	20	2	11.991	2.918	1.910
DCC	18	2	12.437	3.759	1.968
VARMA-GARCH	19	2	12.514	3.348	1.885
VARMA-AGARCH	21	2	12.438	2.517	1.772
VSTOXX	21	2	13.714	1.155	0.774

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.

Figure 1: Single Index Models and Realized Returns VaR Forecasts for the USA

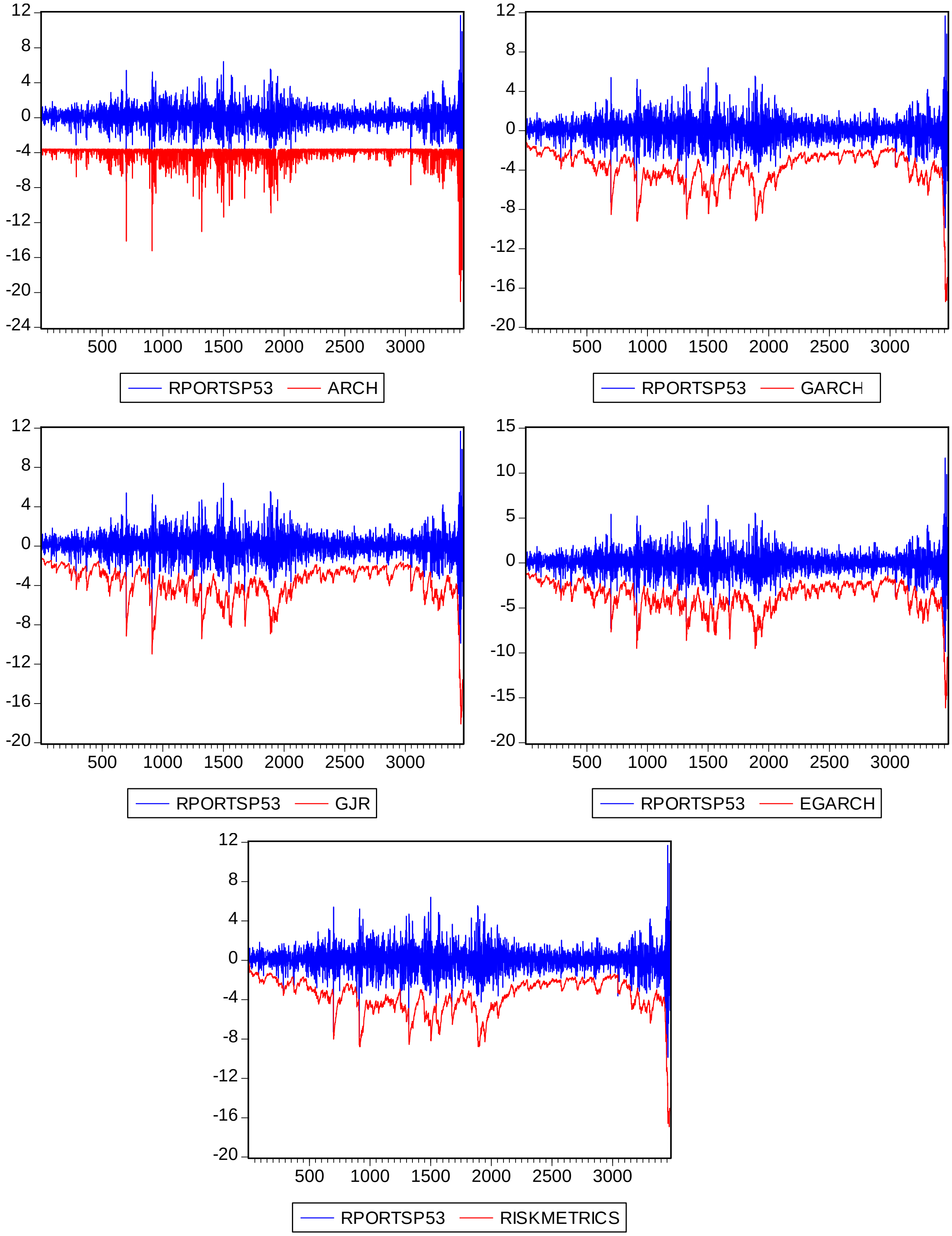


Figure 2: Portfolio Models, VIX and Realized Returns VaR Forecasts for the USA

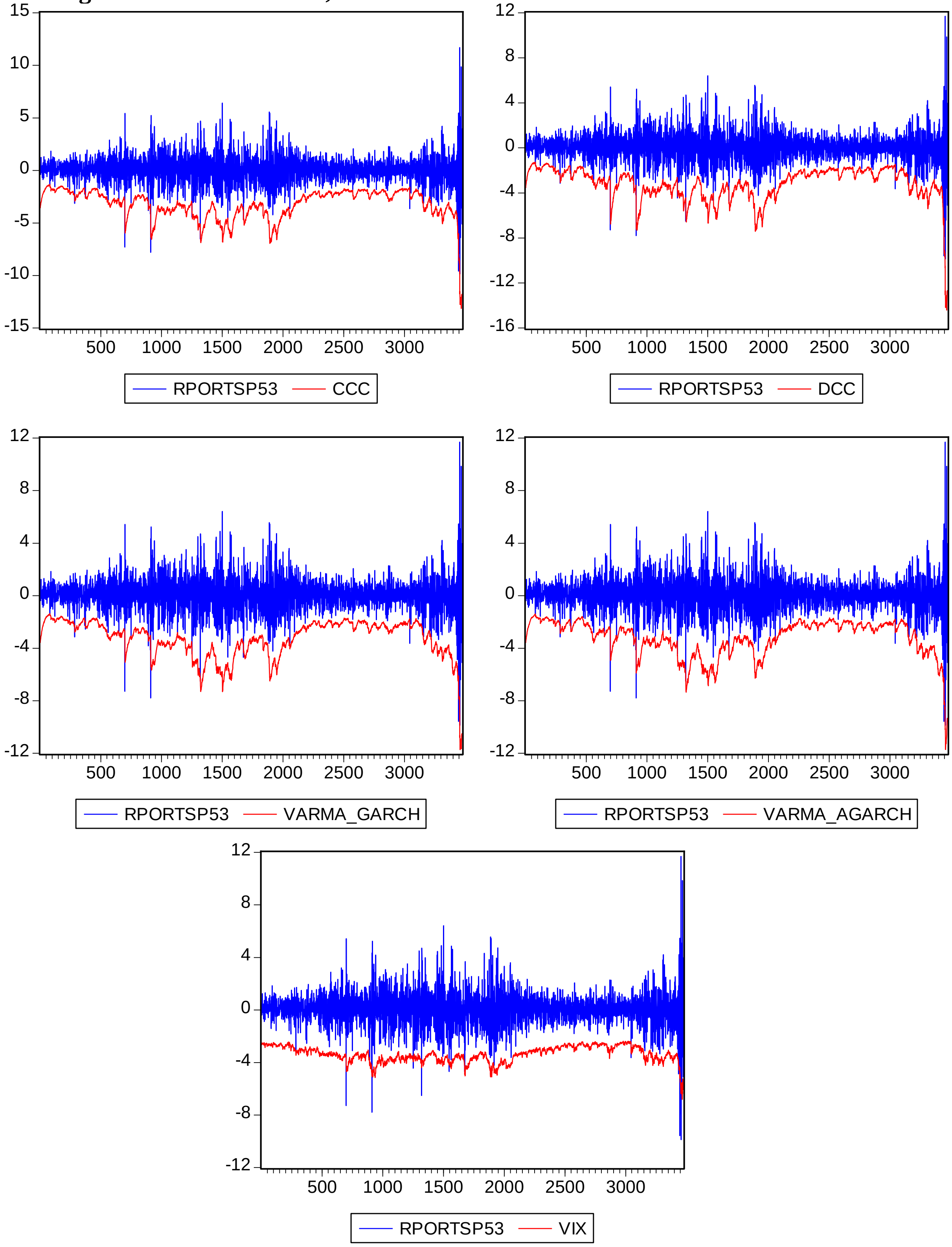


Figure 3: Single Index Models and Realized Returns VaR Forecasts for Europe

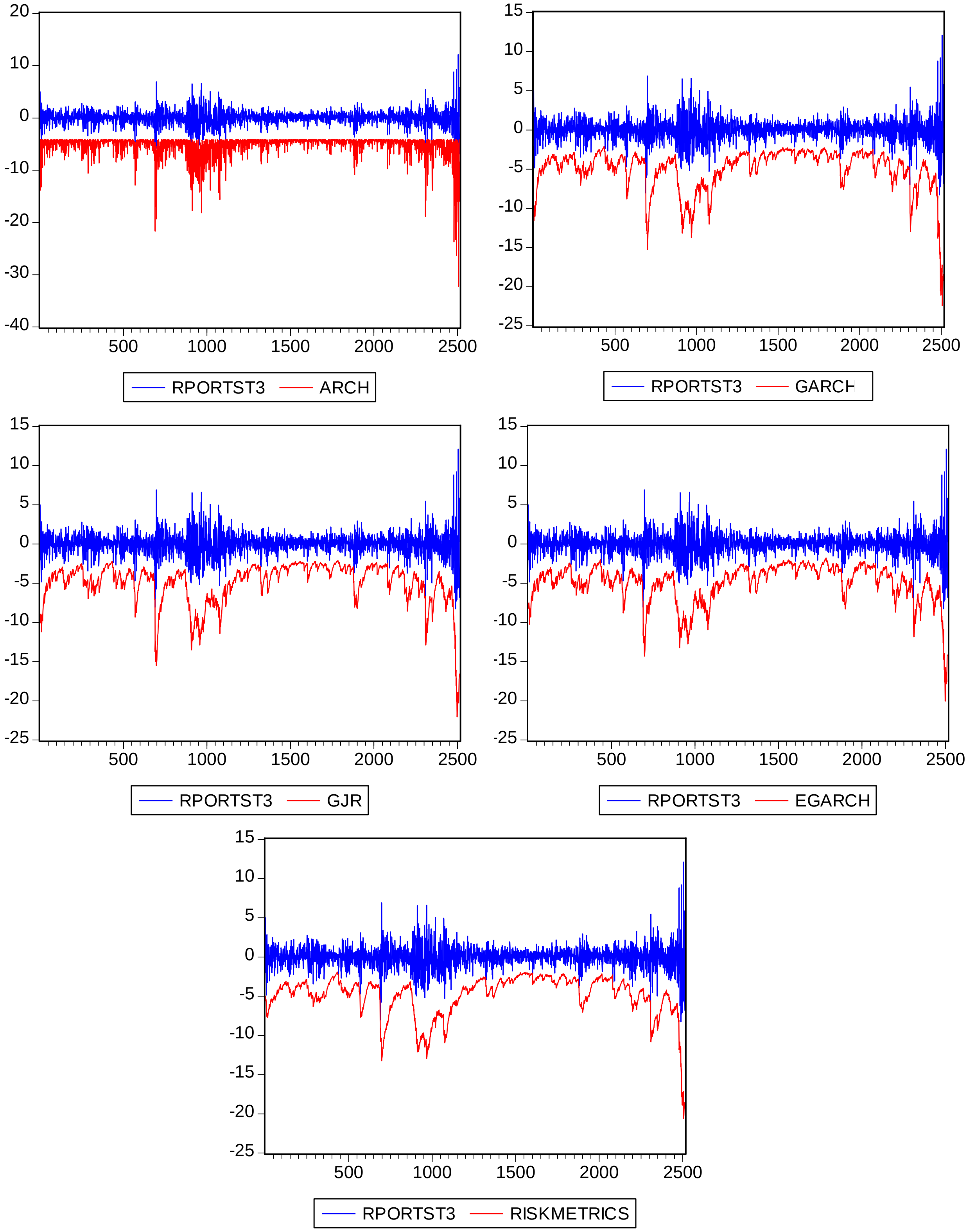
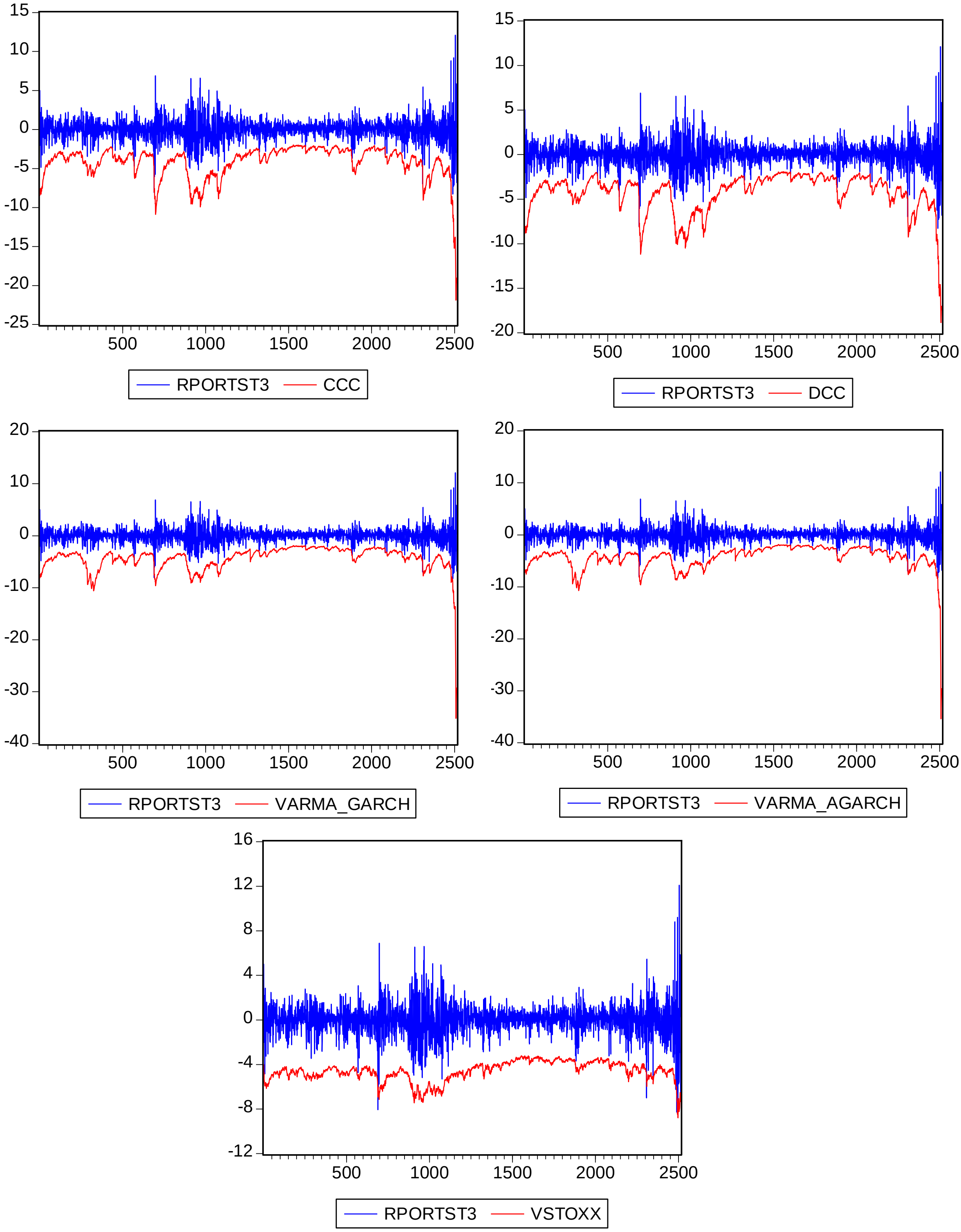


Figure 4: Portfolio Models, VSTOXX and Realized Returns VaR Forecasts for Europe



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APPENDIX B

Index of Volatility for ASEAN

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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

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. (2008))

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 2 presents the Index of Volatility, and section 3 shows the data and estimation. Empirical results, Value-at-Risk, and conclusion are in sections 4, 5, and 6, respectively.

2. Index of Volatility

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

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

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:

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:

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

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

GARCH

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

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \tag{3}$$

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. (1992) accommodate differential impacts on the conditional variance of positive and negative shocks of equal magnitude. The GJR(p,q) model is given by:

$$h_t = \omega + \sum_{j=1}^{p} \left(\alpha_j + \gamma_j I(\varepsilon_{t-j}) \right) \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \qquad (4)$$

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, 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 $\alpha_1 + \gamma_1 / 2 + \beta_1$.

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:

$$\log h_t = \omega + \sum_{j=1}^{p} \alpha_j \left| \eta_{t-j} \right| + \sum_{j=1}^{p} \gamma_j \eta_{t-j} \sum_{i=1}^{q} \beta_i \log h_{t-i} \qquad (5)$$

In equation (5), $\left|\eta_{t-j}\right|$ and η_{t-j} capture the size and sign effects, respectively, of the standardized shocks. EGARCH in (5) uses the standardized residuals. As EGARCH uses the logarithm of conditional volatility, there are no restrictions on the parameters in (5). As the standardized shocks have finite moments, the moment conditions of (5) are entirely straightforward.

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

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \qquad (6)$$

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

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0 \qquad (7)$$

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^{TM}

Riskmetrics^{TM} (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(∞) 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^{TM} model estimate the conditional variances follows:

$$h_t = \lambda h_{t-1} + (1-\lambda)\varepsilon_{t-1}^2 \qquad (8)$$

where λ is a decay parameter. Riskmetrics^{TM} (1996) suggests that λ should be set at 0.94 for purposes of analyzing daily data.

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:

$$IVol_t = \lambda_1^2 h_{1t} + \lambda_2^2 h_{2t} + \lambda_3^2 h_{3t} + 2\lambda_1\lambda_2 h_{12t} + 2\lambda_1\lambda_3 h_{13t} + 2\lambda_2\lambda_3 h_{23t} \qquad (9)$$

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. (2008))

