APPENDICES

APPENDIX A

Multivariate GARCH volatility models for financial portfolio in Thailand

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Multivariate GARCH volatility models for financial portfolio in Thailand

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ABSTRACT

The purpose in time-series financial analysis is to determine an appropriate forecasting model for the future values of volatility. The variance are determined using a single index model called a univariate conditional volatility model and the covariance matrix of a portfolio namely the multivariate conditional volatility models. The paper models the conditional variances belong a class of univariate GARCH models, moreover, to capture the volatility spillover effects among assets as well as to capture the asymmetric effects on the conditional correlations, the multivariate GARCH models are estimated. Both methods are employed in the ten most active trading value stocks in the Stock Exchange of Thailand. The evidences show that the univariate volatility models provide the well performance on each series of the ten most active trading assets and the multivariate models give the high and dynamic correlations among those assets. For incorporating volatility spillovers effects, the VARMA-GARCH model is used which is not superior to the VARMA-AGARCH model which captures the asymmetric effects.

1. Introduction

To invest in stock markets, there are risks involving the expectation of the returns. The volatility in the global financial markets could take place from the international linkage between countries. In order to stabilize the world economy, the financial market that has an increasing influence in the current economy must be effective. The key to manage the market price risk is volatility. The high risks may be caused by either the dramatic changes in the stock prices or the linkages among the world financial markets. Therefore, these risks will have to be managed.

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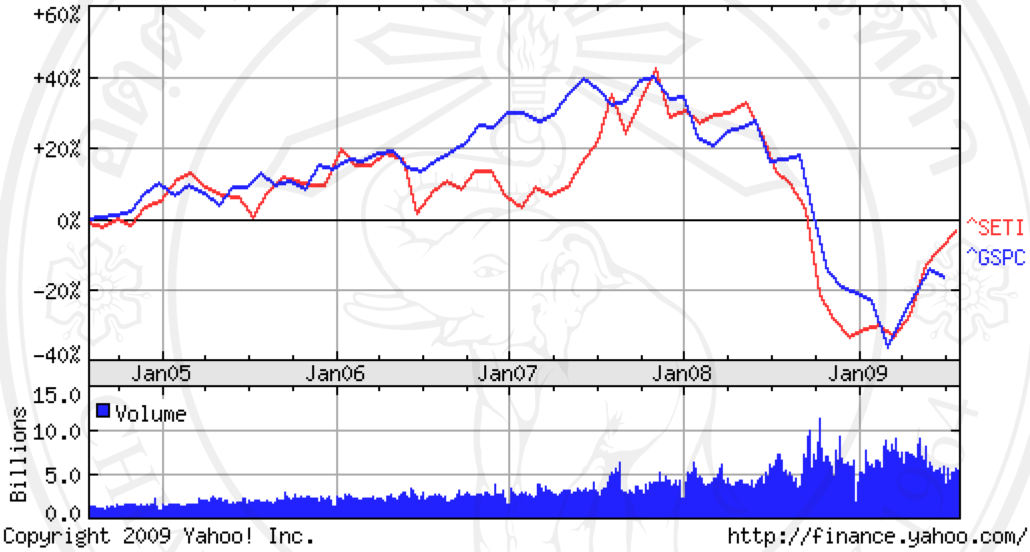
Figure 1 shows the index returns of Stock Exchanges of Thailand (SET) which has high volatile growth. Since the first quarter of 2008, the dramatically down trend of SETI has occurred. Figure 2 shows the total returns of the ten most active trading value stocks in SET in December 24, 2008.

To reach the low expectations of financial volatility while the risks in the market are arising, the risk management needs to be concerned and developed from experiences from conventional investment products, the prediction of volatility of assets in times of significant economic difficulties and partly, a lack of access to the detailed information needed for value in an accurate way.

The well-known tools as the simplest variance models are initially the autoregressive conditional heteroskedasticity (ARCH) model of Bollerslev (1986). In a GARCH model, the variance term depends on the lagged variances as well as the lagged squared residuals. An ARCH-GARCH model known as the univariate GARCH model is widely used in financial time series analysis. Besides the estimation of the conditional variance by fitting a univariate volatility model, the multivariate volatility also contributes to the development of forecasting the condition variance of each asset as well as the conditional correlations among pairs of assets.

Figure 1: The SET Index of Thailand



Source: Yahoo Finance (July 2009)

The initial development of multivariate GARCH model is a constant conditional correlation (CCC) multivariate GARCH model of Bollerslev (1990) that fits a univariate GARCH model to each asset returns first and then calculates the conditional correlation matrix. The correlations of CCC are required to be constant, however, in some applications time-varying correlations are needed. Engle (2002) proposed the Dynamic Condition Correlations (DCC) multivariate GARCH model to relax the constant correlations. Both methods (CCC and DCC) require the standard GARCH model for the variances of the individual processes. The other model is VARMA-GARCH model of Ling and McAleer (2003), which allows large shocks in one asset to affect the variances of the other assets. McAleer et al. (2008) develops the VARMA-AGARCH model to capture the asymmetric spillover effects between the assets in the portfolio.

Most literatures more applied the multivariate GARCH models in stock index returns as well as foreign exchange returns than in individual assets. The main purpose of this paper is to estimate the volatility of individual asset returns using univariate GARCH model and multivariate GARCH models to capture the volatility asymmetric and spillovers effects between assets following the motivation of Hakim and McAlee (2008).

2. Model Specifications

This paper models for the conditional volatility of individual asset returns belong to a class of the univariate GARCH models.

GARCH(1,1)

Following Bollerslev (1986) and Taylor (1986) independently defined and derived the GARCH(1,1) model with conditional normal distributions as

$$h_t = \omega + (r_{t-1} - \mu)^2 + \beta h_{t-1}, \quad (1)$$

based on the independently and identically distributed (i.i.d.) assumption; thus,

$$r_t = \mu + h_t^{1/2} z_t, \quad z_t \sim i.i.d. N(0,1). \quad (2)$$

The four parameters are μ, α, β and ϖ. To ensure nonnegative in the conditional variance, the constraints $\varpi \geq 0$, $\alpha \geq 0$ and $\beta \geq 0$ are required.

Asset prices p_t, and returns r_t, conditional variances h_t, and standardized residuals z_t are connected by these following equations;

$$r_t = \log(p_t / p_{t-1}) = \mu + h_t^{1/2} z_t \quad (3)$$

and

$$h_t = \omega + \alpha(r_{t-1} - \mu)^2 + \beta h_{t-1} = \omega + (\alpha z_{t-1}^2 + \beta) h_{t-1} \quad (4)$$

GJR-GARCH

The GJR(1,1) model of Glosten, Jagannathan, and Runkle (1993) is an asymmetry model of conditional variances. Asymmetry can be introduced by weighting e_{t-1}^2 differently for negative and positive residuals; thus,

$$h_t = \omega + \alpha e_{t-1}^2 + \alpha^- I_{t-1} e_{t-1}^2 + \beta h_{t-1} \quad (5)$$

The squared residual is multiplied by $\alpha + \alpha^-$ when the return is below its conditional expectation $(I_{t-1} = 1)$ and by α when the return is above or equal to the expected value $(I_{t-1} = 0)$. The parameters are constrained by $\omega \geq 0, \alpha > 0$, $\alpha + \alpha^- > 0$ and $\beta \geq 0$.

The additional information based on the sign of the residual e_{t-1} is summarized by the indicator variable

$$I_{t-1} = \begin{cases} 1 & if\ e_{t-1} < 0, \\ 0 & if\ e_{t-1} \geq 0. \end{cases} \quad (6)$$

The GJR (p, q) model is defined as

$$h_t = \omega + \sum_{i=1}^{p} (\alpha_i + \alpha_i^- S_{t-1}) e_{t-1}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \quad (7)$$

Furthermore, to capture volatility asymmetric and spillovers effects, the multivariate GARCH models namely the CCC model of Bollerslev (1990), the DCC model of Engle (2002), the VARMA-GARCH model of Ling and McAleer (2003), and the VARMA-AGARCH model of McAleer et al. (2008) are estimated in this paper.

CCC

The CCC model of Bolerslev (1990) is suggested as a multivariate GARCH model in which all conditional correlations are constant and the conditional variances are modelled by univariate GARCH models. This so-called CCC model (constant conditional correlation) is not a special case of the Vec model, but belongs to another, nonlinear model class. The CCC(1,1) model is given by

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{ii,t-1,} \quad (8)$$

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}} \quad (9)$$

ρ_{ij} equals to the constant correlation between ε_{it} and ε_{jt}, which can be estimated separately from the conditional variances. The weakness of the CCC model is it cannot capture the spillover effects and asymmetric effects. However the advantage of the CCC model is in the unrestricted applicability for large systems of time series. On the other hand, the assumption of constant correlation is possibly quite restrictive.

DCC

To relax the restriction of CCC model, Engel (2002) proposed a model called the dynamic conditional correlation, which providing the time-varying correlations on the correlation matrix. By considering the following:

$$y_t | F_{t-1} \sim (0, Q_t), \qquad t = 1, ..., T \qquad (10)$$

$$Q_t = D_t \Gamma_t D_t, \qquad (11)$$

where $D_t = diag(h_{1t}, ..., h_{kt})$ is a dia-gonal matrix of conditional variances, and F_t is the information set available to time t.

The conditional variance is estimated by using a univariate GARCH model. After the univariate volatility is modelled, the standardized residuals $\eta_{it} = y_{it} / \sqrt{h_{it}}$, are used to estimate the dynamic conditional correlations. So the DCC model is given by the following:

$$Q_t = (1 - \phi_1 - \phi_2) S + \phi_1 \eta_{t-1} \eta'_{t-1} + \phi_2 Q_{t-1} \qquad (12)$$

$$\Gamma_t = \left\{ (diag(Q_t)^{-1/2} \right\} Q_t \left\{ (diag(Q_t)^{-1/2} \right\} \quad (13)$$

where S is the unconditional correlation matrix of the ε, equation (13) is used to standardize the matrix estimated in (12) to satisfy the definition of a correlation matrix.

VARMA-GARCH

Ling and McAleer (2003) proposed the multivariate model to accommodate asymmetric impacts of positive and negative shocks on the conditional variance that can capture the volatility spillover effects among assets that can be across the markets or the countries called the VARMA-GARCH model. To also capture the asymmetric effects on the conditional correlations, McAleer et al. (2008) in the Econometric Theory proposed the VARMA-AGARCH model.

By considering the following model specification:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \qquad (14)$$

$$\varepsilon_t = D_t \eta_t, \qquad (15)$$

where $y_t = (y_{1t}, ..., y_{mt})', \eta_t = (\eta_{1t}, ..., \eta_{mt})'$ is a sequence of independently and identically distributed random vectors, and $D_t = diag(h_{1t}^{1/2}, ..., h_{mt}^{1/2})$.

The VARMA-GARCH model is given by

$$H_t = \omega + \sum_{k=1}^{r} A_k \vec{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \qquad (16)$$

where
$H_t = (h_{1t}, ..., h_{mt})'$, $\varpi = (\varpi_1, ..., \varpi_m)'$,
$D_t = diag(h_{i,t}^{1/2})$, $\eta_t = (\eta_{1t}, ..., \eta_{mt})'$,
$\vec{\varepsilon}_t = (\varepsilon_{1t}^2, ..., \varepsilon_{mt}^2)'$, A_k and B_l are $m \times m$ matrices with typical elements α_{ij} and β_{ij}, respectively, for i,j = 1,…,m, I(η_t) = diag(I(η_{it})) is an $m \times m$ matrix. Based on equation (15), the VARMA-GARCH model assumes the matrix of conditional correlations is given by $E(\eta_t \eta'_t) = \Gamma$.

VARMA-AGARCH

The VARMA-AGARCH model of McAleer et al. (2009) is given by

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-1} + \sum_{i=1}^{r} C_i I_{t-i} \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \quad (17)$$

where C_i are $m \times m$ matrices for i = 1,…,r and It = diag(I1t,…,Imt), so that

$$I = \begin{cases} 0, & \varepsilon_{i,t} > 0 \\ 1, & \varepsilon_{i,t} \le 0 \end{cases} \qquad (18)$$

The VARMA-AGARCH model is reduced to the VARMA-GARCH model when $C_i = 0$ for all i.

3. Description of the studied market, Data and Estimations

3.1 The Stock Exchange of Thailand

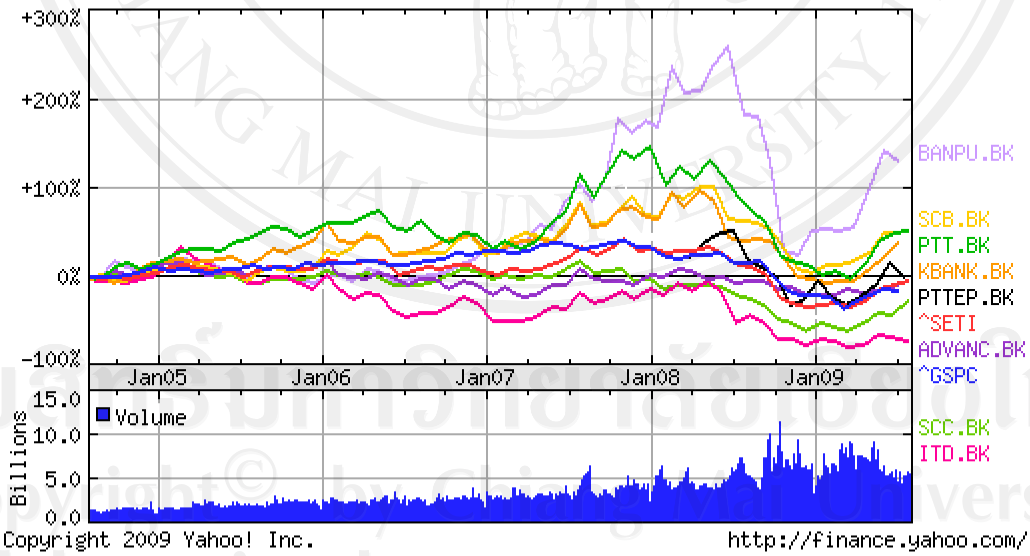
The Thai Stock Market so-called the Stock Exchange of Thailand (SET) is an emerging market and has operated fully computerized trading since April 1991. Trading is restricted to listed and authorized securities and is supervised by the Securities Exchange Commission. Trading day is normally Monday through Friday, and closed on weekend and official holidays. In order to respond to rapid changing in financial activities, SET uses the upgraded trading system called Advance Resilience Matching System (ARMS) since August 2008 which features higher risk management efficiency and improved system redundancy. The trading system ARMS bases on the automatic method called the Automated Order Matching system (AOM). Therefore, the daily trading in SET takes place via a fully computerized trading to perform the order matching process according to price then time priority so the orders that are not matched by the end of a trading day are automatically cancelled. It is conducted in two trading sessions that are the morning sessions from 10:00 to 12:30 a.m. and the afternoon sessions from 2:30 to 4:30 p.m.