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 (≥ 2) financial assets be given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{10}$$

$$\varepsilon_t = D_t \eta_t \tag{11}$$

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \tag{12}$$

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

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:

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{p} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \tag{13}$$

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

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

VARMA-AGARCH reduces to VARMA-GARCH when C_k =0 for all k.

CCC

If the model given by equation (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:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_i \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_i h_{i,t-l} \tag{14}$$

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 (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:

$$y_t \mid F_{t-1} \sim (0, Q_t), \quad t = 1, ..., T \tag{15}$$

$$Q_t = D_t \Gamma_t D_t, \tag{16}$$

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:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{i,k} \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{i,l} h_{i,t-l} \tag{17}$$

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:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta_{t-1}' + \phi_2 Q_{t-1} \tag{18}$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\}, \tag{19}$$

where S is the unconditional correlation matrix of the returns shocks, and equation (19) is used to standardize the matrix estimated in (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).

3. Data and Estimation

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 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 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:

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (20)$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (21)$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (22)$$

where equation (20) has no intercept or trend, equation (21) has intercept but no trend, and equation (22) has intercept and trend. The null hypothesis in equation (20), (21) and (22) is $\theta = 0$, which means that y_t is nonstationary. The test results for all series are given in Table 3. The table shows that the θ for all the returns are significantly less than zero at the 1% level, so that the returns are stationary.

3.2 Estimation

The parameters in models (2), (3), (4), (5), (12), (13), (14), and (17) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, as follows:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{2}\sum_{t=1}^{n}(\log|Q_t| + \varepsilon_t' Q_t^{-1}\varepsilon_t) \tag{23}$$

Where θ 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 η_t does not follow a joint normal distribution, equation (23) is defined as the Quasi-MLE (QMLE).

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. 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 5 to 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 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 6. Asymmetric effects are not significant in any of the countries.

Conditional correlations between the conditional volatilities of IND and PHI for the CCC, VARMA-GARCH, and VARMA-AGARCH in Table 7 are identical at 0.237. Conditional correlations between the conditional volatilities of IND and THA for the three models above are identical at 0.265. PHI and THA have conditional correlations between the conditional volatilities for the three models, which are identical at 0.227. In Table 8, we can see that estimated coefficient is significantly different from zero, which means that the conditional correlations of the overall returns are dynamic.

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. (2008))

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 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):

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \qquad (24)$$

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, ε_t. The variability of Y_t, and hence its distribution, is determined entirely by the variability of ε_t. If it is assumed that ε_t follows a distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t) \qquad (25)$$

where μ_t and σ_t are the unconditional mean and standard deviation of ε_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 α is the critical value from the distribution of ε_t to obtain the appropriate confidence level. Alternatively, σ_t can be replaced by alternative estimates of the conditional variance to obtain an appropriate VaR (see Section 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:

$$\underset{\{k, VaR_t\}}{Minimize} \quad DCC_t = \max\left\{-(3+k)\overline{VaR}_{60}, -VaR_{t-1}\right\} \qquad (26)$$

where DCC is daily capital charges, k is a violation penalty ($0 \le k \le 1$) (see Table 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 α is the critical value from the distribution of ε_t to obtain the appropriate confidence level of 1%.

Figures 1–2 show the VaR forecasts and realized returns of each Single Index Model and Portfolio Model for the USA and Europe, respectively.

Table 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%.

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.

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Table 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 3 countries above

Table 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 3: ADF Test of a Unit Root in the Returns

Variables	Trend and intercept		Intercept		None	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
IND	-0.851	-24.237	-0.850	-24.216	-0.850	-24.215
PHI	-0.835	-59.312	-0.834	-59.304	-0.834	-59.309
THA	-0.848	-60.163	-0.848	-60.160	-0.848	-60.163
PORT	-0.748	-54.150	-0.747	-54.137	-0.747	-54.142

Table 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 5: Portfolio Models for ASEAN: VARMA-GARCH

Countries	ω	α_{IND}	β_{IND}	α_{PHI}	β_{PHI}	α_{THA}	β_{THA}
IND	-0.049 -1.122	**0.288** **5.656**	**0.622** **8.514**	0.033 0.730	0.689 1.502	-0.008 -0.228	0.191 1.082
PHI	**0.199** **2.514**	0.022 0.574	0.130 0.780	**0.169** **5.420**	**0.536** **3.883**	0.016 0.610	**0.690** **2.266**
THA	0.074 1.276	-0.007 -0.410	0.095 1.131	**-0.051** **-2.337**	0.470 1.348	**0.148** **2.271**	**0.737** **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 6: Portfolio Models for ASEAN: VARMA-AGARCH

Countries	ω	α_{IND}	β_{IND}	α_{PHI}	β_{PHI}	α_{THA}	β_{THA}	γ
IND	-0.053 -1.245	**0.278** **5.328**	**0.612** **9.472**	0.030 0.799	0.719 1.682	-0.012 -0.399	0.208 1.306	0.027 0.606
PHI	**0.218** **3.076**	0.020 0.547	0.169 1.016	**0.167** **3.966**	**0.517** **3.754**	0.017 0.688	**0.671** **2.339**	0.119 0.000
THA	0.070 1.129	-0.013 -0.719	0.087 0.840	**-0.042** **-3.035**	0.486 1.713	**0.100** **2.589**	**0.743** **6.774**	-0.145 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 7: Constant Conditional Correlations between countries for ASEAN

Model	$\rho_{IND,PHI}$	$\rho_{IND, THA}$	$\rho_{PHI,THA}$
CCC	**0.239** **17.037**	**0.263** **18.998**	**0.230** **16.496**
VARMA-GARCH(1,1)	**0.237** **17.344**	**0.265** **17.810**	**0.227** **15.237**
VARMA-GARCH(1,1)	**0.237** **19.442**	**0.265** **21.853**	**0.227** **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 8: DCC-GARCH(1,1) Estimates for ASEAN

Model	ϕ_1	ϕ_2
$Q_t = (1-\phi_1-\phi_2)S + \phi_1\eta_{t-1}\eta'_{t-1} + \phi_2 Q_{t-1}$	**0.015** **3.989**	**0.981** **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 9: Basel Accord Penalty Zones

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

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

Table 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.

Figure 1: Single Index Models and Realized Returns VaR Forecasts for ASEAN

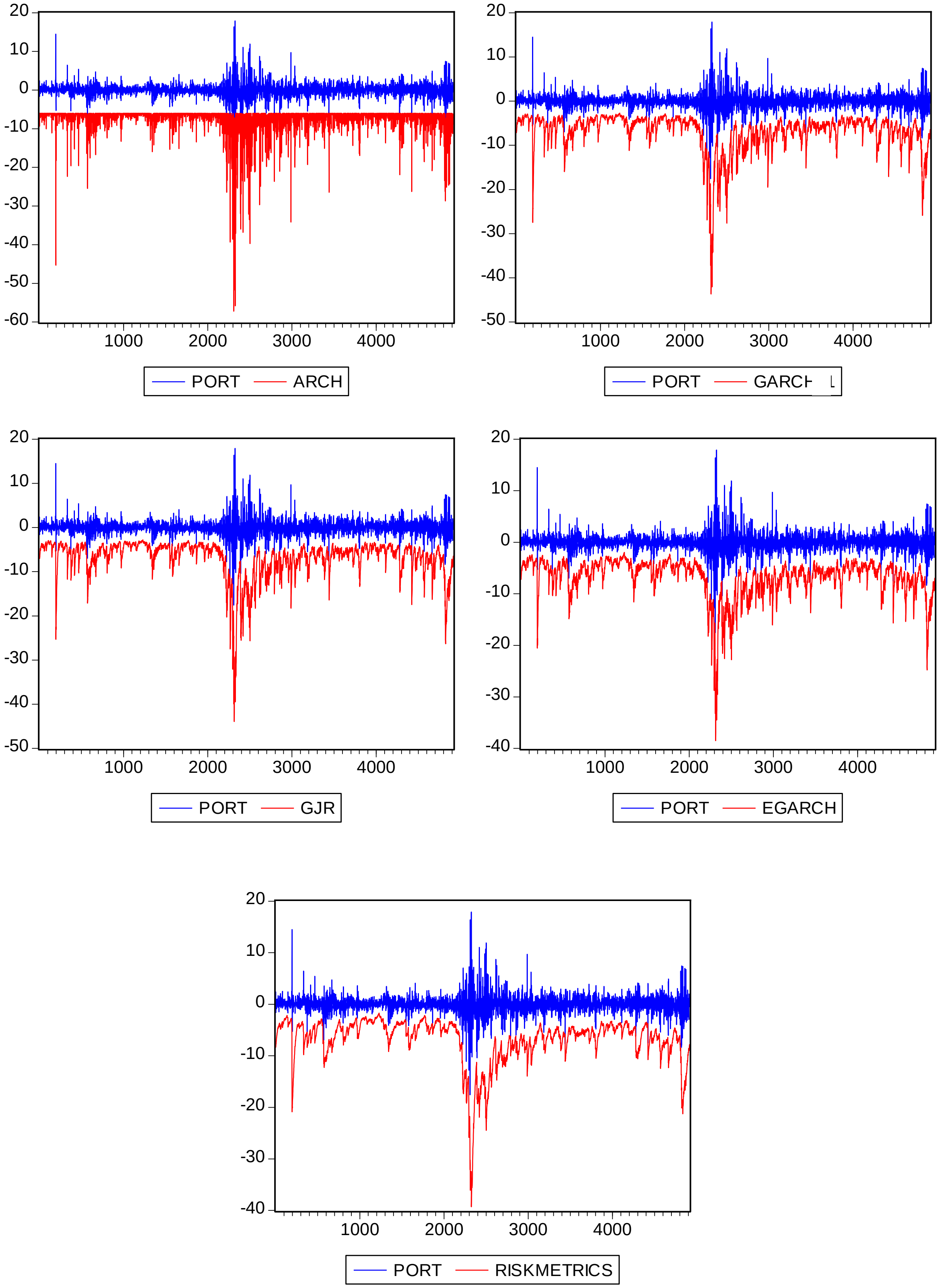
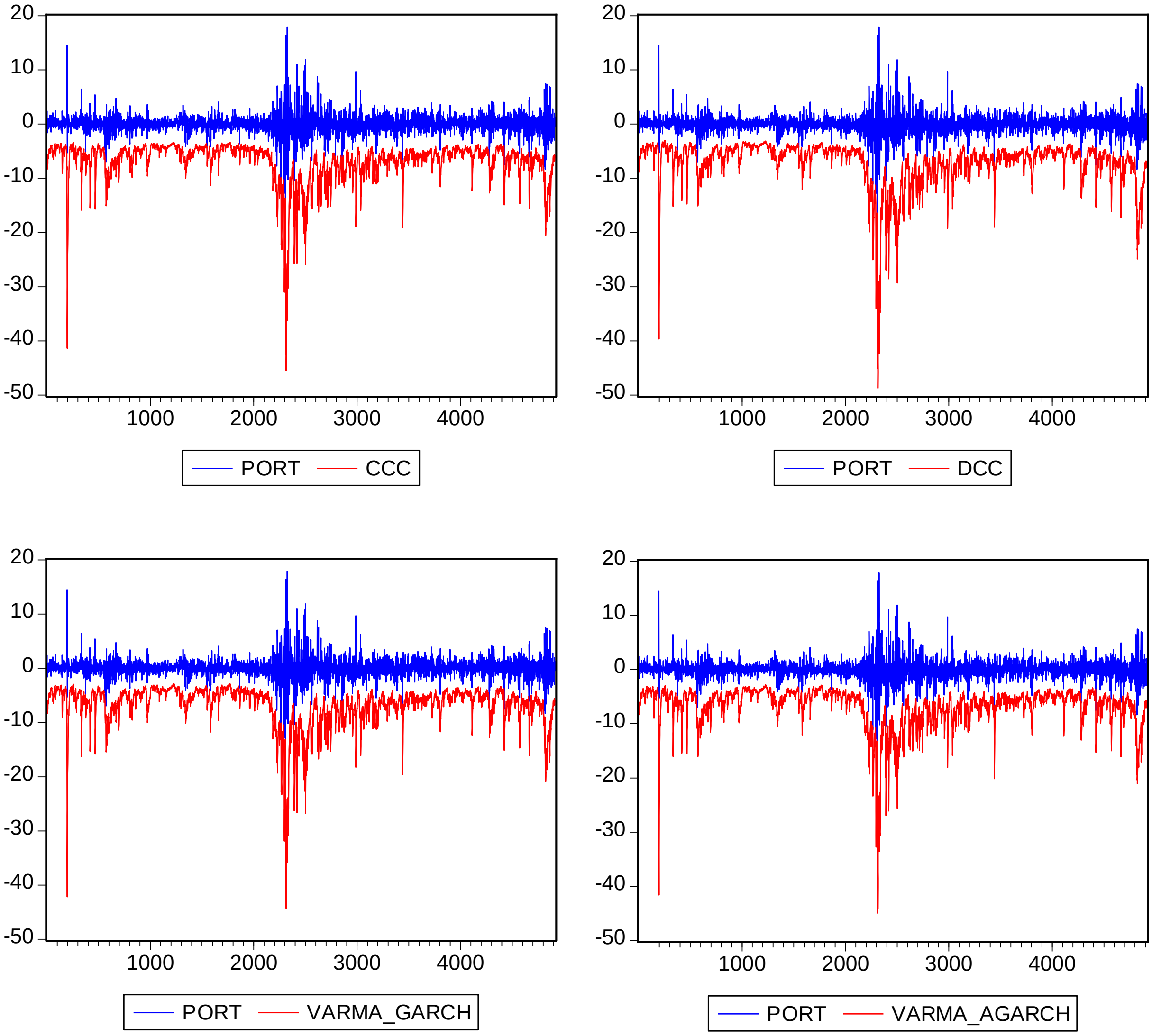