The figure 1 shows the SET Index of Thailand. The dramatically down trend occurred since the first quarter of 2008 which could be reflected from the world financial crash.

3.2 Data

This paper obtains the daily data files available from Reuters, including open, close, high, low prices and volume recorded.

Figure 2: The returns of stocks in Thailand



Source: Yahoo Finance (July 2009)

The daily data used to estimate volatility models are the individual stock prices traded in the Stock Exchange of Thailand (SET) spanning the time period from October 1, 2007 to September 30, 2008, for obtaining 237 observations of daily returns. The original data include prices for every trade time interval during the day by implementing the ten most active trading value single stocks in SET based on December 24, 2008, consisting of BANPU, PTT, and PTTEP in Petrochemicals and Chemicals sector, SCC in Construction Materials sector, and TTA in Transportation and Logistic sector, namely PTT Public Company Limited, PTT Exploration and Production Public Company Limited, Kasikornbank Public Company Limited, The Siam Commercial Bank Public Company Limited, Advanced Info Service Public Company Limited, Italian-Thai Development Public Company Limited, PTT Chemical Public Company Limited, The Siam Cement Public Company Limited, and Thoresen Thai Agencies Public Company Limited, respectively. The returns of the ten most active trading value single stocks in SET are shown in Figure 2 and the variable names are summarized in Table 1.

Table 1: Variable Names

Variables	Names
adva	Advanced Info Service Public Company Limited
banpu	PTT Public Company Limited
itd	Italian-Thai Development Public Company Limited
kbank	Kasikornbank Public Company Limited
ptt	PTT Exploration and Production Public Company Limited
pttch	PTT Chemical Public Company Limited
pttep	PTT Exploration and Production Public Company Limited
scb	The Siam Commercial Bank Public Company Limited
scc	The Siam Cement Public Company Limited
tta	Thoresen Thai Agencies Public Company Limited

The continuously compounded returns of asset *i* at time *t* are calculated by following:

$$r_{it} = \log(\frac{p_{i,t}}{p_{i,t-1}}) * 100 \qquad (19)$$

where $p_{i,t}$ and $p_{i,t-1}$ are the closing prices of market *i* at days *t* and *t-1*, respectively.

3.3 Estimations

The plots of the daily returns for all series used in this study are shown in Figure 2.2. All returns series have constant mean but the time varying variance. These time-series data are tested for the stationary using Augmented Dickey-Fuller (ADF) test in Table 2.2. From the unit root test, all series of asset returns are stationary at level because all series reject the null hypothesis at the 1% level of critical value that is -3.456. The simple descriptive statistics of the time-series of the ten returns are provided in Table 2. Apparently, the empirical mean of the processes are close to zero as well as the median of the processes, the maximum values range between 0.086 and 0.129, and the minimum values range between -0.267 and -0.104. The high degree of kurtosis is in all series and an appropriate time-series models are needed because of the clustering of the returns series.

Table 2: Unit Root Test in the returns of all series

Series	Coefficient	1% level of critical value	t-statistic
adva	-1.106	-3.456	-17.471
banpu	-0.938	-3.456	-14.961
itd	-0.978	-3.456	-15.578
kbank	-1.030	-3.456	-16.473
ptt	-0.965	-3.456	-15.370
pttch	-0.687	-3.456	-8.350
pttep	-1.026	-3.456	-16.386
scb	-1.001	-3.456	-16.011
scc	-0.974	-3.456	-15.601
tta	-0.901	-3.456	-14.261

Note: The null hypothesis $\theta = 0$ is tested for stationary if reject.

Table 3: Descriptive statistics for all series

Statistics	adva	banpu	itd	kbank	ptt	pttch	pttep	scb	scc	tta
Mean	-0.001	-0.003	-0.004	-0.002	-0.003	-0.005	-0.002	-0.002	-0.003	-0.006
Median	0.000	0.000	-0.006	0.000	0.000	-0.007	-0.002	0.000	0.000	-0.006
Maximum	0.086	0.092	0.116	0.079	0.095	0.091	0.125	0.091	0.078	0.129
Minimum	-0.113	-0.186	-0.184	-0.124	-0.139	-0.153	-0.188	-0.173	-0.104	-0.267
Std. Dev.	0.025	0.039	0.043	0.027	0.032	0.035	0.035	0.029	0.019	0.046
Skewness	0.104	-0.953	-0.391	-0.395	-0.255	-0.838	-0.439	-0.667	-0.431	-0.935
Kurtosis	5.670	6.416	4.899	5.629	5.183	6.204	6.068	8.286	7.405	7.752
Jarque-Bera	77.11	164.5	45.35	81.05	54.04	140.6	109.4	319.5	216.6	280.4
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sum	-0.204	-0.788	-1.1667	-0.488	-0.754	-1.349	-0.451	-0.389	-0.958	-1.584
Sum Sq. Dev.	0.161	0.398	0.479	0.188	0.269	0.309	0.323	0.224	0.091	0.551

4. Empirical Results

4.1 Univariate GARCH Models.

The estimations from the class of univariate GARCH models are provided in Table 4-5. The empirical results show the coefficient determining both in conditional mean equation with ARMA(1,1) and condition variance equation. In the short run of the ARMA(1,1)-GARCH(1,1) model, the estimations in variance equations show that all series are significantly different from zero at 5% level. On the other hand, in the long run, all asset returns are significant except for BANPU and TTA. The ARMA(1,1)-GJR(1,1) model shows all estimates are significantly different from zero at 5% level in the long run, only the four assets namely ITD, KBANK, PTTCH, and SCC are significantly different from zero at 5% level in the short run. All of significances are at 5% level. Moreover, the estimated values of γ which is greater than zero indicate the negative shocks give higher impact than the positive shocks or leverage effects for all stocks, except SCB.

Figure 3 and Figure 4 show the plots of the daily returns and the plots of volatility of the ten asset returns, respectively. The volatility of all time-series data is dramatically increasing and persists until the end of the period

The descriptive statistics of the ten volatilities are provided in Table 6. The TTA gives the highest statistics consisting of mean, median, maximum and minimum values, skewness, and kurtosis. All volatilities display a high degree of kurtosis. This can interpret that they are not close to a Gaussian distribution. Then, an appropriate time-series model is needed.

Table 4: ARMA(1,1)-GARCH(1,1)

	Mean equation			Variance equation				
	C	AR(1)	MA(1)	ω	α	β	AIC	SIC
adva	-0.001	**0.753**	**-0.873**	9.41E-06	**0.083**	**0.915**	-4.706	-4.623
	-1.163	**5.554**	**-8.508**	0.689	**2.732**	**21.537**		
banpu	-0.002	0.169	-0.074	**0.001**	**0.198**	0.397	-3.726	-3.643
	-0.809	0.245	-0.107	**2.385**	**2.924**	1.864		
itd	-0.003	0.389	-0.345	0.0001	**0.097**	**0.819**	-3.567	-3.484
	-1.224	0.712	-0.616	1.396	**2.312**	**8.324**		
kbank	-0.001	**0.789**	**-0.828**	1.46E-05	**0.115**	**0.880**	-4.599	-4.517
	-1.005	**3.256**	**-3.765**	1.959	**2.270**	**17.534**		
ptt	-0.001	**-0.783**	**0.842**	2.79E-05	**0.164**	**0.833**	-4.161	-4.078
	-0.437	**-3.995**	**4.883**	1.140	**3.411**	**17.804**		
pttch	-0.002	**-0.717**	0.659	**0.0002**	**0.353**	**0.431**	-4.146	-4.063
	-1.290	**-1.991**	1.653	**3.172**	**3.910**	**3.172**		
pttep	0.001	0.211	-0.166	1.68E-05	**0.127**	**0.877**	-3.994	-3.911
	0.267	0.152	-0.117	0.642	**2.609**	**17.611**		
scb	6.50E-05	-0.355	0.408	1.89E-05	**0.104**	**0.894**	-4.363	-4.280
	0.040	-0.949	0.367	1.226	**2.192**	**22.028**		
scc	**-0.002**	-0.217	0.178	**2.30E-05**	**0.187**	**0.759**	-5.331	-5.248
	-2.313	-0.122	0.100	**2.510**	**3.024**	**10.649**		
tta	**-0.006**	**-0.864**	**0.942**	**0.001**	**0.471**	-0.068	-3.497	-3.414
	-2.242	**-11.386**	**17.913**	**5.810**	**4.367**	-0.669		

Notes: (1) The numbers show the parameter estimates and *t*-ratios.

(2) The significant at 5% level of significance shown in bold.

Table 5: ARMA(1,1)-GJR(1,1)

	Mean equation			Variance equation					
	C	**AR(1)**	**MA(1)**	**ω**	**α**	**γ**	**β**	**AIC**	**SIC**
adva	-0.001	**0.757**	**-0.869**	9.02E-06	-0.004	**0.130**	**0.944**	-4.737	-4.640
	-1.543	**6.527**	**-10.334**	0.758	-0.163	**2.501**	**26.218**		
banp	-0.002	-0.043	0.117	4.21E-05	-0.001	**0.094**	**0.926**	-3.777	-3.681
	-0.731	-0.053	0.146	1.171	-0.036	**2.246**	**21.400**		
itd	**-0.007**	0.384	-0.372	**2.73E-05**	**-0.082**	**0.099**	**1.028**	-3.654	-3.558
	-9.274	0.885	-0.837	**12.981**	**-184.206**	**18.194**	**47592**		
kbank	**-0.003**	**0.913**	**-0.940**	**9.34E-06**	**-0.079**	**0.175**	**0.996**	-4.665	-4.568
	-2.148	**25.114**	**-31.583**	**2.617**	**-3.699**	**5.063**	**46.566**		
ptt	-0.002	**-0.743**	**0.811**	6.97E-05	0.048	**0.238**	**0.782**	-4.184	-4.087
	-1.156	**-3.477**	**4.311**	1.572	1.217	**1.967**	**10.107**		
pttch	**-0.004**	-0.623	0.642	**8.51E-05**	**-0.063**	**0.265**	**0.845**	-4.213	-4.116
	-2.439	-1.034	1.091	**2.993**	**-2.268**	**4.286**	**16.845**		
pttep	-0.002	-0.013	0.087	0.0002	0.028	**0.335**	**0.657**	-4.007	-3.911
	-0.758	-0.014	0.097	1.440	0.455	**2.023**	**3.582**		
scb	-0.001	-0.346	0.412	3.61E-05	0.020	0.152	**0.876**	-4.377	-4.280
	-0.550	-0.772	0.940	1.158	0.436	1.774	**14.820**		
scc	**-0.004**	**0.623**	**-0.718**	**1.73E-05**	**-0.134**	**0.325**	**0.923**	-5.416	-5.319
	-4.961	**2.750**	**-3.729**	**2.597**	**-4.469**	**4.448**	**23.735**		
tta	-0.005	**-0.850**	**0.934**	**0.0002**	-0.014	**0.243**	**0.805**	-3.519	-3.422
	-1.743	**-10.360**	**18.597**	**1.980**	-0.393	**2.748**	**10.510**		

Notes: (1) The numbers show the parameter estimates and t ratios.
(2) The significant at 5% level of significance shown in bold.