Figure 2: Portfolio Models and Realized Returns VaR Forecasts for ASEAN



APPENDIX C

Modeling the volatility spillover and conditional correlations between ASEAN, Europe, and the USA in forecasting Value-at-Risk

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Abstract

This paper will explore the volatility spillover and conditional correlations between ASEAN, Europe, and the USA by using the VARMA-AGARCH model of McAleer, M., et al. (2009), which can be used to estimate the covariance matrix. It is used to test for change in the correlation between ASEAN and Europe and between ASEAN and the USA following the Asian economic crisis. This paper focuses on five countries in ASEAN, namely, Indonesia, Malaysia, The Philippines, Singapore, and Thailand. Moreover, we use the 'rolling windows' approach to examine the time-varying nature of the conditional correlation. We also use a Value-at-Risk (VaR) threshold for a portfolio, which includes countries in ASEAN, Europe and the USA to examine the effects from the Asian crisis to Value-at-Risk. The results show negative volatility spillover from the USA to Indonesia, while evidence of positive volatility spillovers is found from the USA to The Philippines. The calculated conditional correlations between ASEAN countries and Europe after the Asian crisis are significantly higher than before the Asian crisis, except for Malaysia, which after the Asian crisis has significantly lower correlations than before the crisis. The calculated conditional correlations between ASEAN countries and the USA are insignificant. Moreover, we found all the conditional correlations display significant variability. Finally, the results do not appear to be show a direct relationship between the sample size and the number of violations, which suggests that adjusting for the Asian crisis may not be important.

Keywords: volatility spillover, conditional correlation, Value-at-Risk

1. Introduction

International stock markets have had increasing interaction with one another during the past decade. Shocks in one stock market or in one region are very likely to transmit disturbances to other market and regions (for example, the Asian crisis in 1997 that started in Thailand and spread out to the entire region). The behavior of the financial economy has produced negative shocks in the real economy. For example, Korea, Indonesia, and Thailand experienced negative GDP growth rates throughout the period 1997-1998. This effect on the real GDP later transferred to the most important Latin American economies. Although European countries and the United States are those that best adjusted to the effects of the Asian crisis, forecasts of their real growth were revised downwards. (see Fernández-Izquierdo, Á. and Lafuente, J. A. (2004))

Another good example is 9 September 2001. The 9-11 terrorist attacks on the USA affected most world stock markets because the USA is the most influential economy in the world, and most countries have some links with the USA.

Therefore, it is very critical for the investors to understand the behavior of the volatility and mean spillover so as to efficiently implement international hedging strategies with global diversified portfolios. International diversification is often considered to be the best instrument to improve portfolio performance. Because correlations between asset returns from different markets are usually lower than correlations within the same market, international diversification enables the investors to shift to investments of high risk and expected returns without altering the overall risks of their portfolios. Moreover, understanding the volatility and mean spillover also helps the policy makers better evaluate the regulatory proposals, and supervise and restrict the international cash flows, thus protecting national markets and economies from international shocks. (see Liu, L. (2007))

Many papers have studied volatility spillover in several regions, so we classify those we have studied by region. The first group are papers that studied volatility spillover among Asia, Europe, and the USA. For example, Theodossiou, P. and Lee, U. (1993) and Ramchand, L. and Susmel, R. (1998) used weekly data of major stock markets. Santis, G. D. and İmrohoroğlu, S. (1997) also used weekly data, but they studied volatility in emerging financial markets. Moreover, Fernández-Izquierdo, Á. and Lafuente, J. A. (2004) and Sharkasi, A., et al (2004) studied international transmission by using daily data from Europe, America, and Asia. Alternately, Fernández-Izquierdo, Á. and Lafuente, J. A. (2004) were also interested in empirical evidence from the Asian crisis.

The second group of papers studied volatility spillover between Pacific-Asia and the USA. For example, Kim, S.W. and Rogers, J.H. (1995), Ng, A. (2000), Miyakoshi, T. (2003), Lee, S.J. (2006) and Liu, L. (2007) used daily data, except for Ng, A. (2000) who used weekly data. All were interested in the differences among countries in Pacific-Asia. Third, Forte, G. and Manera, M. (2004) and Chai, H. and Rhee, Y. (2005) were interested to study volatility spillover between Asia and Europe, but Forte, G. and Manera, M. (2004) used weekly data, while Chai, H. and Rhee, Y. (2005) used daily data.

Fourth, Booth, G.G., et al (1997) and Baur, D. and Jung, R.C. (2006) studied volatility linkages between Europe and the USA, but Booth, G.G., et al (1997) used daily data, while Baur, D. and Jung, R.C. (2006) used intraday data. Finally, In, F., et al (2001) and da Veiga, B., et al. (2008) studied volatility transmission in Asia, and used daily data, but In, F., et al (2001) were interested in effects from the Asian crisis, while da Veiga, B., et al. (2008) were interested in effects from the B share market reform.

This paper would like to find out about volatility spillover and conditional correlations between ASEAN and Europe, and ASEAN and the USA, by using the vector autoregressive moving average asymmetric generalize autoregressive conditional heteroskedasticity (VARMA-AGARCH) model of McAleer, M., et al. (2009), which can be used to estimate the covariance matrix. It is used to test for a change in the correlation between ASEAN and Europe and between ASEAN and the USA following the 1997 Asian economic crisis. This paper uses five countries in ASEAN, namely, Indonesia, Malaysia, The Philippines, Singapore, and Thailand. Moreover, we use the rolling windows approach to examine the time-varying nature of the conditional correlation. Finally, we use a Value-at-Risk (VaR) threshold for a portfolio, which include countries in ASEAN, Europe, and the USA to examine effects from the Asian crisis to Value-at-Risk.

The organization of this paper is as follows: section 2 presents model and test statistics for testing differences in correlations, and section 3 shows the data and estimations. Empirical results, Value-at-Risk, and conclusions are in sections 4, 5, and 6, respectively.

2. Model and test statistics for testing differences in correlations

This paper use stock price indices of Indonesia, Malaysia, The Philippines, Singapore, Thailand, Europe and the USA. We compute the returns of each country follows:

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

where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of country i (i = 1, 2, 3) at days t and t-1, then we use the vector autoregressive moving average asymmetric generalize autoregressive conditional heteroskedasticity (VARMA-AGARCH) model of McAleer, M., et al. (2009) to find out returns and volatility spillover from Europe and the USA to ASEAN countries. Analyses of the samples before and after the Asian crisis are examined. This paper also investigates whether the spillover of volatility was affected by the Asian crisis.

VARMA-AGARCH

The VARMA-AGARCH model of McAleer, M., et al. (2009) assumes asymmetric impacts of positive and negative shocks of equal magnitude. Let the vector of returns on *m* (≥ 2) financial assets is given by:

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \quad (2)$$

$$\varepsilon_t = D_t \eta_t \quad (3)$$

$$H_t = \omega + \sum_{k=1}^{p} A_k \vec{\varepsilon}_{t-k} + \sum_{k=1}^{p} C_k I_{t-k} \vec{\varepsilon}_{t-k} + \sum_{l=1}^{q} B_l H_{t-l} \quad (4)$$

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. C_k are $m \times m$ matrices for k = 1,…,p and I_t = diag(I_{1t},…,I_{mt}), so that $I = \begin{cases} 0, \varepsilon_{k,t} > 0 \\ 1, \varepsilon_{k,t} \leq 0 \end{cases}$.

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. Based on equation (3), the VARMA-AGARCH model also assumes that the matrix of conditional correlations is given by $E(\eta_t \eta_t') = \Gamma$.

Test statistics for testing differences in correlations

This paper would like to test whether the Asian crisis affected conditional correlation between ASEAN countries and Europe and the USA. Therefore, we estimate the VARMA-AGARCH model for the entire sample, the sub-sample before the Asian crisis (5 January 1988 to 27 December 1996), and the sub-sample after the crisis (5 January 1998 to 13 March 2009) to find out conditional correlation matrices between ASEAN countries, Europe, and the USA. Let ρ_1 and ρ_2 be the correlations from the after and before Asian crisis period, respectively. The test statistic for testing differences in correlations is then given by

$$Z = \frac{\rho_1 - \rho_2}{S.E.} \tag{5}$$

$$S.E. = \sqrt{\frac{1}{n_1 - 3} + \frac{1}{n_2 - 3}} \tag{6}$$

where n_1 and n_2 are sample sizes used to calculate ρ_1 and ρ_2, respectively.

3. Data and Estimation

3.1 Data

The data used in the paper is the daily closing stock price indices of Indonesia, Malaysia, The Philippines, Singapore, Thailand, Europe, and the USA. All the data was obtained from the DataStream and the sample ranges from 5/1/1988 up to 13/3/2009 with 4,916 observations. The normality of the variables and the descriptive statistics for the returns of stock indices are given in Table 1 because two characteristics of the data, namely normality and stationary, will be investigated before the estimate. 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. All series have similar means and medians, which are close to zero, minima that range between -43.081 and -9.514, and maxima which vary between 10.698 and 44.515. The three standard deviations vary between 1.143 and 2.786. The skewness differs among all series, and the kurtosis that range between 10.660 and 67.539, this is a high degree 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, it will be necessary to differencing data before estimation because if the data is not differenced, the result is spurious regression. To test stationarity of data, this paper uses the Augmented Dicky Fuller (ADF) test. The test is given as follows:

$$\Delta y_t = \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{7}$$

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{8}$$

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \tag{9}$$

where equation (7) has no intercept and trend, equation (8) has intercept but no trend, and equation (9) has intercept and trend. The null hypothesis in equation (7), (8) and (9) are $\theta = 0$, which means that y_t is nonstationary. The results for all series are given in Table 2. The table shows that the θ for all the returns are significantly less than zero at the 1% level, so that the returns are stationary.