Figure 3: Daily returns of all series

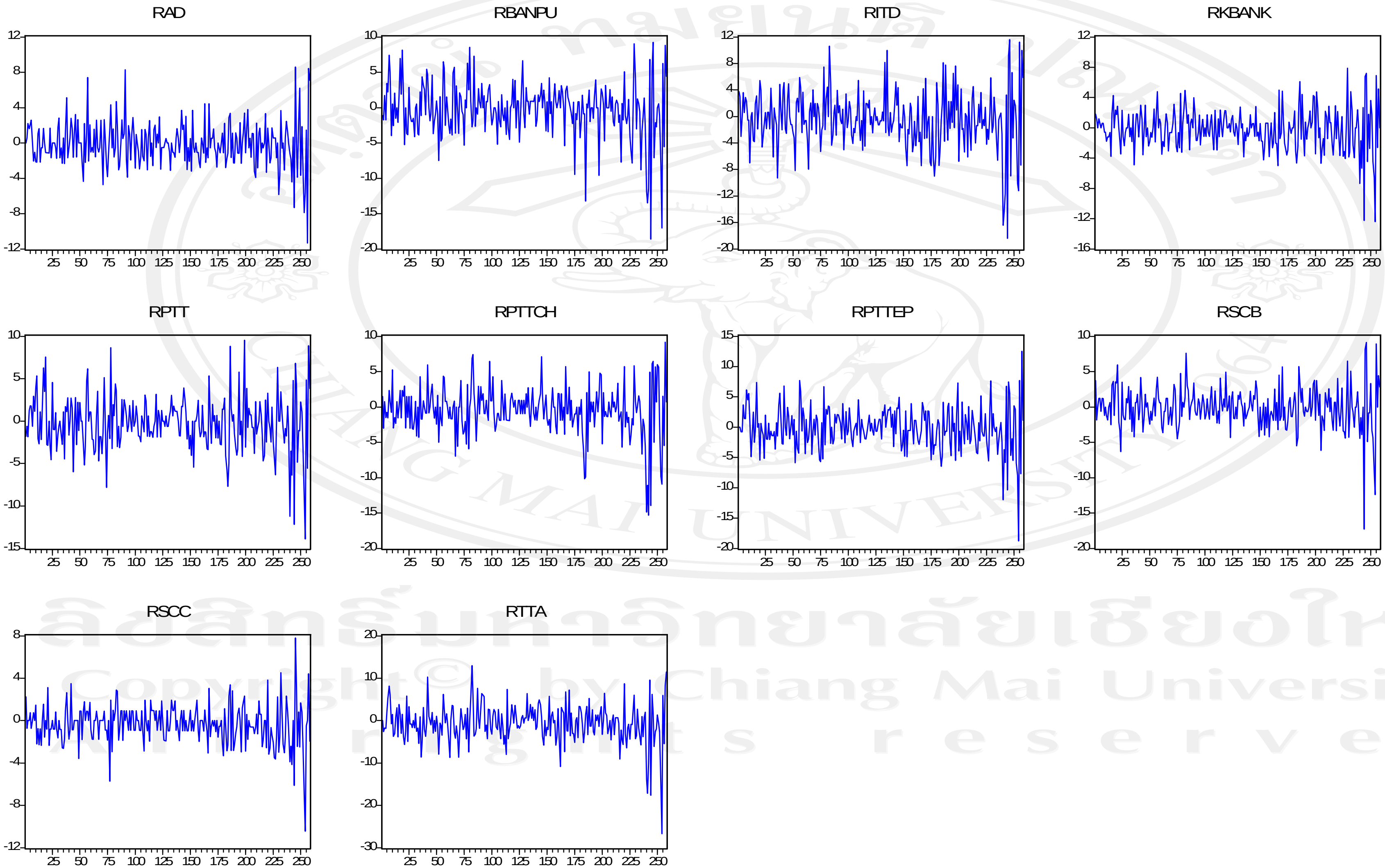


Figure 4: Daily volatility of all series

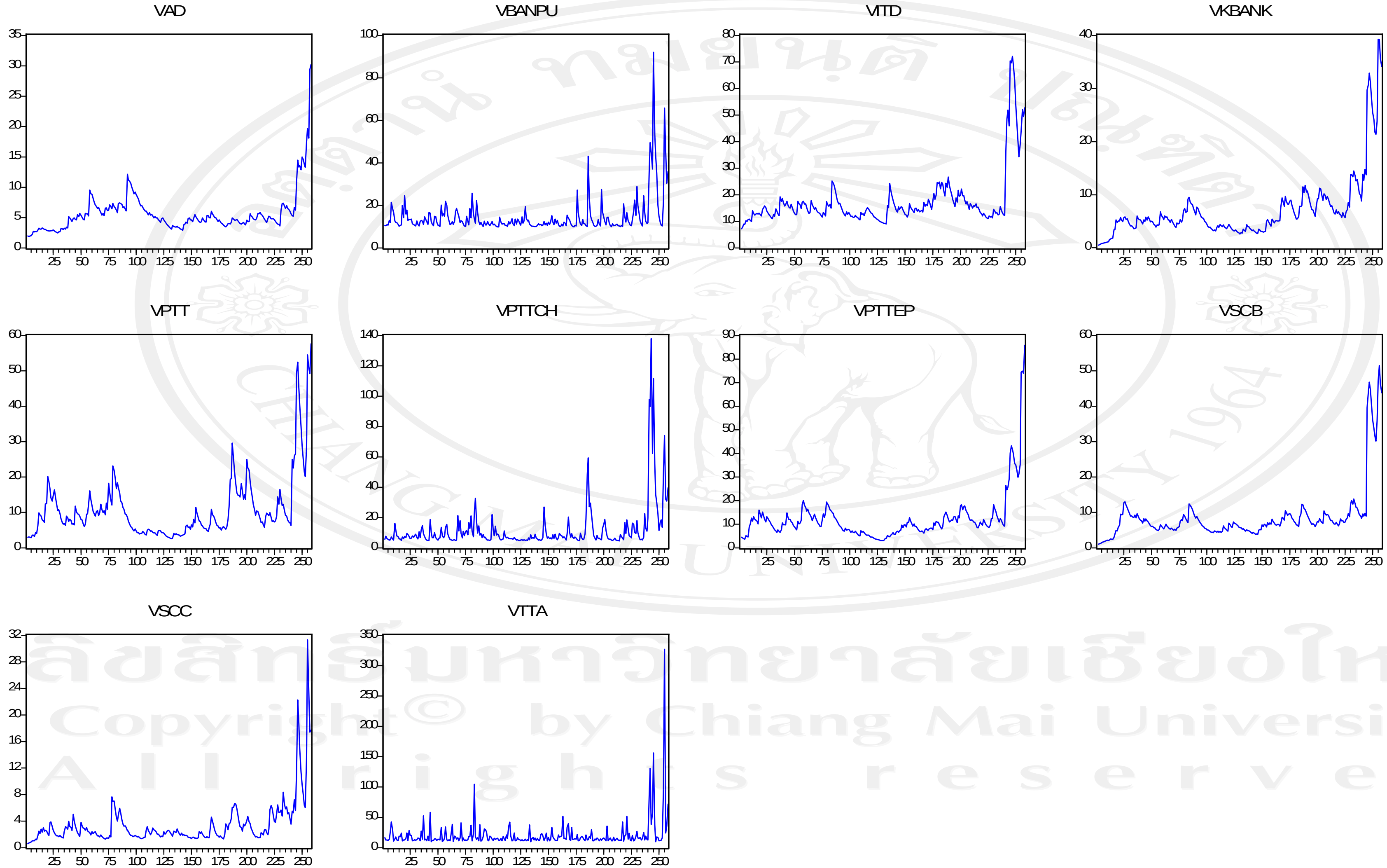


Table 6: Descriptive statistics for the volatilities

Statistics	adva	banpu	itd	kbank	ptt	pttch	pttep	scb	scc	tta
Mean	5.661	14.73	17.51	7.180	10.99	12.09	12.30	8.839	3.478	20.80
Median	4.857	11.96	14.53	5.337	8.552	7.089	10.15	6.961	2.408	14.16
Maximum	30.17	92.03	72.16	39.269	57.65	137.87	85.80	51.44	31.34	327.2
Minimum	1.901	9.861	7.217	0.517	2.585	4.587	3.007	1.046	0.578	9.544
Std. Dev.	3.459	8.962	10.62	6.269	9.171	15.756	10.54	8.187	3.561	25.49
Skewness	3.677	4.597	3.270	3.038	2.718	4.837	4.209	3.567	4.248	8.071
Kurtosis	22.11	30.58	14.26	13.29	11.89	30.57	24.85	15.71	25.75	87.26
Jarque-Bera	4490.9	9051.4	1815.6	1530.2	1162.8	9144.7	5872.5	2273.9	6315.5	78821
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

4.2 Multivariate GARCH Models.

Table 7 gives the estimation of CCC-GARCH(1,1) model which the CCC estimators yield the constant conditional correlation between the ten assets. All of the estimations are significantly different from zero at 5% level of significance. The estimated correlations between assets are 0.32 to 0.63. Unfortunately, the correlation among the ten assets in portfolio are all positive correlations, the portfolio diversification could be inefficient.

The estimated parameters of the conditional correlations for the DCC model are provided in Table 8. Both of the estimated coefficients are significantly different from zero at 5% level of significance. This can interpret that the conditional correlations between the ten returns are dynamic or time-varying. These dynamic conditional correlations can also imply that the ten assets are in the same class or in the same market.

Table 9 shows the estimates of conditional variance of VARMA-GARCH and Table 10 shows the estimates of conditional variance of VARMA-AGARCH models, respectively. Then, the number of volatility spillovers and asymmetric effects of VARMA-GARCH and VARMA-AGARCH models are summarized in Table 11. The empirical results show the volatility spillovers in both models. BANPU is the highest spillovers to the other assets evidenced in both VARMA-GARCH and VARMA-AGARCH models. The correlations are negative for the pair of BANPU and ADVANC, BANPU and ITD, BANPU and PTTCH, and BANPU and PTTEP, positive otherwise. The low and opposite correlations give an efficient of potential gain from portfolio diversification between those stocks. Furthermore, the empirical results in Table 11 also summarize the asymmetric effects from VARMA-AGARCH model. The asymmetric effects exist in five stocks named KBANK, PTT, PTTCH, SCB, and TTA. Therefore, the positive and negative shocks have the different impact on those conditional volatilities. This also can imply the superior of the VARMA-AGARCH to the VARMA-GARCH model.

Table 7: CCC-GARCH(1,1)

Returns	banpu	ptt	pttep	kbank	scb	adva	itd	pttch	scc
ptt	**0.633**								
	13.054								
pttep	**0.654**	**0.792**							
	14.208	**30.538**							
kbank	**0.499**	**0.704**	**0.602**						
	7.807	**17.402**	**13.122**						
scb	**0.455**	**0.614**	**0.545**	**0.853**					
	6.193	**12.479**	**11.795**	**42.199**					
adva	**0.327**	**0.442**	**0.365**	**0.545**	**0.504**				
	5.804	**8.675**	**6.808**	**11.279**	**9.656**				
itd	**0.487**	**0.554**	**0.549**	**0.691**	**0.617**	**0.465**			
	7.390	**10.335**	**10.601**	**15.902**	**13.567**	**8.493**			
pttch	**0.493**	**0.639**	**0.662**	**0.620**	**0.553**	**0.358**	**0.603**		
	9.137	**15.481**	**17.759**	**15.419**	**13.093**	**6.533**	**12.299**		
rscc	**0.448**	**0.551**	**0.555**	**0.695**	**0.648**	**0.443**	**0.593**	**0.593**	
	7.169	**10.984**	**10.946**	**19.905**	**16.019**	**7.237**	**13.112**	**12.492**	
rtta	**0.526**	**0.599**	**0.564**	**0.643**	**0.574**	**0.456**	**0.573**	**0.583**	**0.564**
	8.670	**13.221**	**11.121**	**16.849**	**12.907**	**8.654**	**11.145**	**12.138**	**11.165**

Notes: (1) The two entries for each parameter are their respective estimates and Bollerslev and Woodridge robust *t*-ratios.
(2). The significant at 5% level of significance shown in bold.

Table 8: The DCC Estimates of the Q_t Model

Parameter Estimates	Estimates in the Q_t Equation
$Ø_1$	**0.032**
	2.702
$Ø_2$	**0.673**
	4.865

Notes: (1) The two entries for each parameter are their respective estimates and Bollerslev and Woodridge robust *t*-ratios.
(2). The significant at 5% level of significance shown in bold.

Table 9: VARMA-GARCH(1,1)

Returns	ω	α_{adva}	α_{banpu}	α_{itd}	α_{kbank}	α_{ptt}	α_{pttch}	α_{pttep}	α_{scb}	α_{scc}	α_{tta}
adva	**-0.0001**	**-0.1510**	0.0154	**-0.0422**	**0.1431**	0.0051	0.0331	0.0038	-0.0725	-0.0727	**0.0251**
banpu	**0.0004**	-0.0483	**-0.1850**	0.0344	**-0.4676**	**0.1702**	**0.1970**	0.0330	0.0812	0.2085	0.0433
itd	**0.0003**	-0.0915	**-0.0795**	**-0.0576**	-0.2984	0.0559	0.1295	**0.3456**	-0.1485	0.6975	**0.1931**
kbank	**0.0002**	**-0.0349**	0.0531	-0.0201	0.0862	0.1082	-0.0031	**-0.1241**	**-0.1276**	**0.3524**	-0.0241
ptt	**3.13E-05**	**-0.1070**	-0.0064	**-0.0401**	**-0.1215**	**-0.0947**	**0.1620**	0.0582	**-0.1369**	**0.4340**	**0.0266**
pttch	**-0.0001**	**-0.0668**	0.0353	0.0322	-0.0527	**0.2973**	-0.0680	-0.0612	**-0.1625**	-0.0239	0.0435
pttep	6.07E-05	-0.0122	-0.0396	-0.0226	-0.1340	0.0304	0.0531	0.0813	-0.0585	-0.0806	0.0206
scb	**0.0002**	-0.0144	0.0002	**-0.0436**	0.0669	0.0672	**0.1571**	0.0063	**-0.1988**	0.2152	0.0122
scc	**0.0001**	0.0609	0.0054	**0.0186**	-0.0645	0.0315	0.0108	**-0.0772**	0.0433	-0.0057	0.0200
tta	**0.0005**	0.0806	**-0.1217**	0.0838	0.1812	-0.0297	**0.2431**	0.0776	**-0.4304**	-0.3329	**0.1486**

Notes: (1) The 2 entries for each parameter are the parameter estimates and Bollerslev and Woodridge robust t-ratios.
(2) The significant at 5% level of significance shown in bold.

Table 9: VARMA-GARCH(1,1) (Continued)

Returns	β_{adva}	β_{banpu}	β_{itd}	β_{kbank}	β_{ptt}	β_{pttch}	β_{pttep}	β_{scb}	β_{scc}	β_{tta}
adva	**0.8988**	**0.2270**	**0.0727**	**-0.3105**	-0.0537	**-0.0933**	**0.1603**	-0.0101	-0.0941	0.0214
banpu	**-0.2776**	**0.8536**	**-0.2404**	**0.3202**	0.1969	**-0.1809**	**-0.3017**	**0.2624**	-0.2776	**0.1534**
itd	**-0.5629**	0.1273	**0.7322**	**0.7722**	-0.0822	-0.0394	-0.1784	0.1038	**-1.265**	-0.0363
kbank	-0.1018	-0.1615	-0.0475	**0.3527**	0.1440	0.0218	0.0121	**0.3370**	-0.1704	0.0864
ptt	**-0.2507**	0.0982	**0.0656**	0.1023	**1.0016**	**-0.1884**	0.0349	5.57E-05	-0.4254	**0.0561**
pttch	**0.4737**	0.0531	0.1405	-0.4261	0.0198	**0.6705**	-0.0415	**0.3685**	-0.4128	-0.0008
pttep	-0.2555	0.1767	-0.0890	0.1814	-0.0860	0.0099	**0.9485**	0.0375	-0.1050	0.0367
scb	**-0.4237**	0.1311	-0.0353	0.1349	-0.0208	0.0019	0.0501	**0.6300**	**-0.5746**	0.0685
scc	**0.1824**	-0.0540	0.0410	**-0.2160**	**0.1855**	-0.0042	-0.0772	**0.2667**	0.0213	**-0.0618**
tta	0.8178	0.1662	**-0.4893**	**-0.9025**	-0.1940	0.1566	0.6792	0.4785	-0.2451	**0.4961**

Notes: (1) The 2 entries for each parameter are the parameter estimates and Bollerslev and Woodridge robust t-ratios.
(2) The significant at 5% level of significance shown in bold.

Table 10: VARMA-AGARCH(1,1)

Returns	ω	α_{adva}	α_{banpu}	α_{itd}	α_{kbank}	α_{ptt}	α_{pttch}	α_{pttep}	α_{scb}	α_{scc}	α_{tta}
adva	**-0.0001**	**-0.1517**	0.0107	**-0.0449**	**0.1712**	0.0063	0.0204	-0.0003	**-0.0888**	-0.0808	0.0304
banpu	**0.0005**	-0.0341	**-0.1923**	0.0448	**-0.4709**	**0.1454**	**0.2234**	0.0599	0.0723	0.2854	0.0315
itd	**0.0004**	**-0.1888**	0.0050	-0.0603	-0.1818	0.0302	0.1347	0.1554	-0.1829	0.2349	**0.1579**
kbank	**0.0002**	-0.0284	0.0561	-0.0187	-0.0565	0.0655	0.0194	-0.0769	**-0.1168**	0.2314	-0.0040
ptt	**2.17E-05**	-0.0203	0.0178	-0.0308	-0.0716	-0.0963	**0.1037**	-0.0073	**-0.1254**	0.1558	0.0040
pttch	1.20E-05	0.0206	0.0435	**0.0738**	-0.0749	**0.2476**	**-0.1556**	-0.1029	**-0.2096**	-0.2572	0.0323
pttep	**1.36E-05**	-0.0599	-0.0476	-0.0197	-0.0861	0.0017	0.0670	0.0194	-0.1288	-0.0253	0.0259
scb	**0.0002**	**-0.0671**	0.0110	**-0.0451**	0.0461	0.0319	**0.1857**	-0.0186	**-0.1891**	-0.0486	0.0080
scc	**0.0001**	0.0630	0.0015	-0.0049	-0.0089	0.0188	0.0121	-0.0393	0.0510	**-0.2010**	0.0129
tta	**0.0005**	0.1232	-0.0799	0.0255	0.1492	-0.0087	**0.2641**	-0.0327	**-0.3900**	-0.4997	-0.0625

Notes: (1) The 2 entries for each parameter are the parameter estimates and Bollerslev and Woodridge robust t-ratios.
(2) The significant at 5% level of significance shown in bold.

Table 10: VARMA-AGARCH(1,1) (Continued)

Returns	γ	β_{adva}	β_{banpu}	β_{itd}	β_{kbank}	β_{ptt}	β_{pttch}	β_{pttep}	β_{scb}	β_{scc}	β_{tta}
adva	0.0445	**0.8401**	**0.2383**	**0.0694**	**-0.3372**	-0.0493	-0.0700	**0.1688**	-0.0068	-0.1607	0.0318
banpu	0.0039	**-0.3450**	**0.8262**	**-0.2908**	**0.3096**	**0.2369**	**-0.1939**	**-0.3270**	**0.2859**	-0.3687	**0.1873**
itd	0.0639	-0.3972	0.3843	**0.7482**	0.4246	0.0599	-0.0440	-0.4068	0.1344	-0.9247	-0.0832
kbank	**0.1885**	-0.1589	-0.0923	-0.0136	0.3976	**0.2798**	0.0062	-0.1636	**0.2918**	-0.0930	0.0441
ptt	**0.2213**	-0.1296	0.0742	**0.0775**	0.0071	**0.9923**	**-0.1897**	0.0514	0.0224	-0.1979	0.0299
pttch	**0.3807**	**0.8097**	-0.0742	0.2050	**-0.9125**	0.3062	**0.4410**	-0.1405	0.6041	-0.2594	0.0014
pttep	0.0280	**-0.3667**	**0.2661**	-0.0725	0.1425	-0.0692	-0.0030	**1.0265**	0.0248	-0.2920	0.0706
scb	**0.2465**	**-0.4241**	0.0698	-0.0305	0.0829	0.0537	0.0081	0.0921	**0.4813**	-0.3382	**0.0923**
scc	0.2314	0.0919	0.0107	0.0040	-0.1348	0.1060	0.0234	-0.0460	**0.1290**	0.3490	**-0.0574**
tta	**0.3792**	0.8057	0.1266	-0.2813	**-0.9888**	0.1495	-0.0207	0.3616	0.3814	0.1867	**0.5631**

Notes: (1) The 2 entries for each parameter are the parameter estimates and Bollerslev and Woodridge robust t-ratios.
(2) The significant at 5% level of significance shown in bold.

Table 11: Spillovers and asymmetric effects of negative and positive shocks

Returns	Number of volatility spillovers		Asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
adva	5	4	N
banpu	7	8	N
itd	3	-	N
kbank	1	2	Y
ptt	4	2	Y
pttch	2	2	Y
pttep	-	2	N
scb	2	2	Y
scc	5	2	N
tta	2	1	Y

Note: Y = asymmetric effects and N = no asymmetric effects

5 Conclusion

The main purpose of this paper is to model the conditional variances belonging to a class of univariate and multivariate GARCH models. The multivariate GARCH models are employed for capturing the volatility spillovers effects between assets to the others as well as capturing the asymmetric effects on the conditional correlations. Both methods are conducted in the ten most active trading value stocks in the Stock Exchange of Thailand in December 24, 2008. We employed the ARMA(1,1)-GARCH(1,1) and ARMA(1,1)-GJR(1,1) to estimate the volatility of individual stock returns. The estimations provide statistic significant measures of the conditional mean and variance. However, the estimates from univariate conditional volatility models suggest that the leverage effects occur in stock volatility for all return series except SCB. This means, in the long run, the asymmetric volatility model, -- the GJR model -- is superior to GARCH model.

The constant conditional correlations (CCC) model is employed to observe increasing correlation in terms of market situations in the unrestricted applicability for large systems of time series. The estimated correlations between assets are 0.32 to 0.63. The correlation among the ten assets in portfolio are all positive correlations, the portfolio diversification could be inefficient. Because the assumption of constant correlation is strong and restrictive, the dynamic conditional correlations (DCC) model is used for the conditional correlations are not constant or time-varying. The empirical results show moderate correlations between the ten assets in portfolio, but all correlations are positive. By the way, the positive correlations would yield the potential gain from investment and hardly to diversify risk for the portfolio. From the DCC model, the conditional correlations between the ten stocks are dynamic or time-varying.

For incorporating volatility spillover effects, the VARMA-GARCH model is used for the ten assets. The evidence for the highest volatility spillovers is BANPU which would affect volatility of most assets. Asymmetric effects are statistically significant in five stocks named KBANK, PTT, PTTCH, SCB, and TTA, means positive and negative shocks have the same impact on conditional volatility. Therefore, the VARMA-AGARCH model which captures the asymmetric effects is superior to the VARMA-GARCH model.

In the near future, research could conduct the conditional correlations forecast and investigate the well-perform result of the multivariate GARCH models.

The considering and employing of the appropriate volatility models to forecast value-at-risk (VaR) would be also carried out for risk management and to examine the optimal strategies especially in the risky emerging markets.

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APPENDIX B

Long Memory in Volatility of Southeast Asia Stock Markets

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Abstract

For several daily financial return series, most empirical literatures reveal that volatility has a long memory property. Consequently, an advanced model -- the fractionally integrated ARFIMA model which allows the intermediate degrees of volatility persistence --, is needed. The purpose of the paper is to estimate the long memory models in volatility of index returns of four stock markets in South-East Asia. Furthermore, the time-dependent heteroskedasticity of the returns is described by the autoregressive fractionally integrated moving average with a generalized autoregressive conditional heteroskedasticity (ARFIMA-GARCH) models. The ARFIMA-FIGARCH and ARFIMA-FIEGARCH models are highly considered and then seriously taken into account as to how the performances of those several models for asset returns and volatility measures reveal. Our results show the presence of long memory process in volatility of all series. The ARFIMA-FIEGARCH performs excellently in estimating the volatility of all series as well.

1. Introduction

In financial investment, the investors, traders, fund managers, etc., certainly encounter changes with their own asset prices. As the price fluctuation depends on several sources of unexpected news, the rate change of asset prices is commonly defined as volatility in finances. At any event, measuring and predicting volatility is the crucial task in financial analysis.

The first models for long memory in mean were introduced by Granger and Joyeux (1980), and Hosking (1981). Most empirical evidences show the long memory process in volatility. The fractionally integrated models are widely used and become popular in financial time series analysis. Granger (1980) proved that long memory process, which the autocorrelation of unknown shocks decays slowly, can arise when short memory -- the memory decays exponentially fast --, is aggregated. As the persistence of shocks depends on several sources, it reflects on volatility which indicates a long memory property. According to Ding, Granger, and Engle (1993), the volatility tends to change quite slowly at times, and the effects of unknown shocks can take a considerable time to decay. Therefore, models for long memory are of great interest in financial work. Again, in short memory, the exponential decay is too fast to describe the data. Consequently, it is necessary to have a model that allows for intermediate degrees of volatility persistence. In the conditional mean, Granger and Joyeux (1980), and Hosking (1981) proposed that the autoregressive fractionally integrated moving-average (ARFIMA) specification fill the gap between short and complete persistence. This model captures the short-run behavior of the time-series by the autoregressive moving-average (ARMA) parameters. Thus the fractional differencing parameter $(1-L)^d$ is added to model the long-run dependence in the ARFIMA model. The characteristic of this long memory process is that the autocorrelation function has a hyperbolically decaying shape. In other words, the autocorrelation of shocks decays slowly to zero. Eventually, in the conditional variance, Baillie, Bollerslev and Mikkelsen (1996) introduced the fractionally integrated autoregressive conditional heteroskedasticity (FIGARCH) model which relates to financial volatility dynamics and allows for the long memory in the conditional variance. Ling and Li (1997a) extended the ARFIMA process to an autoregressive fractionally integrated moving average with GARCH model (ARFIMA-GARCH), which has a fractionally integrated conditional mean with the GARCH to describe time-dependent heteroskedasticity. An apparent of long range dependence in financial asset volatility introduced by Robinson and Hidalgo (1997) could be modeled by long memory.

Bollerslev and Mikkelsen (1999) have confirmed the assumption that long memory models would yield the most accurate empirical out-of-sample volatility forecasts.

From this point of view, there are a number of studies using long memory models for both the daily returns of assets and the high-frequency ones. The true volatility, known as realized volatility (RV), is found in the model that a fractionally integrated process can highly explain the slow decay in the autocorrelations of RV. The empirical studies for RV show that fractionally integrated processes are discussed in this section. Alizadeh, Brandt, and Diebold (2002) showed that a sum of AR(1) component is likely to have long memory process. Pong, Shackleton, Taylor, and Xu (2004) showed that a sum of AR(1) component accurately forecasted currency volatility. The literatures on RV are growing rapidly. McAleer and Medeiros (2008) show an excellent review of how to perform modelling and forecast volatility of their several techniques of volatility estimation, and hence the strengths and limitations of the various approaches also widen their points of view.

In this paper, we highly consider the long memory process, the fractionally integrated ARFIMA process with the GARCH specification (ARFIMA-GARCH) underlying the concept model of Granger and Joyeux (1980), Hosking (1981), Baillie (1996), Baillie, Bollerslev and Mikkelsen (1996), and Long and Li (1997a). We investigate the dynamic behavior of the daily returns, the ARFIMA process in the conditional mean as well as in the conditional variance. The data used in this paper are the daily index returns data, under the assumption of time-varying conditional heteroscedasticity. We take into account the index returns of the stock exchanges in South-East Asia, namely Indonesia, Malaysia, Thailand, Singapore in so far as they are available from DataStream. The different models of the ARFIMA with GARCH type models are also considerable for comparison purposes including of ARFIMA-FIGARCH, and ARFIMA-FIEGARCH models.

2. Model Specifications

A complicated model involving long memory process to model return volatility is applied in this paper. The following section describes the models that we implement in stock index returns of Southeast Asia stock markets. The (generalized) autoregressive conditional heteroskedasticity models (ARCH and GARCH), the fractionally integrated models (FIGARCH and FIEGARCH) of Baillie, Bollerslev and Mikkelsen (1996), and Bollerslev and Mikkelsen (1996) and the ARFIMA-GARCH model of Long and Li (1997a) are reviewed by following subsequences; (1) shot memory model, and (2) long memory model.

(1) Short Memory Model

2.1 ARMA

We first describe an autoregressive moving average (ARMA) process. This process is an underlying from which a generalized autoregressive conditional heteroskedaticity (GARCH) is derived. The ARMA process is presented as a white noise process (ε_t). By constructing a white noise process, the basic properties of white noise are used as $E[\varepsilon_t]=0,\quad E[\varepsilon_t^2]=\sigma_\varepsilon^2,\quad E[\varepsilon_t \varepsilon_{t+\tau}]=0$ for all t and for all $\tau \neq 0$.

An autoregressive model with p lags, AR(p), is given by

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

where μ is the mean, ϕ is the weight. An AR(1) is referred to a first-order one process which volatility based upon only the previous value of y_t.

A moving average model or MA(q), is given by

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

where μ is the mean, ϕ is the parameter. ε_{t-i} and ε_t are the previous and current weighted average values of a white noise disturbance term, respectively. This linear combination of white noise processes makes a variable y_t dependent on the previous and current values of a white noise disturbance term.

A model for predicting future values of a variable y_t is an autoregressive moving average model, or ARMA(p,q), given by

$$y_t = \phi_1 y_{t-1} + ... + \phi_p y_{t-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - ... - \theta_q \varepsilon_{t-q} \tag{3}$$

This equation is the linear combination between a variable y_t and its own previous values (AR) plus the previous and current values of a white noise disturbance term (MA).

2.2 ARCH

Engle (1982) proposed the autoregressive conditional heteroscedasticity of order *q*, or ARCH (*q*), defied as

$$h_t = \omega + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}^2 \qquad (4)$$

where $\omega > 0, \alpha_j \geq 0$ to ensure $h_t > 0$ or strictly positive conditional variance. The ARCH effect α captures the dependence in the condition variance or the short-run persistence of shocks.

2.3 GARCH

Bollerslev (1986) and Taylor (1986) proposed the Generalized ARCH (GARCH) model allowing for an infinite number of squared errors to influence the current conditional variance. The next period's variance can be forecasted in effect of which:-

- Weight average of the long run average variance (mean),
- The variance predicted for this period (GARCH) and,
- Information about volatility during the previous period that is the squared residual (ARCH).

The GARCH (*p*,*q*) model is given by

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

where $\omega > 0$. For GARCH(1,1), the constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ are needed to ensure $h_t > 0$ or strictly positive conditional variance. This model assumes that the positive shocks ($\varepsilon_t > 0$) and negative shocks ($\varepsilon_t < 0$) have the same impact on the conditional variance.

2.4 EGARCH

Nelson (1991) introduced the Exponential GARCH (EGARCH) model as follows

$$\log(h_t) = \omega + \sum_{i=1}^{q} \alpha_i |\eta_{t-i}| + \sum_{i=1}^{q} \gamma_i \eta_{t-i} + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) \qquad (6)$$

where $|\eta_{t-i}|$ and η_{t-i} capture the size and sign effects of the standardized shocks respectively. The positive shocks provide less volatility than the negative shocks when γ_i < 0. Then the model allows asymmetric and leverage effects.

These stationary GARCH and EGARCH models have a short memory property. In empirical studies of Dacorogna, Müller, Nagler, Olsen, and Pictet (1993), Ding et al. (1993), Bollerslev and Mikkelsen (1996) give evidence that their theoretical autocorrelations of conditional variances decay slowly, so a long memory model is appropriate.

(2) Long Memory Model

Considering the following process { y_t }

$$y_t = \phi(L)\varepsilon_t \qquad (7)$$

where $\phi(L) = \sum_{i=0}^{\infty} \phi_i L^i$, $\phi_0 = 1$, $\sum_{i=0}^{\infty} \phi_i^2 < \infty$, and ε_t has finite kurtosis. A process in (7) generates a linear process if { ε_t } is a strict white noise and the nonlinear if not.

Long memory models are usually defined by applying the filter $(1-L)^d$ to a process followed by assuming the filtered process as a stationary ARMA (*p*, *q*) process. The lag operator *L* shifts any process backwards by one time period, $Ly_t = y_{t-1}$, while the differencing parameter *d* is between 0 and 1 for volatility applications. The filter then represents fractional differencing which is defined by the binomial expansion as

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!} L^2 - \frac{d(d-1)(d-2)}{3!} L^3 + \ldots \qquad (8)$$

2.5 ARFIMA

Granger (1980) and Hosking (1981) introduced a well-known class of linear dependent processes; the autoregressive fractionally integrated moving average (ARFIMA (p,d,q) model). An ARFIMA process $\{y_t\}$ is defined by

$$\phi(L)(1-L)^d y_t = \theta(L)(\varepsilon_t) \tag{9}$$

where $|d| < 0.5$, $\{\varepsilon_t\}$ is a strict white noise sequence with zero mean and variance σ_ε^2, L is the backshift operator

$$Ly_t = y_{t-1}, \quad \phi(L) = 1 - \phi_1 L - ... - \phi_p L^p \quad \text{and} \quad \theta(L) = 1 - \theta_1 L - ... - \theta_q L^q \tag{10}$$

are polynomials of degrees p and q, respectively. $(1-L)^d$ is the fractional difference operator defined by the binomial series in (8).