3.2 Estimation

The parameters in models (4) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, as follows:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{2} \sum_{t=1}^{n} (\log |Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t) \tag{10}$$

where θ denotes the vector of parameters to be estimated in the conditional log-likelihood function, and $|Q_t|$ denotes the determinant of Q_t, the conditional covariance matrix. When η_t does not follow a joint normal distribution, equation (10) is defined as the Quasi-MLE (QMLE).

4. Empirical Results

4.1 Returns, volatility spillover, and testing differences in correlations

Tables 3 and 4 give the estimated parameter of the VARMA-AGARCH model for the entire sample. Evidence of returns spillover is found from EU and USA to IND, PHI, SNG and THA, indicating that past returns of EU and USA affect future returns of IND, PHI, SNG and THA. Returns spillover also exists from USA to MAL, which indicates that past returns of USA affect future returns to MAL. In conditional variance equation, the results show negative volatility spillover from USA to IND. Moreover, evidence of negative volatility spillover is found from EU to SNG and

THA. Table 4 also shows a positive effect of shock or news from USA to IND, MAL, SNG, and THA. Furthermore, it has positive effect of shock or news from EU to SNG, however, shock or news from EU has a negative effect to MAL. The VARMA-AGARCH model shows PHI and SNG have an asymmetric effect.

The sub-sample before the Asian crisis (5 January 1988 to 27 December 1996) is estimated by using the VARMA-AGARCH model as shown in Tables 5 and 6. Evidence of returns spillover is found from EU and USA to MAL, PHI, SNG and THA, indicating that past returns of EU and USA affect future returns of MAL, PHI, SNG and THA. For returns spillover from EU to IND, the result indicates that past returns of EU affect future returns to IND. Table 6 contains the results for the conditional variance equation. The results show evidence of positive volatility spillover from EU to PHI, and negative effect of shocks or news from EU to IND and PHI. Moreover, positive affect to SNG from shocks or news of USA is also shown. Furthermore, the VARMA-AGARCH model shows MAL and SNG have a significantly asymmetric effect.

The results for the sub-sample after the Asian crisis (5 January 1998 to 13 March 2009) are quite different. The results for the conditional mean equation can be found in Table 7. The results suggest that IND, MAL and PHI returns are positively affected by past returns of EU and USA. Moreover, SNG and THA returns are positively affected by past returns of USA. The results of positive effect of shocks or news from USA to PHI and SNG and positive affect to SNG of shocks or news from EU are shown in Table 8. The VARMA-AGARCH model shows SNG has a significantly asymmetric effect.

Tables 9–11 give the conditional correlation for the entire sample and sub-sample before and after Asian crisis, respectively. As can be seen, the calculated conditional correlations between ASEAN countries and EU after the Asian crisis are significantly higher than before the crisis, except for MAL, which after the Asian crisis has significantly lower correlations than before the crisis. However, the calculated conditional correlations between ASEAN countries and USA are insignificant. Because trading times of stock market in ASEAN and USA are not overlaps as EU. Moreover, only MAL is less affected by EU and USA after the crisis, which can be attributed to the success of its capital and currency controls. The results same Tan and

Tse (2002) in Click, R., et al (2005), which examine the linkages among U.S., Japan, and seven Asian stock markets including Malaysia, The Philippines, Singapore, and Thailand. The test for differences in correlations between samples is shown in Table 12.

4.2 Correlation dynamics

The VARMA-AGARCH model, as with all the nested variations, imposes the assumption of constant conditional correlations. In the constant conditional correlation framework, Γ is the constant conditional correlation matrix of the standardized shocks, η_t, which are assumed to be either a vector of independently and identically distributed (iid) random variables, or a martingale difference process. However, in the dynamic conditional correlation framework proposed by Engle (2002), the conditional correlation matrix, Γ, is no longer constant, but follows a restricted multivariate GARCH (1,1) specification.

Using the 'rolling windows' approach, we can examine the time-varying nature of the conditional correlation using the VARMA-AGARCH model. Rolling windows is a recursive estimation procedure whereby the model is estimated for a restricted sample, then re-estimated by adding one observation to the end of the sample and deleting one observation from the beginning of the sample. The process is then repeated until the end of the sample. If the rolling conditional correlations are found to vary substantially over time, the assumption of constant conditional correlations may be too restrictive. In order to strike a balance between efficiency in estimation, and a viable number of rolling regressions, the rolling window size is set at 1,000.

Figure 1-10 plots the dynamic paths of the conditional correlation matrices for the VARMA-AGARCH model using rolling windows. All the conditional correlations display significant variability. These results suggest that the assumption of constant conditional correlations may not be valid.

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. (2008))

For 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 given in Table 13.

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. (2008))

$$Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{11}$$

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, ε_t. The variability of Y_t, and hence its distribution, is determined entirely by the variability of ε_t. If it is assumed that ε_t follows a distribution such that:

$$\varepsilon_t \sim D(\mu_t, \sigma_t) \tag{12}$$

where μ_t and σ_t are the unconditional mean and standard deviation of ε_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 α is the critical value from the distribution of ε_t to obtain the appropriate confidence level. Alternatively, σ_t can be replaced by alternative estimates of the conditional variance to obtain an appropriate VaR.

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 the expected returns for all models and α is the critical value from the distribution of ε_t to obtain the appropriate confidence level of 1%. This paper constructs portfolio returns of each country in ASEAN with Europe and the USA, and in order to eliminate exchange rate risk, all returns are converted to US dollars.

In order to examine the impact of the Asian crisis, the VaR thresholds for the period 3 January 2007 to 13 March 2009 are forecasted using observation from the previous year, 2006, and the number of violations is recorded. The sample is then expanded by adding observations from next previous year, 2005, to the beginning of the sample (1988), and again the VaR threshold for the period 3 January 2007 to 13 March 2009 is forecasted. This process is repeated until the beginning of the sample is reached. The results in Table 14 do not appear to show a direct relationship between sample size and the number of violations, which suggests that adjusting for the Asian crisis may not be important.

6. Conclusion

Interaction between international stock markets and other stock markets have increased during the past decade. Shocks in one stock market or in one region are very likely to transmit to other market and regions. This paper uses the VARMA-AGARCH model of McAleer, M., et al. (2009) to provide more information about volatility spillover and conditional correlations between ASEAN, Europe, and the USA. We also test the changes from the 1997 Asian crisis the find the affect to the correlation between ASEAN and Europe, and between ASEAN and the USA. This paper used five countries in ASEAN—namely, Indonesia, Malaysia, The Philippines, Singapore, and Thailand.

Evidence of returns spillover is found from EU and USA to IND, PHI, SNG and THA. Returns spillover also exists from USA to MAL. The results show negative volatility spillover from USA to IND. Moreover, evidence of negative volatility spillover is found from EU to SNG and THA. The results also show a positive effect of shock or news from USA to IND, MAL, SNG, and THA. Furthermore, it has a positive effect of shock or news from EU to SNG. However, shock or news from EU has a negative affect to MAL. Furthermore, the calculated conditional correlations between ASEAN countries and EU after the Asian crisis are significantly higher than before Asian crisis, except MAL, which after the Asian crisis has significantly lower correlations than before the crisis because in after the Asian crisis MAL control capital and currency. Finally, the calculated conditional correlations between ASEAN countries and USA are insignificant.

This paper uses the 'rolling windows' approach to examine the time-varying nature of the conditional correlation. We found all the conditional correlations display significant variability. These results suggest that the assumption of constant conditional correlations may not be valid.

Finally, we use a Value-at-Risk (VaR) threshold for a portfolio, which include countries in ASEAN, Europe and the USA to examine effect from Asian crisis to Value-at-Risk. The results do not appear to show a direct relationship between sample size and the number of violations, which suggests that adjusting for the Asian crisis may not be important.

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Table 1: Descriptive Statistic for Returns

Statistics	IND	MAL	PHI	SNG	THA	EU	USA
Mean	0.017	0.006	0.003	0.011	-0.017	0.002	0.008
Median	0.041	0.029	0.012	0.041	-0.022	0.056	0.047
Maximum	44.515	25.854	21.972	11.846	18.100	10.698	11.043
Minimum	-43.081	-36.967	-10.942	-10.760	-18.084	-10.178	-9.514
Std. Dev.	2.786	1.786	1.759	1.393	2.113	1.146	1.143
Skewness	0.080	-1.192	0.512	-0.147	0.400	-0.269	-0.245
Kurtosis	43.254	67.539	13.502	10.660	12.517	13.726	12.553
Jarque-Bera	331,912.000	854,363.000	22,805.550	12,036.140	18,682.520	23,624.030	18,743.820

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

Variables	Trend and intercept		Intercept		None	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
IND	-0.851	-24.237	-0.850	-24.216	-0.850	-24.215
MAL	-0.918	-64.575	-0.918	-64.569	-0.918	-64.575
PHI	-0.835	-59.312	-0.834	-59.304	-0.834	-59.309
SNG	-0.924	-64.943	-0.923	-64.915	-0.923	-64.918
THA	-0.848	-60.163	-0.848	-60.160	-0.848	-60.163
EU	-1.077	-30.666	-1.070	-30.559	-1.070	-30.562
USA	-1.044	-73.245	-1.043	-73.193	-1.043	-73.197

Table 3: Conditional mean equation of VARMA-AGARCH for ASEAN:
5 January 1988 to 13 March 2009