Then, more complex models are produced by specifying an ARMA filter in a time series process $\{y_t\}$ in (7) in a short memory input sequence (see Palma and Zevallos (2001)). The class of ARMA-GARCH models can be obtained when $\{\varepsilon_t\}$ follows a GARCH process.

We now review a number of specifications for the long memory process by describing in three combinations of these two elements: short- or long-memory filter and short- or long-memory input ε_t^2 as follow:

Long-memory input, short-memory filter

2.6 FIGARCH

Baillie (1996) and Baillie, Bollerslev and Mikkelsen (1996) investigated a model with long-memory input for the conditional variance h_t, by inserting the additional filter $(1-L)^d$ and short-memory filter, ARMA, and then making the GARCH more general known as the fractional integration (FI) GARCH model. The FIGARCH (1,d,1) model is defined by

$$h_t = \omega + [1 - \beta_1 L - (1-\phi_1 L)(1-L)^d]\varepsilon_t^2 + \beta_1 h_{t-1} \tag{11}$$

2.7 FIEGARCH

Bollerslev and Mikkelsen (1996) found that the fractionally integrated exponential GARCH (FIEGARCH) model performs better than FIGARCH model.

From the EGARCH model of Nelson (1991), the returns are assumed to have conditional distributions that are normal with constant mean and with variances. The FIEGARCH (1,*d*,1) model is defined by

$$\log(h_t) = \omega_t + [(1-\beta(L)]^{-1}[(1+\alpha(L)]g(z_{t-1}) \tag{12}$$

$$g(z_t) = \theta_1 z_{t-1} + \theta_2[|z_t| - E|z_t|] \tag{13}$$

where ω_t and h_t denote conditional means and conditional variance respectively. The standardized residuals are

$$z_t = e_t / \sqrt{h_t} \tag{14}$$

Short-memory input, long-memory filter

2.8 ARFIMA-GARCH

Ling and Li (1997a) proposed a fractionally integrated autoregressive model with conditional heteroskedasticity, ARFIMA(*p*,*d*,*q*)-GARCH(*r*,*s*). This is discrete time process with $\phi(L)$ as in (7), z_t as in (14) with standard normal distribution and the GARCH model as

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{15}$$

If $|d| < 0.5,$ and $\sum_{i=1}^{r} \alpha_i + \sum_{j=1}^{s} \beta_j < 1,$ then { y_t } is invertible and stationary. Palma and Zevallos (2001) showed that in ARFIMA-GARCH model, the data have long memory if $0 < d < 0.5$. The squared data have intermediate-memory if $0 < d < 0.25$ and long memory if $0.25 < d < 0.5$. An ARFIMA-EGARCH gives the same conclusions.

Long-memory input, long-memory filter

2.9 ARFIMA-FIEGARCH

This model is the combination of ARFIMA filters and conditionally heteroskedastic input with long-range dependency such as FIEGARCH model. Eventually, we obtain ARFIMA-FIEGARCH model. Robinson and Hidalgo (1997), and Palma and Zevallos (2001) showed the similar type of result for this context which the squares of the input sequence $\{\varepsilon_t\}$ has a long memory with filter parameter $d^* = d_\varepsilon + d_y < 0.5$, then the process $\{y_t\}$ has long memory. d_ε is the differencing parameter of long-memory input, FIEGARCH, and d_y is the differencing parameter of long-memory filter, ARFIMA, where $0 < d_\varepsilon, d_y < 0.5$. However, they concluded that the results will hold when the underlying distribution of the input error sequence is non-Gaussian but has finite kurtosis.

3. Empirical Volatility Modelling

In this section, we will explain the data set that are analyzed and the way to generate a daily volatility time series.

3.1 DATA

The time-series data used in this paper are daily closing prices for four stock market indexes in South-East Asia, namely JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore) available on DataStream. The variable names are summarized in Table 1. We select these stock markets from the index values. Those are very high values and potential investment alternatives compared with other markets in Southeast Asia. The index values of each market from Bloomberg are shown in Figure 1. The latest stock exchange founded in 1999 is Singapore Exchange (SGX), therefore the data are collected at that starting time. We consider for a long time period from September 1, 1999 to April 27, 2009, giving a total of 2,519 return observations. Each stock market index is calculated in the local currency as IDR, MYR, THB and SGD standing for Rupiah (Indonesia), Ringgit (Malaysia), Baht (Thailand), and Singapore dollar (Singapore) respectively.

3.2 Volatility measures

First, we adjust the closing price to obtain the returns for each market by taking logarithmic different. We employ the daily returns in modelling volatility of index returns because the yesterday information may be significant in explaining today prices changes. The daily data can capture the different responses on news that cause the volatility clustering (see

Engle (1990)). The rationale to employ daily data in modelling volatility transmission is mentioned in McAleer and da Veiga (2008a). The returns at time t are calculated as follows

$$r_t = \log(\frac{p_t}{p_{t-1}})*100 \tag{16}$$

where p_t is the index price at time t. p_{t-1} are the index price at time $t-1$. The plots of the daily returns for all series are shown in Figure 2.

The plots show that all returns have constant mean but the time-varying variance. The returns of JKSE and STI are more volatile than those of the KLCI and SETI, evidence by the plots of volatility in Figure 3. Then, an appropriate model is necessary to estimate.

Second, we test all daily time-series returns for the stationary using Augmented Dickey-Fuller (ADF) test. Table 2 shows the unit root test which all series of stock market index returns are stationary at level because the ADF test statistics of all series reject the null hypothesis which the series are unit root at the 1% level of critical value equals -2.5658.

Third, we investigate the standard descriptive statistics of the daily time-series data, provided in Table 3. From Table 3, we can summarize as follows. First, All series have similar constant means at close to zero. Second, the maximum values of percentage changes of index returns range approximately between 4.5% for KLCI and 10.5% for SETI. And, the minimum values of percentage changes of index returns range approximately between -8.9% for STI and -16.0% for SETI. Finally, all series exhibit the clustering as is the common stylized facts for financial returns. The high degree of kurtosis is displayed. This excess kurtosis indicates a fat-tailed distribution compared to a standard normal distribution with kurtosis 3 and similar for all series. The Jarque-Bera test strongly rejects the null hypothesis of normally distributed returns. Then, an appropriate time-series model is needed.

Then, we estimate the various model described in the previous section. We take into account as to compare how the performance of those several models for volatility measures. Both the conditional volatility models and long memory models are estimated under the assumption that the returns follow a t-distributional because this distribution performs far better than normal distribution (see McAleer and da Veiga (2008b)). We model the returns as a stationary ARMA(1,1) process in both short- and long-memory GARCH models. The auto-correlation function plot (ACF) is used to identify the orders of an ARMA process for ARFIMA filters in ARFIMA-GARCH, ARFIMA-FIGARCH and ARFIMA-FIEGARCH models, and then we obtain an appropriate model fitted to the data.

Finally, we monitor the performance of the specifications by optimizing the information criterion of either Akaike (1974) or Schwarz (1978), denoted as AIC and SIC, respectively. Those criteria are given either $-2\frac{LogL}{n}+2\frac{k}{n}$ for AIC, or $-2\frac{LogL}{n}+2\frac{\log(k)}{n}$ for SIC, with the MLE for a model that has k parameters estimated from n observations. As the SIC criterion consistently estimates the order p and q of a GARCH (p, q), then SIC may be preferred to AIC. In this paper, we consider both values of AIC and SIC across models. In addition, the p-value tests are used to identify the hypothesis that the variable is zero, i.e is not included in the model.

4. Empirical Result

In this section, we report the estimations of those models as mention in the previous section. The fitted models and volatility modelling performance of the models are also indicated at last. Table 4, 5, 6, and 7 summarize the estimations from GARCH, FIGARCH, FIEGARCH and ARFIMA-GARCH type models using 2,519 daily return observations of the stock market indexes in South-East Asia, namely JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore) respectively. The parameters are estimated using maximum likelihood estimation (MLE) method. We employed the student t distribution and the result of descriptive statistics show the high observed kurtosis. The student t distribution parameters are indicated by *df* in the Table 4, 5, 6, and 7, they are significantly different from zero at 5% level. We now divide the empirical results into two subsequences as follows

4.1 Short- and long-memory GARCH models

The results showing the maximum likelihood estimates of d from FIGARCH model are 0.32, 0.31, 0.52, and 0.43 for JKSE, KLCI, SETI, and STI respectively which are less than 0.5. As the t-ratios of the estimations are not close to zero, the null hypothesis d = 0 is rejected by the process which exhibits short memory, the ARCH and GARCH model. Consequently, the null hypothesis d = 1 which indicates that an integrated process is not appropriate, is ipso facto rejected. Therefore the estimations of parameters d which are significantly different from zero at 5% level show a stationary (d < 0.5) and the existence of long memory process for JKSE, KLCI, and STI, excluding SETI, are not significantly different from zero. From FIEGARCH model, the estimates of d are 0.035, 0.033, 0.034, and 0.064 for JKSE, KLCI, SETI, and STI respectively which are less than 0.25. All of them are significantly different from zero at 5% level for KLCI, SETI, and STI, and at 10% level for

JKSE. The FIEGARCH model shows asymmetric effects and also leverage terms, which negative shocks increase volatility and positive shocks decrease volatility in all series. Again, these empirical results clearly show a stationary and the existence of long memory process for volatility by FIGARCH and FIEGARCH models.

An appropriate model fitted to the data are criteria by measuring goodness of fit as mentioned before (AIC and SIC). The GARCH specifications of the condition variance, judged by the AIC and SIC criteria, are far inferior to those of FIGARCH and FIEGARCH. However, involving FIGARCH and FIEGARCH could not obviously be indicated by the quality. Eventually, according to some ARFIMA-GARCH type models, we find long memory process in the mean and in the volatility.

4.2 ARFIMA-GARCH models

For long-range dependence ARFIMA-GARCH models, we find out the stationary ARMA process based on the ACF and PACF plots in Table 4 - 7, it is not clear what model is most appropriate for all series. The possibilities include an ARMA process with an autoregressive component of level 1, AR(1) and a moving average of 1, MA(1) for JKSE and KLCI, AR(2) and MA(2) for SETI, and AR(0) and MA(0) for STI. Based on AIC and BIC criteria, and *p*-value to test for the significantly different from zero of the variable, the best fit for JKSE and KLCI series is an ARFIMA(1,1)-FIEGARCH(1,d,1) plus leverage term, with approximately d^* = 0.06 which are less than 0.25 in both series and most estimates are highly statistically significant at 5% level. For SETI, the best fit is an ARFIMA(2,2)-FIEGARCH(1,d,1) plus leverage term, with approximately d^* = 0.09 which is less than 0.25 and also most estimates are significantly different from zero at 5% level. For STI, the best fit is an ARFIMA(0,1)-FIEGARCH(0,d,1) plus leverage term, with d^* = 0.18 and all estimates are significantly different from zero at 5% level. These results show that the long memory models are preferred to short memory for volatility estimation in all index return series. The ARFIMA-FIEGARCH model performs far better for volatility modelling.

5. Conclusion

In this paper, we consider the different time-varying volatility models and investigate the long memory property in volatility. Most empirical evidences show that volatility has a long memory property, as the result the fractionally integrated models are used in financial time series analysis. For comparison purpose, we apply both short memory models, GARCH model and long memory models, FIGARCH, FIEGARCH and the ARFIMA with GARCH models including ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-FIEGARCH models. Our finding can be summarized as follows. First of all, our estimation results show that the fractional integration that apparently show the existence of long memory in volatility of all index returns. Therefore the results show that the volatility has a long persistence of shocks.

Second, for the performance of various models, a model for the volatility of the set of data is selected by comparing the values of AIC and SIC across models. The results suggest that the long memory models are preferred to short memory models. Especially ARFIMA-FIEGARCH model is superior to ARFIMA-FIGARCH and ARFIMA-GARCH models.

Finally, this paper considers only model-based volatility measures from the univariate conditional volatility models and the long memory models. Using more long term information from financial data by including exogenous regressors may lead to an increased accuracy volatility modelling. Moreover, the multivariate conditional volatility models to capture spillover effects from the returns shocks of financial assets in the portfolio would be appropriate for further discussion.

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Appendix

Figure 1: Index value ratio of the Stock Markets in South-East Asia

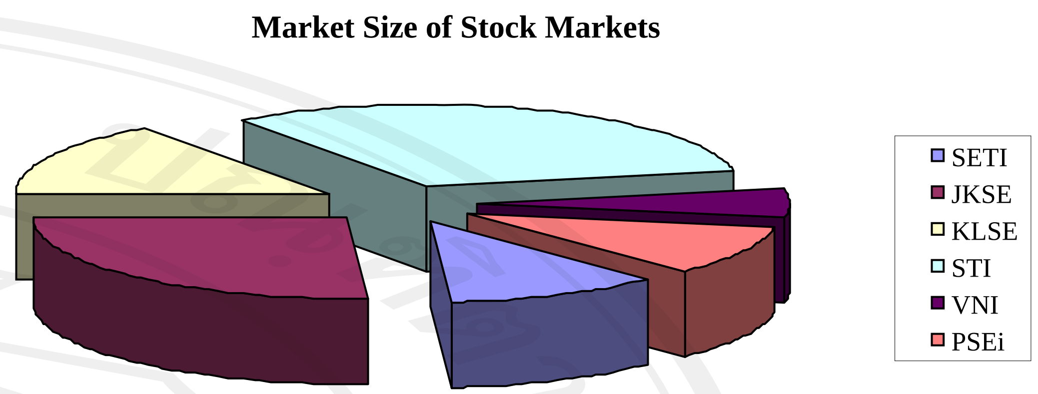

Figure 2: Daily returns for all series

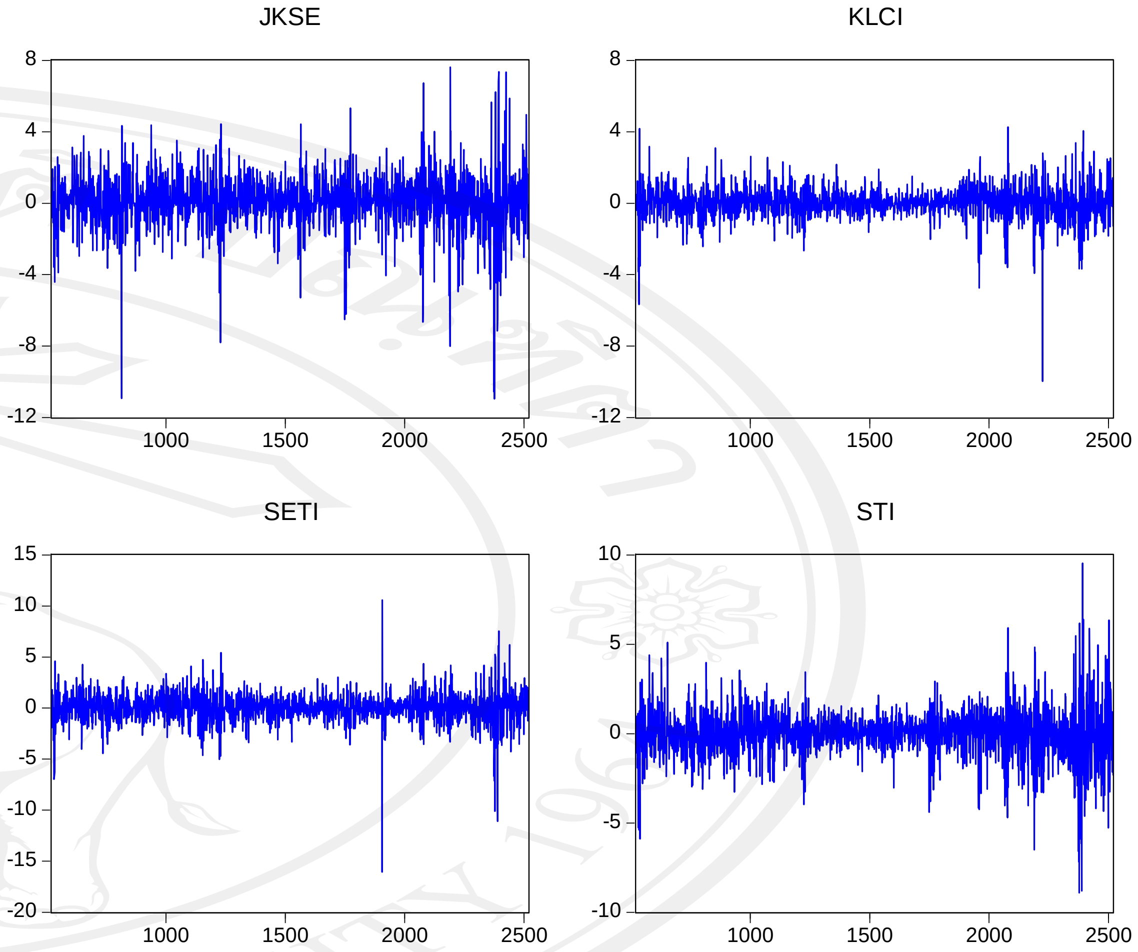

Figure 3: Volatility of returns for all series

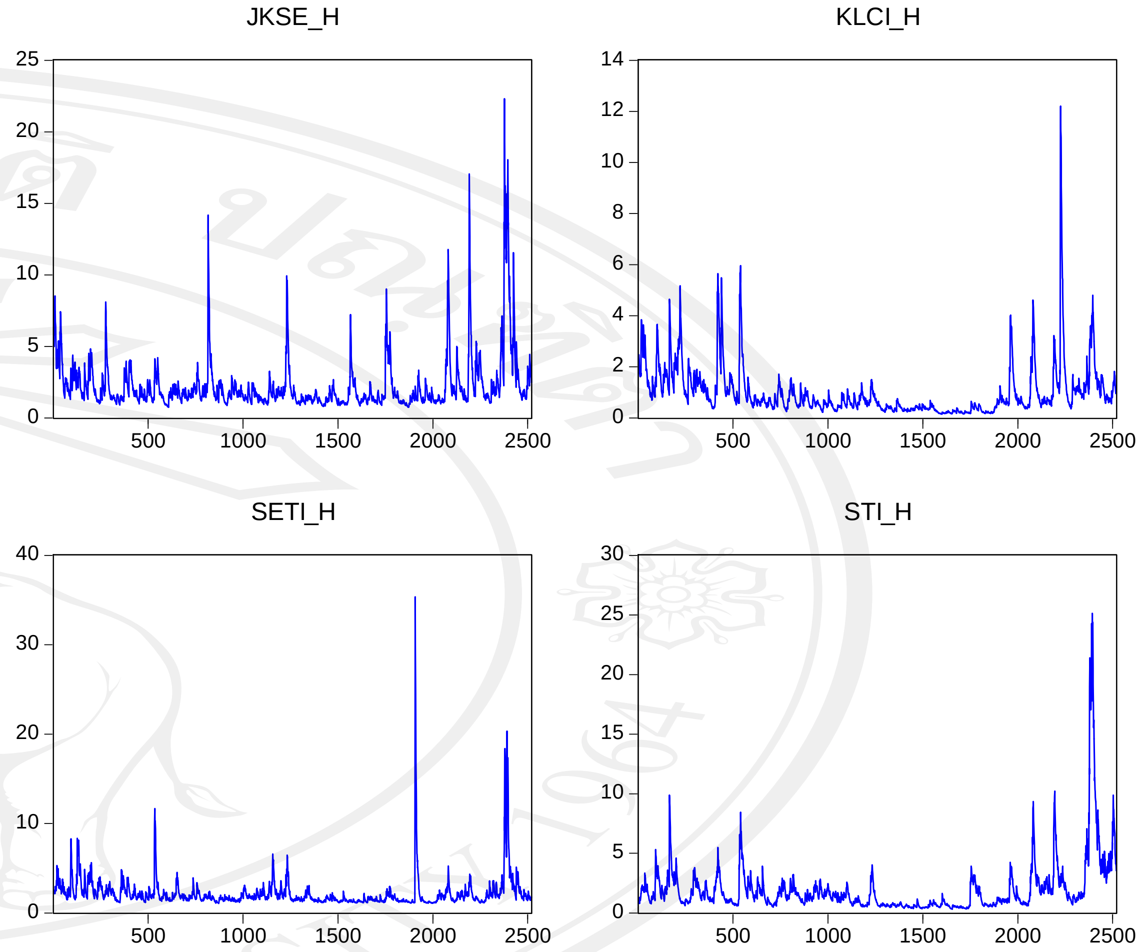

Table 1: Summary of stock index names

Codes	**Names**
JKSE	Jakarta Composite Index
KLCI	Kuala Lumpur Composite Index
SETI	Stock Exchange of Thailand Index
STI	Straits Times Index

Table 2: ADF Test of a Unit Root in all index returns

Index Returns	Coefficient	t-statistic
JKSE	-0.8718	-44.1039
KLCI	-0.8470	-43.0193
SETI	-0.8995	-32.2940
STI	-0.9592	-48.1396

Note: The null hypothesis θ = 0 is tested for stationary if reject.

Table 3: Descriptive Statistics of all index returns

	JKSE	KLCI	SETI	STI
Mean	0.0405	0.0097	0.0030	-0.0066
Maximum	7.6231	4.5027	10.5770	9.5324
Minimum	-10.9540	-9.9785	-16.0632	-8.9151
Std. Dev.	1.5129	0.9750	1.5071	1.3727
Skewness	-0.6622	-0.7459	-0.7625	-0.3749
Kurtosis	9.2069	11.6161	12.7928	8.3114
Jarque-Bera	4227.6	8025.5	10309.7	3020.0

Table 4: Correlogram of JKSE (Indonesia) returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.129	0.129	42.082	0.000
		2	0.002	-0.015	42.094	0.000
		3	0.003	0.005	42.120	0.000
		4	0.008	0.007	42.297	0.000
		5	-0.037	-0.040	45.753	0.000
		6	-0.029	-0.019	47.825	0.000
		7	-0.005	0.000	47.895	0.000
		8	-0.024	-0.024	49.394	0.000
		9	0.001	0.008	49.395	0.000
		10	-0.005	-0.007	49.456	0.000
		11	0.021	0.021	50.519	0.000
		12	0.031	0.026	52.950	0.000
		13	0.020	0.011	53.924	0.000
		14	0.067	0.064	65.409	0.000
		15	0.034	0.017	68.388	0.000
		16	0.011	0.005	68.673	0.000
		17	0.031	0.033	71.040	0.000
		18	0.037	0.030	74.484	0.000
		19	-0.002	-0.005	74.499	0.000
		20	-0.008	-0.001	74.674	0.000
		21	0.026	0.029	76.357	0.000
		22	-0.016	-0.019	76.992	0.000
		23	0.004	0.012	77.029	0.000
		24	0.003	0.001	77.047	0.000
		25	0.010	0.007	77.310	0.000
		26	0.004	0.000	77.347	0.000
		27	-0.031	-0.036	79.782	0.000
		28	0.049	0.054	86.022	0.000
		29	0.005	-0.014	86.087	0.000
		30	0.007	0.004	86.199	0.000
		31	-0.025	-0.029	87.821	0.000
		32	-0.018	-0.021	88.606	0.000
		33	-0.008	-0.003	88.771	0.000
		34	-0.013	-0.011	89.205	0.000
		35	-0.018	-0.022	90.033	0.000
		36	-0.032	-0.027	92.634	0.000

Notes: (1) Autocorrelation represents a moving average (MA) process.
(2) Partial Correlation represents an autoregressive component (AR) process.

Table 5: Correlogram of KLCI (Malaysia) returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.147	0.147	54.194	0.000
		2	0.011	-0.010	54.512	0.000
		3	0.026	0.026	56.159	0.000
		4	-0.004	-0.012	56.206	0.000
		5	0.012	0.015	56.588	0.000
		6	-0.011	-0.016	56.868	0.000
		7	0.009	0.014	57.077	0.000
		8	0.016	0.012	57.708	0.000
		9	0.024	0.021	59.172	0.000
		10	0.057	0.051	67.488	0.000
		11	0.001	-0.016	67.489	0.000
		12	-0.007	-0.006	67.601	0.000
		13	-0.035	-0.037	70.768	0.000
		14	-0.025	-0.013	72.318	0.000
		15	0.019	0.024	73.212	0.000
		16	-0.005	-0.009	73.279	0.000
		17	-0.007	-0.006	73.390	0.000
		18	-0.037	-0.038	76.776	0.000
		19	0.017	0.028	77.542	0.000
		20	0.001	-0.009	77.544	0.000
		21	0.021	0.028	78.690	0.000
		22	0.041	0.035	82.977	0.000
		23	0.014	0.009	83.506	0.000
		24	-0.024	-0.030	84.937	0.000
		25	0.024	0.030	86.384	0.000
		26	0.047	0.040	91.907	0.000
		27	0.035	0.024	94.966	0.000
		28	0.025	0.020	96.561	0.000
		29	0.022	0.011	97.763	0.000
		30	0.003	-0.007	97.790	0.000
		31	0.022	0.016	99.081	0.000
		32	-0.018	-0.028	99.884	0.000
		33	0.018	0.028	100.69	0.000
		34	-0.029	-0.037	102.79	0.000
		35	0.008	0.019	102.96	0.000
		36	0.023	0.010	104.33	0.000

Notes: (1) Autocorrelation represents a moving average (MA) process.
(2) Partial Correlation represents an autoregressive component (AR) process.

Table 6: Correlogram of SETI (Thailand) returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.071	0.071	12.805	0.000
		2	0.064	0.060	23.273	0.000
		3	-0.012	-0.020	23.620	0.000
		4	-0.014	-0.016	24.106	0.000
		5	0.005	0.010	24.182	0.000
		6	-0.056	-0.056	32.231	0.000
		7	-0.017	-0.011	32.943	0.000
		8	0.009	0.018	33.156	0.000
		9	-0.009	-0.011	33.349	0.000
		10	0.023	0.021	34.686	0.000
		11	0.039	0.039	38.562	0.000
		12	0.014	0.003	39.079	0.000
		13	0.037	0.030	42.513	0.000
		14	0.006	0.004	42.592	0.000
		15	0.025	0.020	44.160	0.000
		16	-0.018	-0.019	44.953	0.000
		17	-0.016	-0.011	45.624	0.000
		18	-0.008	-0.003	45.802	0.000
		19	-0.021	-0.016	46.890	0.000
		20	-0.021	-0.018	48.000	0.000
		21	-0.032	-0.027	50.559	0.000
		22	-0.023	-0.021	51.956	0.000
		23	-0.009	-0.008	52.168	0.000
		24	-0.005	-0.005	52.236	0.001
		25	0.032	0.029	54.795	0.001
		26	-0.007	-0.015	54.921	0.001
		27	0.008	0.004	55.075	0.001
		28	-0.016	-0.017	55.734	0.001
		29	0.016	0.020	56.401	0.002
		30	-0.001	-0.000	56.403	0.002
		31	-0.014	-0.009	56.890	0.003
		32	-0.019	-0.013	57.798	0.003
		33	0.006	0.013	57.888	0.005
		34	-0.017	-0.015	58.638	0.005
		35	-0.025	-0.023	60.231	0.005
		36	0.027	0.033	62.133	0.004

Notes: (1) Autocorrelation represents a moving average (MA) process.
(2) Partial Correlation represents an autoregressive component (AR) process.

Table 7: Correlogram of STI (Singapore) returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.020	0.020	1.0124	0.314
		2	0.010	0.010	1.2760	0.528
		3	-0.010	-0.011	1.5418	0.673
		4	0.032	0.033	4.1913	0.381
		5	0.025	0.024	5.8057	0.326
		6	-0.039	-0.041	9.6888	0.138
		7	0.026	0.028	11.420	0.121
		8	0.011	0.011	11.739	0.163
		9	0.001	-0.003	11.741	0.228
		10	-0.010	-0.008	11.993	0.286
		11	-0.044	-0.043	16.871	0.112
		12	0.030	0.029	19.204	0.084
		13	0.021	0.022	20.274	0.089
		14	0.029	0.028	22.441	0.070
		15	0.002	0.004	22.451	0.097
		16	-0.053	-0.054	29.540	0.021
		17	0.068	0.066	41.415	0.001
		18	0.001	0.001	41.417	0.001
		19	0.025	0.021	42.942	0.001
		20	-0.028	-0.024	44.918	0.001
		21	0.009	0.005	45.107	0.002
		22	-0.000	-0.009	45.108	0.003
		23	-0.019	-0.011	46.066	0.003
		24	-0.010	-0.009	46.302	0.004
		25	-0.004	-0.001	46.338	0.006
		26	0.035	0.029	49.434	0.004
		27	0.008	0.004	49.588	0.005
		28	0.027	0.036	51.484	0.004
		29	0.068	0.066	63.229	0.000
		30	-0.023	-0.027	64.545	0.000
		31	0.014	0.007	65.039	0.000
		32	-0.005	-0.006	65.114	0.000
		33	-0.020	-0.022	66.127	0.001
		34	-0.059	-0.064	75.038	0.000
		35	-0.006	0.002	75.145	0.000
		36	0.043	0.035	79.884	0.000

Notes: (1) Autocorrelation represents a moving average (MA) process.
(2) Partial Correlation represents an autoregressive component (AR) process.