Equation		Constant	ASEANi (-1)	EU (-1)	USA(-1)	MA (1)
IND	ASEANi	0.026	**0.228**	**0.103**	**0.210**	-0.071
		1.372	**2.443**	**2.416**	**6.190**	-0.827
	EU	0.009	-0.007	0.054	**0.299**	**-0.110**
		0.820	-1.486	1.114	**20.375**	**-2.165**
	USA	0.019	-0.002	0.017	0.014	-0.027
		1.585	-0.450	1.115	0.107	-0.200
MAL	ASEANi	**0.108**	**0.400**	0.012	**0.352**	**-0.356**
		7.972	**7.802**	0.368	**16.874**	**-6.113**
	EU	0.008	0.001	0.039	**0.298**	-0.096
		0.746	0.097	0.774	**20.356**	-1.879
	USA	0.019	0.005	0.014	-0.038	0.028
		1.528	0.712	0.876	-0.319	0.230
PHI	ASEANi	0.010	0.027	**0.171**	**0.326**	**0.134**
		0.448	0.442	**5.316**	**13.120**	**2.080**
	EU	-0.009	0.002	0.042	**0.313**	-0.084
		-0.876	0.185	0.901	**21.175**	-1.732
	USA	0.020	-0.007	0.017	-0.006	-0.006
		1.685	-1.015	1.109	-0.049	-0.043
SNG	ASEANi	0.017	**0.138**	**0.043**	**0.332**	-0.081
		1.362	**2.941**	**2.268**	**17.592**	-1.679
	EU	0.008	0.001	0.039	**0.299**	-0.096
		0.738	0.119	0.756	**20.421**	-1.877
	USA	0.019	-0.007	0.019	0.026	-0.038
		1.605	-0.630	1.194	0.195	-0.285
THA	ASEANi	0.004	**0.343**	**0.073**	**0.315**	**-0.217**
		0.216	**6.185**	**2.305**	**10.974**	**-3.954**
	EU	0.009	0.004	0.032	**0.298**	-0.091
		0.832	0.701	0.662	**20.405**	-1.774
	USA	0.019	0.004	0.015	-0.007	-0.005
		1.576	0.529	0.924	-0.056	-0.036

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 4: Conditional variance equation of VARMA-AGARCH for ASEAN:
5 January 1988 to 13 March 2009

Equation		ω	α_{ASEANi}	β_{ASEANi}	α_{EU}	β_{EU}	α_{USA}	β_{USA}	γ
IND	ASEANi	**0.059**	**0.290**	**0.698**	0.025	0.008	**0.212**	**-0.024**	0.025
		2.261	**4.572**	**27.176**	0.690	0.180	**3.524**	**-5.340**	0.303
	EU	**0.025**	**0.028**	**0.863**	0.000	0.000	**0.020**	-0.001	**0.123**
		4.178	**2.625**	**40.727**	-0.008	0.408	**3.367**	-0.244	**3.803**
	USA	**0.012**	0.008	**0.950**	0.000	0.000	**0.022**	**-0.022**	**0.059**
		5.290	1.041	**109.048**	-1.884	1.953	**2.431**	**-2.009**	**4.151**
MAL	ASEANi	0.720	0.143	**0.775**	**-0.053**	-0.123	**0.128**	0.056	0.018
		1.369	1.339	**4.928**	**-2.378**	-1.516	**2.721**	0.941	0.245
	EU	**0.026**	**0.027**	**0.859**	0.000	0.001	**0.020**	-0.001	**0.128**
		4.172	**2.502**	**39.042**	0.177	0.949	**3.357**	-0.296	**3.845**
	USA	**0.013**	0.007	**0.944**	**-0.001**	**0.001**	**0.022**	**-0.021**	**0.068**
		5.328	0.847	**86.513**	**-3.102**	**2.272**	**2.448**	**-2.009**	**4.448**
PHI	ASEANi	**0.106**	**0.115**	**0.781**	-0.003	0.013	**0.080**	-0.001	**0.075**
		4.970	**5.513**	**37.103**	-0.215	0.484	**2.246**	-0.048	**2.021**
	EU	**0.064**	**0.047**	**0.683**	**-0.002**	**0.007**	0.017	**0.037**	**0.319**
		5.401	**2.919**	**20.345**	**-8.843**	**3.464**	1.627	**2.922**	**6.259**
	USA	**0.011**	0.006	**0.951**	0.004	-0.002	**0.019**	**-0.022**	**0.060**
		2.890	0.954	**113.570**	1.036	-0.527	**2.462**	**-2.395**	**4.339**
SNG	ASEANi	**0.043**	**0.063**	**0.820**	**0.027**	**-0.029**	**0.063**	-0.009	**0.103**
		5.381	**4.527**	**29.245**	**2.257**	**-2.263**	**3.479**	-0.747	**4.039**
	EU	**0.026**	**0.027**	**0.858**	0.002	0.000	**0.020**	-0.001	**0.126**
		4.059	**2.508**	**39.395**	0.643	0.096	**3.110**	-0.179	**3.912**
	USA	**0.012**	0.009	**0.949**	0.001	-0.001	**0.022**	**-0.021**	**0.059**
		5.392	1.086	**99.035**	0.358	-0.184	**2.352**	**-2.001**	**3.889**
THA	ASEANi	**0.117**	**0.094**	**0.827**	0.039	**-0.069**	**0.060**	0.009	0.093
		3.379	**5.063**	**22.487**	1.348	**-2.725**	**2.305**	0.385	1.422
	EU	**0.022**	**0.026**	**0.868**	**0.000**	**0.001**	**0.020**	-0.002	**0.120**
		3.935	**2.517**	**43.438**	**-2.192**	**2.851**	**3.386**	-0.689	**3.821**
	USA	**0.010**	0.007	**0.951**	0.000	0.001	**0.021**	**-0.021**	**0.058**
		4.687	0.967	**113.492**	-1.677	1.427	**2.299**	**-1.974**	**3.850**

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 5: Conditional mean equation of VARMA-AGARCH for ASEAN:
5 January 1988 to 27 December 1996

Equation		Constant	ASEANi (-1)	EU (-1)	USA(-1)	MA (1)
IND	ASEANi	0.045	**0.411**	**0.175**	0.138	-0.144
		1.201	**4.040**	**2.291**	0.845	-1.412
	EU	0.014	**-0.008**	-0.059	**0.273**	0.100
		0.773	**-5.948**	-0.768	**11.517**	1.224
	USA	0.022	**-0.011**	0.007	**0.086**	-0.044
		1.460	**-8.837**	0.299	**2.079**	-0.887
MAL	ASEANi	0.032	**0.370**	**0.098**	**0.350**	**-0.219**
		1.709	**3.452**	**2.184**	**9.873**	**-1.988**
	EU	0.012	0.017	-0.069	**0.274**	0.104
		0.659	0.791	-0.840	**11.384**	1.313
	USA	0.026	0.009	0.025	-0.139	0.181
		1.369	0.441	1.184	-1.044	1.355
PHI	ASEANi	0.029	**0.225**	**0.095**	**0.237**	-0.047
		1.161	**2.615**	**6.149**	**5.537**	-0.517
	EU	0.012	-0.004	-0.073	**0.270**	0.115
		0.674	-0.380	-0.961	**11.372**	1.418
	USA	**0.035**	-0.016	0.016	0.052	-0.015
		2.270	-1.499	0.742	0.375	-0.107
SNG	ASEANi	0.029	0.121	**0.086**	**0.288**	-0.020
		1.648	1.603	**3.315**	**10.289**	-0.267
	EU	0.013	0.016	-0.083	**0.272**	0.118
		0.738	0.752	-1.027	**11.193**	1.479
	USA	-0.018	0.020	0.020	0.018	0.069
		-1.022	0.852	0.745	0.165	0.592
THA	ASEANi	0.012	**0.375**	**0.161**	**0.290**	**-0.236**
		0.561	**4.989**	**3.697**	**7.410**	**-3.001**
	EU	0.012	0.013	-0.067	**0.268**	0.105
		0.638	1.228	-0.841	**11.255**	1.248
	USA	**0.031**	-0.010	0.019	**0.128**	-0.093
		2.171	-0.992	0.855	**2.114**	-1.419

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 6: Conditional variance equation of VARMA-AGARCH for ASEAN:
5 January 1988 to 27 December 1996

Equation		ω	α_{ASEANi}	β_{ASEANi}	α_{EU}	β_{EU}	α_{USA}	β_{USA}	γ
IND	ASEANi	**2.827**	0.159	**0.535**	**-0.070**	-0.170	-0.055	-0.054	-0.192
		2.214	0.765	**2.556**	**-5.156**	-0.629	-0.625	-0.849	-0.811
	EU	**0.062**	0.020	**0.756**	**0.000**	0.000	**0.030**	-0.001	**0.195**
		2.906	0.956	**10.546**	**-14.177**	-0.079	**2.012**	-0.110	**2.020**
	USA	**0.404**	0.008	0.321	**0.000**	**0.000**	-0.003	0.002	**0.107**
		2.615	0.236	1.382	**-4220.139**	**-2.546**	-0.098	0.053	**2.253**
MAL	ASEANi	**0.107**	**0.070**	**0.729**	0.065	-0.047	0.081	-0.017	**0.194**
		4.574	**2.165**	**9.155**	1.898	-0.715	0.993	-0.733	**2.593**
	EU	**0.060**	0.020	**0.788**	0.009	-0.015	**0.032**	-0.002	**0.162**
		3.146	1.129	**13.083**	1.524	-1.707	**2.035**	-0.349	**2.053**
	USA	**0.031**	-0.012	**0.906**	-0.002	0.002	0.013	0.016	**0.052**
		2.451	-1.002	**23.876**	-1.602	0.417	1.129	0.650	**2.579**
PHI	ASEANi	0.014	**0.108**	**0.794**	**-0.023**	**0.202**	0.067	0.004	0.038
		0.298	**3.900**	**22.770**	**-5.925**	**2.716**	1.239	0.126	0.847
	EU	**0.041**	0.001	**0.779**	0.003	0.008	0.024	-0.004	0.191
		2.274	0.035	**10.283**	0.935	1.200	1.748	-0.728	1.915
	USA	0.007	0.008	**0.982**	0.004	-0.003	0.007	-0.015	0.007
		1.433	0.800	**154.924**	1.126	-0.703	0.783	-0.978	0.513
SNG	ASEANi	**0.133**	**0.069**	**0.574**	0.001	0.003	**0.098**	0.015	**0.200**
		4.469	**2.431**	**8.453**	0.030	0.065	**2.141**	0.477	**2.517**
	EU	**0.060**	0.018	**0.815**	0.025	-0.042	**0.028**	-0.002	**0.140**
		3.078	1.130	**15.166**	1.559	-1.672	**1.987**	-0.312	**2.068**
	USA	**0.209**	**-0.062**	**0.653**	**-0.024**	**0.064**	**0.031**	0.067	**0.113**
		2.298	**-3.316**	**5.114**	**-4.887**	**2.897**	**2.228**	1.297	**3.872**
THA	ASEANi	**0.178**	**0.140**	**0.727**	0.087	-0.084	0.060	-0.011	0.104
		4.327	**3.490**	**18.493**	1.529	-1.726	1.261	-0.585	1.917
	EU	**0.047**	0.011	**0.787**	0.000	0.004	**0.027**	-0.002	0.175
		2.450	0.657	**11.347**	-0.160	0.926	**1.973**	-0.337	1.889
	USA	0.006	0.009	**0.981**	-0.001	0.001	0.010	-0.016	0.008
		1.130	0.813	**167.899**	-0.781	0.601	1.002	-0.991	0.502

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 7: Conditional mean equation of VARMA-AGARCH for ASEAN: 5 January 1998 to 13 March 2009

Equation		Constant	ASEANi (-1)	EU (-1)	USA(-1)	MA (1)
IND	ASEANi	0.076	0.107	**0.117**	**0.400**	0.013
		1.901	1.270	**2.413**	**9.167**	0.153
	EU	0.005	0.002	**0.143**	**0.340**	**-0.292**
		0.418	0.325	**2.335**	**16.812**	**-4.645**
	USA	-0.004	0.002	**0.048**	**0.550**	**-0.607**
		-0.471	0.465	**2.319**	**2.465**	**-2.790**
MAL	ASEANi	0.026	0.098	**0.045**	**0.228**	0.039
		1.473	1.507	**2.235**	**11.664**	0.574
	EU	0.006	-0.003	**0.145**	**0.340**	**-0.292**
		0.490	-0.280	**2.388**	**16.803**	**-4.657**
	USA	-0.022	0.014	0.008	**-0.792**	**0.773**
		-0.673	1.937	0.627	**-6.082**	**5.706**
PHI	ASEANi	0.008	-0.036	**0.211**	**0.352**	**0.186**
		0.241	-0.490	**4.548**	**12.641**	**2.196**
	EU	-0.002	0.014	0.085	**0.353**	**-0.231**
		-0.113	0.667	1.379	**17.444**	**-3.706**
	USA	-0.005	**0.007**	**0.045**	**0.545**	**-0.605**
		-0.649	**3.923**	**2.291**	**2.777**	**-3.185**
SNG	ASEANi	0.022	**0.237**	0.008	**0.378**	**-0.245**
		1.356	**3.957**	0.277	**14.463**	**-4.009**
	EU	0.006	-0.005	**0.148**	**0.339**	**-0.293**
		0.432	-0.349	**2.360**	**16.795**	**-4.611**
	USA	-0.004	-0.002	**0.050**	**0.582**	**-0.638**
		-0.501	-0.137	**2.386**	**2.889**	**-3.273**
THA	ASEANi	0.011	**0.315**	0.026	**0.334**	**-0.201**
		0.427	**4.332**	0.647	**9.102**	**-2.751**
	EU	0.007	-0.004	**0.143**	**0.341**	**-0.291**
		0.527	-0.510	**2.368**	**16.861**	**-4.663**
	USA	-0.004	0.009	**0.042**	**0.568**	**-0.624**
		-0.547	1.433	**2.084**	**3.035**	**-3.431**

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 8: Conditional variance equation of VARMA-AGARCH for ASEAN:
5 January 1998 to 13 March 2009

Equation		ω	α_{ASEANi}	β_{ASEANi}	α_{EU}	β_{EU}	α_{USA}	β_{USA}	γ
IND	ASEANi	**0.161**	**0.082**	**0.852**	0.111	-0.195	0.107	0.058	0.051
		4.235	**3.831**	**42.417**	1.597	-1.853	1.439	0.583	1.239
	EU	**0.032**	0.027	**0.837**	0.000	0.000	0.020	0.019	**0.130**
		3.948	1.615	**29.670**	0.833	-0.444	1.895	1.185	**4.705**
	USA	**0.014**	**-0.025**	**0.919**	0.000	0.000	**0.029**	-0.006	**0.147**
		2.967	**-2.010**	**65.236**	-0.065	0.013	**2.202**	-0.453	**5.818**
MAL	ASEANi	**0.010**	**0.075**	**0.904**	0.008	-0.017	0.016	-0.004	0.053
		2.377	**4.557**	**72.465**	0.694	-1.208	1.616	-0.316	1.879
	EU	**0.033**	0.027	**0.833**	0.001	0.000	0.019	0.022	**0.133**
		3.936	1.632	**28.972**	0.982	-0.296	1.745	1.308	**4.705**
	USA	**0.015**	**-0.029**	**0.921**	**-0.001**	**0.001**	**0.030**	-0.009	**0.155**
		3.292	**-2.354**	**68.815**	**-6.781**	**3.941**	**2.277**	-0.675	**6.031**
PHI	ASEANi	**0.170**	**0.132**	**0.723**	0.033	-0.086	**0.091**	0.056	0.096
		4.744	**3.705**	**21.054**	1.288	-1.421	**2.516**	0.930	1.414
	EU	**0.025**	0.030	**0.827**	**-0.003**	**0.006**	**0.025**	0.016	**0.138**
		2.981	1.810	**29.935**	**-2.735**	**2.813**	**2.334**	1.024	**4.867**
	USA	0.008	**-0.025**	**0.912**	**-0.003**	**0.005**	**0.027**	-0.004	**0.158**
		1.576	**-1.960**	**54.408**	**-12.356**	**4.246**	**2.089**	-0.278	**6.436**
SNG	ASEANi	**0.031**	**0.051**	**0.891**	**0.034**	-0.035	**0.052**	-0.025	**0.051**
		4.915	**3.448**	**55.224**	**2.098**	-1.780	**3.334**	-1.661	**2.505**
	EU	**0.032**	0.026	**0.839**	-0.002	0.002	**0.021**	0.016	**0.133**
		3.940	1.566	**30.512**	-0.508	0.757	**1.959**	1.028	**4.859**
	USA	**0.014**	-0.023	**0.927**	0.002	0.000	**0.028**	-0.012	**0.138**
		3.060	-1.799	**74.430**	0.554	-0.212	**2.130**	-0.896	**5.316**
THA	ASEANi	0.153	0.065	**0.874**	0.030	-0.102	0.042	0.037	0.048
		1.922	3.187	**19.274**	0.971	-2.364	1.208	0.781	0.678
	EU	**0.029**	0.026	**0.836**	**-0.001**	**0.002**	0.021	0.019	**0.131**
		3.488	1.556	**29.732**	**-8.254**	**2.475**	1.941	1.201	**4.731**
	USA	**0.013**	**-0.025**	**0.919**	**0.000**	0.001	**0.027**	-0.006	**0.148**
		2.940	**-1.973**	**65.044**	**-2.131**	1.321	**2.088**	-0.398	**5.774**

Notes:
(1)ASEANi denote country i; i= IND, MAL, PHI, SNG, THA related that equation, ASEANi (-1), IND(-1), EU(-1) and USA(-1) denote the lagged returns for each index.
(2) The 2 entries for each parameter are the parameter estimate and Bollerslev-Wooldridge(1992) robust t-ratios.
(3) Entries in bold are significant at the 95% level.

Table 9: Conditional correlation between ASEAN and EU,USA:
5 January 1988 to 13 March 2009

Countries	EU	USA
IND	0.112	0.045
MAL	0.138	0.060
PHI	0.065	0.049
SNG	0.286	0.135
THA	0.155	0.073

Table 10: Conditional correlation between ASEAN and EU,USA:
5 January 1988 to 27 December 1996

Countries	EU	USA
IND	0.063	0.037
MAL	0.192	0.086
PHI	0.019	0.031
SNG	0.252	0.116
THA	0.102	0.069

Table 11: Conditional correlation between ASEAN and EU,USA:
5 January 1998 to 13 March 2009

Countries	EU	USA
IND	0.166	0.063
MAL	0.116	0.044
PHI	0.111	0.066
SNG	0.328	0.172
THA	0.212	0.094

Table 12: Test for differences in correlation between samples

Countries	EU	USA
IND	**3.465**	0.871
MAL	**-2.559**	-1.419
PHI	**3.133**	1.202
SNG	**2.597**	1.907
THA	**3.713**	0.859

Notes:
(1)The values given are the z scores given by Eq. (5).
(2)Values in bold are significant at the 99% level.

Table 13: Number of violations IND, MAL, PHI, SNG, and THA portfolio for the period 3 January 2007 to 13 March 2009

Sample size	IND	MAL	PHI	SNG	THA
2006	5	4	5	5	5
2005	5	4	5	5	5
2004	5	4	5	5	5
2003	5	4	5	5	5
2002	5	4	5	5	5
2001	5	4	5	5	5
2000	5	4	5	5	5
1999	5	4	5	5	5
1998	5	4	5	5	5
1997	5	5	5	5	5
1996	5	5	5	5	5
1995	5	5	5	5	5
1994	5	5	5	5	5
1993	5	5	5	5	5
1992	5	5	5	5	5
1991	5	3	5	5	5
1990	5	3	5	5	5
1989	5	5	5	5	5
1988	5	5	5	5	5

Notes:
(1)The expected number of violations is 5 at 1% level of significance.