Table 8: Estimation Results for JKSE (Indonesia)

Var.	Model	Mean equation				Variance equation							LL	
		μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*	AIC	SIC
JKSE	**GARCH (1, 1)**	**0.1208**				**0.1922**		**0.1515**	**0.7767**	0.9282		**4.1234**	-4256.779	
		5.456				**2.144**		**3.318**	**10.36**			**11.15**	3.3837	3.3802
								ϕ	β	θ_1	θ_2			
	FIGARCH (1, *d*, 1)	**0.1235**				**0.3821**	**0.3223**	-0.0530	0.0931			**4.1096**	-4252.269	
		5.602				**3.382**	**4.338**	-0.3623	0.5358			**10.82**	3.3809	3.3767
	FIEGARCH (1, *d*, 1)	**0.1084**				**6.7538**	**0.0358***	-0.1141	**0.8632**	**-0.1467**	**0.2827**	**4.1888**	-4240.280	
		5.021				**4.534**	**1.782***	-0.4774	**15.04**	**-4.229**	**5.230**	**10.81**	3.3729	3.3673
	ARFIMA-	**0.1214**	0.0205	-0.2347	**0.3071***	**0.1986**		**0.1571**	**0.7659**				-4245.781	
	GARCH (1, 1)	**4.503**	0.9380	-1.228	**1.702***	**2.119**		**3.378**	**9.700**				3.3773	3.3717
	ARFIMA-	**0.1351**	**0.0596**			**0.4627**	**0.2333**					**4.3969**	-4248.685	
	FIGARCH (0, *d*, 0)	**3.981**	**3.239**			**5.774**	**7.115**					**10.98**	3.3772	3.3738
	ARFIMA-	**0.1256**	0.0216	-0.2221	**0.3015***	**0.4549**	**0.2347**					**4.4381**	-4243.779	
	FIGARCH (0, *d*, 0)	**4.607**	0.9716	-1.245	**1.799***	**5.801**	**7.163**					**10.86**	3.3749	3.3700
	ARFIMA-	**0.1234**	0.0219	-0.2225	**0.2975***	**0.3805**	**0.3137**	-0.0823	0.0516			**4.2773**	-4240.539	
	FIGARCH (1, *d*, 1)	**4.532**	1.004	-1.216	**1.725***	**3.471**	**4.488**	-0.5630	0.2998			**10.33**	3.3739	3.3676
	ARFIMA-	**0.0891**	**0.0672**			**7.3816**	**0.0329***	-0.1339	**0.8790**	**-0.1584**	**0.2726**	**4.3601**	-4230.773	
	FIEGARCH (1, *d*, 1)	**2.390**	**3.926**			**4.485**	**1.813***	-0.6062	**17.56**	**-4.570**	**5.367**	**10.30**	3.3662	3.3598
	ARFIMA-	**0.0897***	0.0343	-0.3055	**0.3698***	**7.1690**	**0.0328***	-0.1393	**0.8713**	**-0.1624**	**0.2816**	**4.3807**	-4227.068	
	FIEGARCH (1, *d*, 1)	**1.861***	1.602	-1.409	**1.807***	**4.543**	**1.792***	-0.6508	**16.67**	**-4.704**	**5.434**	**10.14**	3.3648	3.3569

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.
(2) Entries in bold are significant at the 95% level.
Entries in bold * are significant at the 90% level.

Table 9: Estimation Results for KLCI (Malaysia)

Var.	Model	Mean equation				Variance equation							LL		
		μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*		AIC	SIC
KLCI	**GARCH(1, 1)**	**0.0269**				**0.0139**		**0.1151**	**0.8839**	0.9991		**4.1445**	-3057.023		
		2.153				**2.068**		**4.188**	**31.97**			**11.74**		2.4311	2.4277
								φ	β	θ_1	θ_2				
	FIGARCH(1, *d*, 1)	**0.0285**				**0.0741**	**0.3116**	-0.1105	0.0836			**4.7515**	-3039.816		
		2.268				**2.673**	**8.624**	-0.6701	0.4676			**12.57**		2.4182	2.4141
	FIEGARCH(1, *d*, 1)	**0.0241**				**14.9327**	**0.0335**	-0.1041	**0.9541**	**-0.0553**	**0.2314**	**4.2693**	-3041.551		
		1.864				**3.478**	**2.250**	-0.4380	**45.05**	**-3.062**	**4.448**	**11.70**		2.4212	2.4156
	ARFIMA-	0.0256	0.0366	-0.1504	0.2436	**0.0138**		**0.1166**	**0.8811**				-3033.352		
	GARCH(1, 1)	1.438	0.8903	-0.1947	0.3289	**2.063**		**4.437**	**32.24**					2.4147	2.4090
	ARFIMA-	0.0233	**0.0908**			**0.1137**	**0.2276**					**4.9096**	-3034.825		
	FIGARCH(0, *d*, 0)	0.9072	**4.599**			**5.005**	**12.83**					**12.29**		2.4135	2.4101
	ARFIMA-	0.0271	0.0328	-0.0242	0.1290	**0.1131**	**0.2268**					**4.9230**	-3028.144		
	FIGARCH(0, *d*, 0)	1.525	0.8163	-0.0400	0.2226	**5.015**	**13.01**					**12.13**		2.4098	2.4049
	ARFIMA-	0.0277	0.0324	0.0010	0.0969	**0.0692**	**0.3159**	-0.1041	0.0990			**4.9751**	-3016.116		
	FIGARCH(1, *d*, 1)	1.580	0.8495	0.0016	0.1553	**2.560**	**8.313**	-0.6224	0.5381			**11.62**		2.4018	2.3954
	ARFIMA-	-0.0056	**0.2030**	**0.7859**	**-0.8668**	**15.567**	**0.0315**	-0.0930	**0.9533**	**-0.0703**	**0.2306**	**4.4800**	-3016.812		
	FIEGARCH(1, *d*, 1)	-0.1335	**3.901**	**9.933**	**-16.99**	**3.533**	**2.226**	-0.3948	**43.62**	**-3.459**	**4.959**	**11.02**		2.4039	2.3960

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.
(2) Entries in bold are significant at the 95% level.
Entries in bold * are significant at the 90% level.

Table 10: Estimation Results for SETI (Thailand)

Var.	Model	Mean equation						Variance equation							LL	
		μ	*d*	AR(1)	AR(2)	MA(1)	MA(2)	ω	*d*	α	β	α+β		*df*	AIC	SIC
SETI	**GARCH(1, 1)**	**0.050**						**0.065**		**0.112**	**0.863**	0.9755		**5.155**	-4231.430	
		2.308						**3.158**		**6.741**	**42.48**			**7.601**	3.363	3.360
										ϕ	β	θ_1	θ_2			
	FIGARCH(1, *d*, 1)	**0.049**						**0.113**	0.522	0.116	**0.542***			**4.961**	-4232.179	
		2.211						**1.895**	1.578	1.610	**1.726***			**6.446**	3.364	3.360
	FIEGARCH(1, *d*, 1)	**0.044**						**12.23**	**0.034**	0.040	**0.9294**	**-0.058**	**0.181**	**5.305**	-4221.891	
		1.987						**4.798**	**2.999**	0.183	**48.05**	**-3.357**	**5.560**	**7.507**	3.358	3.352
	ARFIMA-	0.055	**0.060**	-0.313		0.280		**0.067**		**0.114**	**0.8604**				-4226.923	
	GARCH(1, 1)	1.638	**2.482**	-1.393		1.346		**3.176**		**6.818**	**41.69**				3.3623	3.356
	ARFIMA-	0.042	**0.042**					**0.430**	**0.193**					**5.2640**	-4241.659	
	FIGARCH(0, *d*, 0)	1.375	**2.461**					**5.861**	**9.969**					**7.978**	3.3717	3.368
	ARFIMA-	0.042	**0.064**	-0.308		0.267		**0.432**	**0.192**					**5.2496**	-4240.449	
	FIGARCH(0, *d*, 0)	1.178	**2.615**	-1.592		1.481		**5.846**	**9.939**					**7.985**	3.3723	3.367
	ARFIMA-	0.053	**0.061**	-0.317		0.282		**0.117**	**0.514***	0.109	**0.526***			**5.0132**	-4227.516	
	FIGARCH(1, *d*, 1)	1.538	**2.551**	-1.496		1.433		**1.950**	**1.686***	0.0711	**1.759***			**6.533**	3.3636	3.357
	ARFIMA-	0.032	**0.078**	-0.299		0.252		**12.16**	**0.034**	0.050	**0.9275**	**-0.071**	**0.179**	**5.436**	-4214.582	
	FIEGARCH(1, *d*, 1)	0.659	**3.441**	-1.427		1.267		**4.963**	**3.088**	0.232	**48.72**	**-3.748**	**5.784**	**7.111**	3.354	3.347
	ARFIMA-	0.029	**0.065**	**-1.033**	**-0.670**	**0.998**	**0.687**	**12.05**	**0.035**	0.021	**0.9257**	**-0.072**	**0.187**	**5.424**	-4208.685	
	FIEGARCH(1, *d*, 1)	0.771	**1.964**	**-2.253**	**-2.679**	**2.386**	**3.458**	**4.992**	**3.118**	0.102	**47.62**	**-3.726**	**5.972**	**7.150**	3.351	3.342

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.
(2) Entries in bold are significant at the 95% level
Entries in bold * are significant at the 90% level

Table 11: Estimation Results for STI (Singapore)

Var.	Model	Mean equation				Variance equation							LL	
		μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*		SIC
STI	**GARCH(1, 1)**	**0.0661**				**0.0203**		**0.0954**	**0.8974**	0.9929		**6.8754**	-3932.835	
		3.446				**2.914**		**6.425**	**59.38**			**7.409**	3.1265	3.1230
								φ	β	θ_1	θ_2			
	FIGARCH(1, *d*, 1)	**0.0676**				**0.0529**	**0.4320**	0.1164	**0.4982**			**7.2255**	-3925.273	
		3.524				**2.321**	**5.826**	1.597	**4.216**			**7.367**	3.1212	3.1171
	FIEGARCH(1, *d*, 1)	**0.1804**				**1.0032**	**0.6499**	0.5406		**-0.1418**	**0.0092**	**3.8158**	-4032.902	
		7.891				**3.749**	**7.954**	1.102		**-2.898**	**2.566**	**10.34**	3.2083	3.2027
	ARFIMA-	**0.0720**	0.0526	0.2332	-0.2640	**0.0204**		**0.0958**	**0.8969**				-3930.295	
	GARCH(1, 1)	**2.666**	1.535	0.8955	-0.9932	**2.902**		**6.351**	**58.20**				3.1268	3.1212
	ARFIMA-	**0.0691**	**0.0388**			**0.2396**	**0.2207**					**6.9456**	-3952.807	
	FIGARCH(0, *d*, 0)	**2.720**	**2.268**			**5.969**	**14.60**					**8.229**	3.1423	3.1389
	ARFIMA-	**0.0718**	0.0610	0.2623	-0.2957	**0.2411**	**0.2202**					**6.8687**	-3952.469	
	FIGARCH(0, *d*, 0)	**2.502**	1.629	0.8003	-0.8830	**5.971**	**14.47**					**8.201**	3.1436	3.1387
	ARFIMA-	**0.0735**	0.0502	0.2155	-0.2436	**0.0537**	**0.4274**	0.1171	**0.4918**			**7.3068**	-3922.823	
	FIGARCH(1, *d*, 1)	**2.753**	1.458	0.7796	-0.8639	**2.296**	**5.788**	1.558	**4.055**			**7.097**	3.1217	3.1153
	ARFIMA-	**0.0533**	0.0195			**3.7642**	**0.1789**	**1.1873**		**-0.1179**	**0.2396**	**3.2738**	-4036.400	
	FIEGARCH(0, *d*, 1)	**2.853**	1.243			**12.70**	**6.681**	**2.918**		**-2.664**	**4.139**	**12.86**	3.2111	3.2054
	ARFIMA-	**0.0534**	**0.0465***		-0.0463	**3.7769**	**0.1796**	**1.2380**		**-0.1115**	**0.2374**	**3.2456**	-4035.408	
	FIEGARCH(0, *d*, 1)	**1.895**	**1.833***		-1.333	**13.03**	**6.867**	**2.781**		**-2.538**	**3.975**	**12.90**	3.2111	3.2047

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.
(2) Entries in bold are significant at the 95% level.
Entries in bold * are significant at the 90% level.

APPENDIX C

Value-at-Risk in Single-Index of Southeast Asia Stock Markets

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Abstract

The variance of a portfolio or the volatility is the key item in financial time series analysis and risk management to reduce and diversify portfolio risk. In order to compare the performance of the univariate conditional volatility models (single-index models) and the long memory models in forecasting Value-at-Risk (VaR) thresholds of a portfolio, we apply those models in the portfolio returns of four stock market indexes in South-East Asia, namely the JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore). The size of the average capital charge and the magnitude of the average violations are used to compare the forecasting performance of both the univariate conditional volatility models and the long memory models. The results suggest that penalties imposed under the Basel Accord are too relaxed, and tend to favour the model that had an excessive number of violations -- the single-index model under the normal distribution assumptions --, than the long memory model. The univariate conditional volatility models seem to lead to lower daily capital charges.

1. Introduction

An important task in financial time series have involved modelling and forecasting volatility since it is the key item in risk management. The most interesting financial assets for investors are common stocks which have higher risk than other assets, i.e. bonds. Typically in finances, commentators and traders define the price risks as volatility that can cause loss or gain from trading. There are many fantastically complex mathematical models for measuring the risk in their various portfolios, but the most widely used is called VaR -- Value-at-Risk. According to the amendment, the Basel II Accord attempts to encourage banks to hold their capital reserves to encounter their risks appropriately in financial investments, but banks are still free to specify their own model for VaR measurement (see Basel Committee on Banking Supervision (1988), (1995) for further details). Therefore the model providing accurate volatility measures to forecast VaR is important for banks' self regulation.

McAleer (2008) gives the analysis and has concerned about risk management under the Basel II Accord. The Ten Commandments for optimizing Value-at-Risk (VaR) and daily capital charges are presented in the 4th National Conference of Economists at Chiang Mai University, Thailand (2008). The suggestions and guidelines for risk management are that holding and managing cash is better than dealing with risky financial investments. McAleer, Jiménez-Martin and Peréz-Amaral (2009) also present the intended Ten Commandments to assist in risk management and importance of VaR forecasts.

As mentioned in McAleer (2008), McAleer and da Veiga (2008a, 2008b), McAleer (2009), and McAleer, Jiménez-Martin and Peréz-Amaral (2009), the key items for banks have their own VaR and the accuracy of the various volatility models (see Li, Ling and McAleer (2002), and McAleer (2005) for excellent reviews of the conditional volatility, Asai, McAleer and Yu (2006) for recent reviews of stochastic volatility, and the reviews of realized volatility models in McAleer and Medeiros (2008)), the number of violations from the VaR forecasts, the penalty of the Basel Accord k, and the daily capital charges.