Figure 1: Rolling conditional correlation between IND and EU

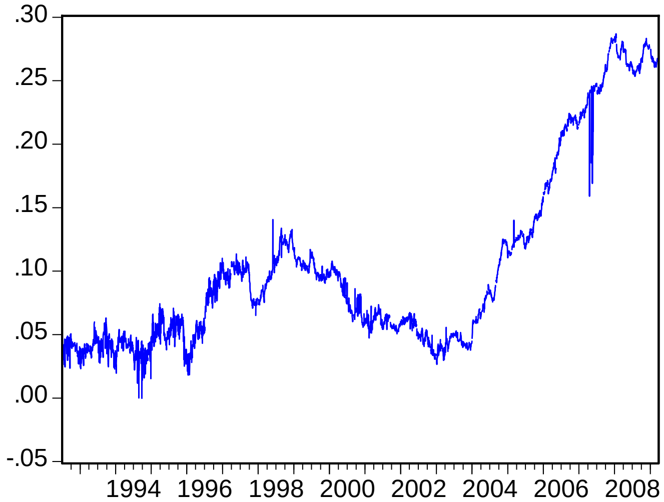


Figure 2: Rolling conditional correlation between MAL and EU

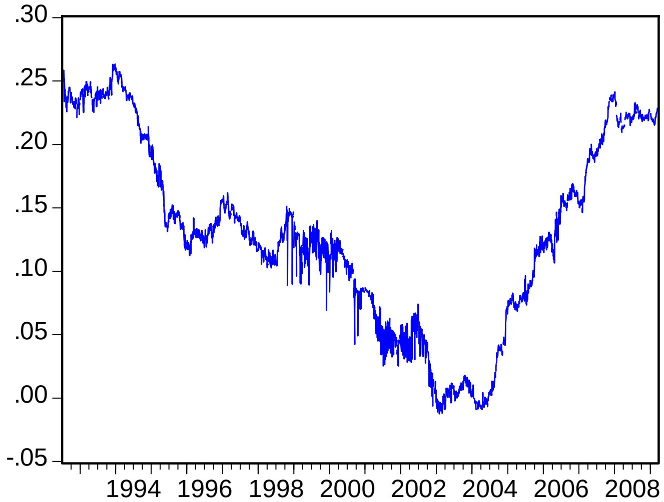


Figure 3: Rolling conditional correlation between PHI and EU

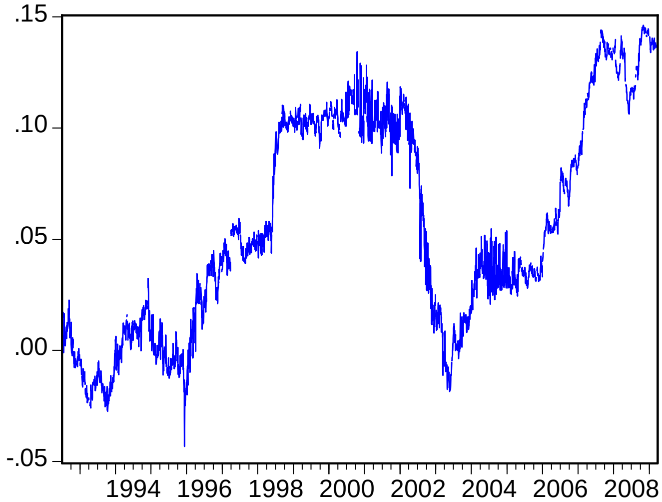


Figure 4: Rolling conditional correlation between SNG and EU

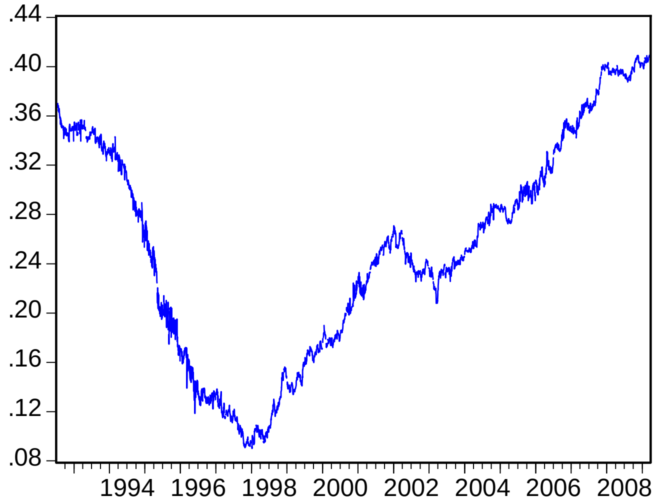


Figure 5: Rolling conditional correlation between THA and EU

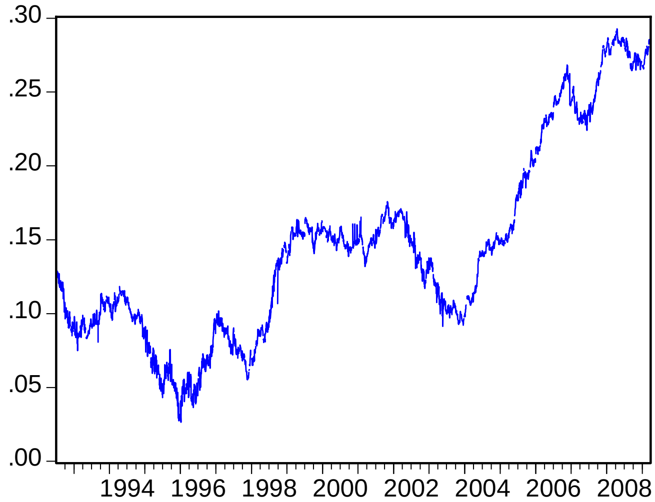


Figure 6: Rolling conditional correlation between IND and USA

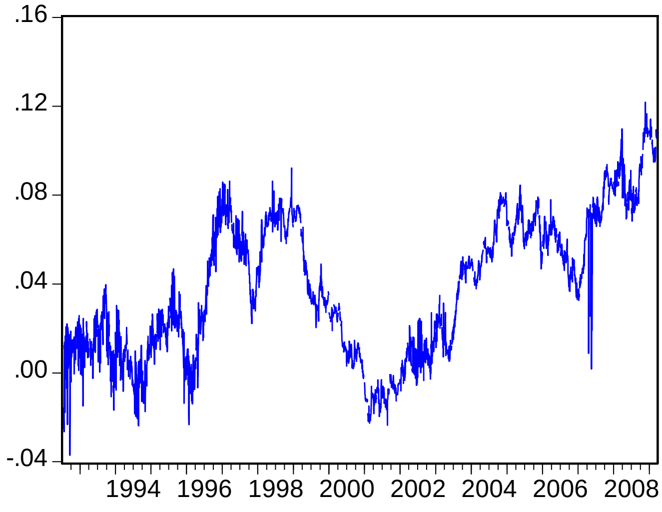


Figure 7: Rolling conditional correlation between MAL and USA

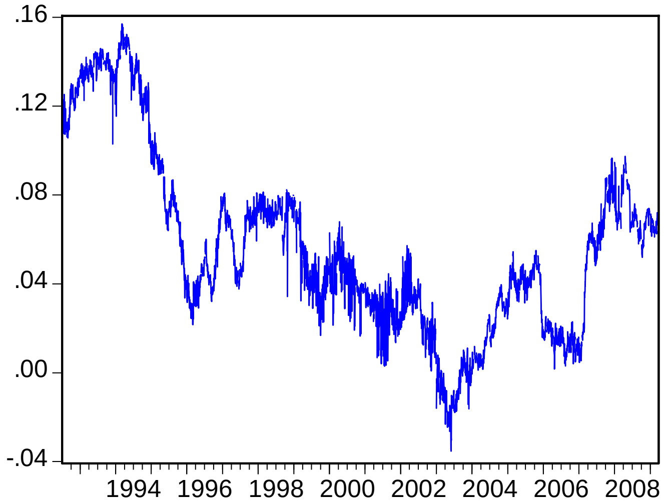


Figure 8: Rolling conditional correlation between PHI and USA

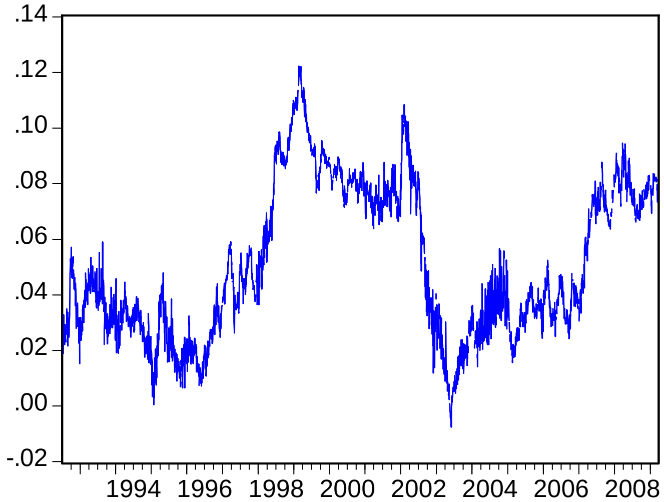


Figure 9: Rolling conditional correlation between SNG and USA

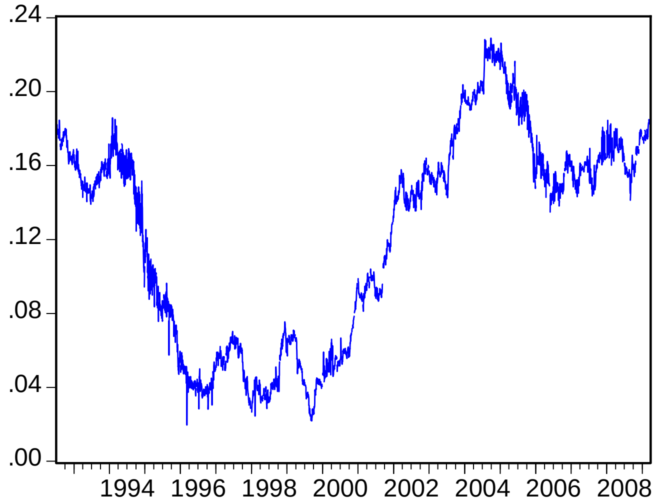
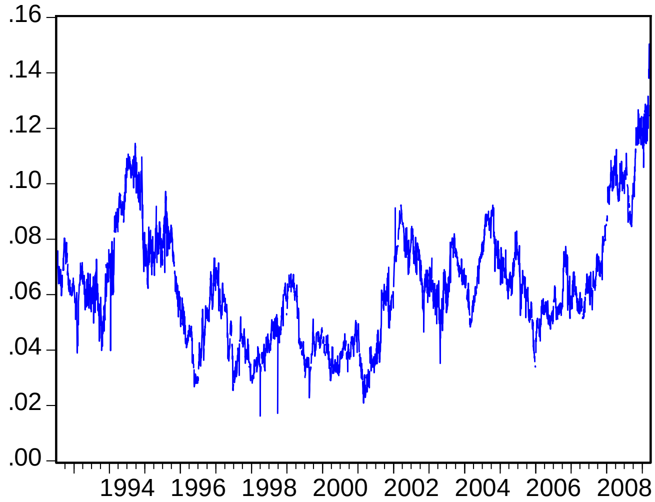


Figure 10: Rolling conditional correlation between THA and USA



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Publications (if any)	None