In order to obtain the accuracy VaR forecasts and less capital charges, banks should have their preferable volatility model. McAleer and da Veiga (2008a) developed a new parsimonious and computationally convenient portfolio spillover GARCH (PS-GARCH) model to capture portfolio spillover effects and allowing spillover effects to be included parsimoniously. They found the similarity of this model and multivariate volatility models to yield volatility and VaR threshold forecasts. McAleer and da Veiga (2008b) compare the performance of the single-index and portfolio models in forecasting VaR thresholds. They found that the single-index models lead to lower daily capital charges by taking into account the Basel Capital Accord penalties. The interesting matter from their results is that the penalties imposed under the Basel Accord are too lenient, and tend to favour models that had an excessive number of violations.

In this paper, therefore, we will investigate the fit model for modelling and forecast volatility based on the univariate volatility models (single-index models) and the long memory models. Since many literatures show the persistence of shocks in volatility, the volatility has long memory property. We apply those models in order to measure and forecast volatility of the portfolio returns of four stock market indexes in South-East Asia, namely the JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore). The size of the average capital charge and the magnitude of the average violations are used to compare the forecasting performance of both the univariate conditional volatility models and the long memory models.

2. Model Specifications

In this section, the univariate conditional volatility models and the long memory models are introduced for forecasting Value-at-Risk. We consider the models using daily returns and several specifications for the conditional variance of shocks.

The series of daily returns are known to be conditional heteroskedastic. They are modelled by

$$y_t = \mu_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sigma_t z_t \tag{2}$$

$$\mu_t = c(\eta | I_{t-1}) \tag{3}$$

$$\sigma_t = h(\eta | I_{t-1}) \tag{4}$$

where $c(\cdot | I_{t-1})$ and $h(\cdot | I_{t-1})$ are functions of past information, I_{t-1}, and depend on an unknown of parameter η. z_t is an independently and identically distributed (i.i.d.) with a mean zero and a unit variance. μ_t and σ_t^2 are the condition mean and variance of returns y_t respectively.

The series of daily returns are known to have serial correlation that can be solved by constructing a white noise process, the ARMA(p,q) process. This process can be written using the lag operator as

$$\phi L(y_t - \mu) = \theta(L)\varepsilon_t \tag{5}$$

where $\phi(L) = 1 + \phi_1 L + ... + \phi_p L^p$ and $\theta(L) = 1 + \theta_1 L + ... + \theta_q L^q$ are the autoregressive and moving-average operators, respectively. μ_t equals $\mu_t + \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu)$.

Now the various models that are used to measure volatility for VaR forecasts are straightforward introduced. In this paper, we consider the RiskMetric^{TM} model, the univariate models such as the ARCH and GARCH models, the GJR, the EGARCH model, and the long memory models; FIGARCH, FIEGARCH, ARFIMA-GARCH, ARFIMA-EGARCH, ARFIMA-FIGARCH, and ARFIMA-FIEGARCH models.

2.1 Riskmetrics^{TM}

RiskMetrics^{TM} of J. P. Morgan (1996) is a standard in the market risk measurement due to its simplicity. Basically, the RiskMetrics^{TM} model is a model where the ARCH and GARCH coefficients are fixed to 0.06 and 0.94 respectively, which is given by

$$\sigma_t^2 = 0.06\varepsilon_{t-1}^2 + 0.94\sigma_{t-1}^2 \tag{6}$$

Therefore the RiskMetrics^{TM} model is not required to estimate any unknown parameter. However, it is simply for practitioners to use.

2.2 ARCH

Engle (1982) proposed the autoregressive conditional heteroscedasticity of order *q*, or ARCH (*q*), defined as

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{7}$$

The parameters $\omega > 0, \alpha_1 > 0$ are sufficient to ensure positive in the conditional variance $h_t > 0$ when *q* = 1. The α_i represents the ARCH effect that captures the short-run persistence of shocks.

2.3 GARCH

Bollerslev (1986) generalized ARCH (*q*) to the GARCH (*p*,*q*) model, given by

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{8}$$

The parameters $\omega > 0, \alpha_1 > 0$ and $\beta_1 \geq 0$ are sufficient to ensure positive in the conditional variance $h_t > 0$. The α_i represents the ARCH effect and β_j represents the GARCH effect that indicates the contribution of shocks to long run persistence ($\alpha_1 + \beta_1$).

2.4 GJR

Glosten, Jagannathan, and Runkle (1992) proposed the model to accommodate differential impact on the conditional variance between positive and negative shocks, here after the GJR model, given by

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I(\varepsilon_{t-i}))\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{9}$$

where the conditional volatility is positive when parameters satisfy $\alpha_0 > 0, \alpha_i + \gamma_i \geq 0$ and $\beta_j \geq 0,$ for *i* = 1,…, *q* and *j* = 1,…, *p*. $I(\varepsilon_{t-i})$ is an indicator function that takes value 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. The impact of positive shocks and negative shocks on conditional variance is allowing asymmetric impact. The expected value of γ_i is greater than zero that means the negative shocks give higher impact than the positive shocks, $\alpha_i + \gamma_i \geq \alpha_i$.

2.5 EGARCH

Nelson (1991) introduced the Exponential GARCH (EGARCH) model which is re-expressed by Bollerslev and Mikkelsen (1996) as follows

$$\log(h_t) = \omega + \sum_{i=1}^{p} \alpha_i |\eta_{t-i}| + \sum_{i=1}^{p} \gamma_i \eta_{t-i} + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) \tag{10}$$

where $|\eta_{t-i}|$ and η_{t-i} capture the size and sign effects of the standardized shocks respectively. The positive shocks provide less volatility than the negative shocks when γ_i < 0. Then the model allows asymmetric and leverage effects.

2.6 FIGARCH

Baillie (1996), and Baillie, Bollerslev and Mikkelsen (1996) investigated a model with long-memory input for the conditional variance h_t, by inserting the additional filter $(1-L)^d$ and short-memory filter, ARMA, and then making the GARCH more general known as the fractional integration (FI) GARCH model. The FIGARCH (1, d, 1) model is defined by

$$h_t = \omega + [1 - \beta_1 L - (1-\phi_1 L)(1-L)^d]\varepsilon_t^2 + \beta_1 h_{t-1} \tag{11}$$

while the differencing parameter d is between 0 and 1. The filter then represents fractional differencing which is defined by the binomial expansion as

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \ldots \tag{12}$$

2.7 FIEGARCH

Bollerslev and Mikkelsen (1996) purposed the fractionally integrated GARCH (FIEGARCH) specifications.

From the EGARCH model of Nelson (1991), the returns are assumed to have conditional distributions that are normal with constant mean and with variances. The FIEGARCH (1,d,1) model is defined by

$$\log(h_t) = \omega_t + [(1-\beta(L)]^{-1}[(1+\alpha(L)]g(z_{t-1}) \tag{13}$$

$$g(z_t) = \theta_1 z_{t-1} + \theta_2[|z_t| - E|z_t|] \tag{14}$$

where ω_t and h_t denote conditional means and conditional variance respectively. The standardized residuals are $z_t = e_t / \sqrt{h_t}$.

2.8 ARFIMA-GARCH

Ling and Li (1997a) proposed a fractionally integrated autoregressive model with conditional heteroskedasticity, ARFIMA(*p*,*d*,*q*)-GARCH(*r*,*s*). This is discrete time process y_t with standard normal distribution z_t and the GARCH model as

$$h_t = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j} \tag{15}$$

If $|d| < 0.5$, and $\sum_{i=1}^{r} \alpha_i + \sum_{j=1}^{s} \beta_j < 1$, then { y_t } is invertible and stationary. Palma and Zevallos (2001) showed that in ARFIMA-GARCH model, the data have long memory if 0 < *d* < 0.5. The squared data have intermediate-memory if 0 < *d* < 0.25 and long memory if 0.25 < *d* < 0.5. An ARFIMA-EGARCH gives the same conclusions.

2.9 ARFIMA-FIEGARCH

The combination of ARFIMA filters and conditionally heteroskedastic input with long-range dependency such as FIEGARCH model gives the ARFIMA-FIEGARCH model. Robinson and Hidalgo (1997), and Palma and Zevallos (2001) showed the similar type of result for this context which the squares of the input sequence { ε_t } has a long memory with filter parameter $d^* = d_\varepsilon + d_y < 0.5$, then the process { y_t } has long memory. d_ε is the differencing parameter of long-memory input, FIEGARCH, and d_y is the differencing parameter of long-memory filter, ARFIMA, where $0 < d_\varepsilon, d_y < 0.5$.

3. Empirical Volatility Modelling

The data used in this paper are explained in this section. In addition to forecast the VaR, the portfolio returns are also described as follow:

3.1 DATA

We use the daily closing price indexes based on four South-East Asia stock markets. They are JKSE (Jakarta Stock Exchange Index), KLCI (Kuala Lumpur Composite Index), SETI (Stock Exchange of Thailand Index), and STI (Straits Times Index), as available on DataStream. We select these stock markets from the index values. Those are very high values and potential investment alternatives compared with other markets in Southeast Asia. The index values of each market from Bloomberg are shown in Figure 1. The latest stock exchange founded in 1999 is Singapore Exchange (SGX), therefore the data are collected at that starting time. We consider for a long time period from September 1, 1999 to April 27, 2009, giving a total of 2,519 return observations. All stock indexes are computed and converted into a common currency, namely the US dollar for controlling exchange rate risk purpose by the Morgan Stanley Capital International (MSCI).

3.2 Volatility forecasts

To forecast the conditional volatility, we first adjust the closing price to obtain the returns for each market by taking logarithmic different. The rationale to employ daily data in modelling volatility transmission is mentioned in McAleer and da Veiga (2008a, 2008b). The returns for each index *i* at time *t* are calculated as follows

$$r_{it} = \log(\frac{p_{i,t}}{p_{i,t-1}}) * 100 \qquad (16)$$

where $p_{i,t}$ is the price of index *i* at time *t*. $p_{i,t-1}$ is the price of index *i* at time *t-1*. Each return series of index *i* is calculated for portfolio returns by assuming as the portfolio weights are equal and constant overtime. Therefore, the portfolio returns at time *t* of four stock markets are the sum the weights of 0.25 multiply by the returns of index *i* at time *t*. The plots of the daily returns for all series are shown in Figure 2 and of the volatility for all series in Figure 3.

Figure 2 shows that all returns series exhibit the clustering. The descriptive statistics of each series is provided in Table 2. The results show the excess kurtosis in all series that indicates a fat-tailed distribution compared to a standard normal distribution with kurtosis 3. Then, an appropriate model to model volatility more accuracy is necessary to estimate. All series have similar constant means at close to zero. The maximum values of percentage changes of index returns range approximately between 5.4% and 15.1%. The minimum values of percentage changes of index returns range approximately between -20.0% and -9.8%. Finally, The Jarque-Bera test strongly rejects the null hypothesis of normally distributed returns.

Then, we estimate, forecast and fit the univariate conditional volatility models to portfolio returns known as single-index models (see McAleer and da Veiga (2008a, 2008b)). We also fit the long memory models to portfolio returns in comparison purpose how the performance of those single-index and long memory models in forecasting VaR. Both the univariate conditional volatility models and long memory models are used to estimate the variance of portfolio returns directly. The estimations are undertaken under the distributional assumptions of shocks as (1) normal and (2) *t*, with estimated degrees of freedom. We model the returns as a stationary ARMA(1,1) process for both the univariate GARCH models and the long memory models.

Finally, we forecast the 1-day-ahead conditional variance of portfolio returns and VaR threshold. To be compatible, the number of forecast with efficiency in estimation, we set the sample size at 2,000 (T=2,000), giving a forecasting period from May 2, 2007 to April 27, 2009. The daily capital charge and the number of violations are used to evaluate the forecasts of the VaR threshold, next.

3.3 Value-at-Risk (VaR), Daily capital charge and Violation magnitude.

(a) Value-at-Risk

A VaR threshold is the lower bound of a confidence interval for the mean. Suppose the daily returns y_t following the conditional mean and a random component ε_t, i.e. $\varepsilon_t \sim D(\mu_t, \sigma_t)$ with the unconditional mean μ_t and the standard deviation σ_t. Then we can estimate VaR with various methods. The VaR threshold for y_t can be calculated by

$$VaR_t = E(y_t | I_{t-1}) - \alpha\sigma_t \tag{17}$$

where α is the critical value from the distribution of ε_t to get the appropriate confidence level. σ_t can be replaced by any estimate of the conditional variance to get an appropriate VaR (see McAleer and da Veiga (2008a) for more detail).

(b) Daily capital charge and the number of violations

In practice, Basel II Accord requires banks hold their capital reserves appropriate to the risk the banks expose themselves to through their investment practices. In other words, the greater risk to which the banks are exposed, the greater the amount of capital the banks need to hold called capital charges. The Basel Accord imposes penalties in the form of higher multiplicative factor *k* on banks. In order to optimize the capital charges or minimize problem, the number of violations and the VaR forecasts are taken into account and defined by (see McAleer (2009), and McAleer, Jiménez-Martin and Peréz-Amaral (2009) for more detail).

$$\underset{\{k,VaR\}}{Minimize}\, DCC_t = \sup\left\{-(3+k)\overline{VaR}_{60}, -VaR_{t-1}\right\} \tag{18}$$

where

DCC = daily capital charges, which is the higher of $-(3+k)\overline{VaR}_{60}$ or $-VaR_{t-1}$,

VaR_t = Value-at-Risk for day t, as in (17),

$\overline{VaR}_{60}$ = mean VaR over the previous 60 working days,

k = the Basel Accord violation penalty, that is greater than or equal zero but less than or equal one ($0 \le k \le 1$), in Table 1.

In this context, Banks can control their daily capital charges by a good quality of volatility in VaR and the value of k arising from the violation penalty.

4. Empirical Results

In this section, we divide the empirical results into (1) the results of the estimations and (2) the daily capital charge and the violation magnitude as follow:

4.1 Model Estimations

We report the estimations for the single-index models and the long memory models in Table 4 and Table 5 respectively. Table 4 summarizes the estimations from Riskmetrics^{TM}, ARCH(1), GARCH(1,1), GJR(1,1), and EGARCH(1,1) models, estimated under the normal distributional assumptions and *t*-distribution. The parameters are estimated using maximum likelihood estimation (MLE) method. The results show that most estimates of all single-index models are highly statistically significant at 1% level. The single-index models estimated under assumption that returns follow a *t*-distribution perform far better, judged by optimizing the information criterion of either Akaike (1974) or Schwarz (1978), denoted as AIC and SIC, respectively.

Those criteria are given either $-2\frac{LogL}{n}+2\frac{k}{n}$ for AIC, or $-2\frac{LogL}{n}+2\frac{\log(k)}{n}$ for SIC, with the k parameters estimated from n observations.

The parameters γ in GJR and θ_1 and θ_2 in EGARCH models which are significantly different from zero indicate that the volatility of portfolio returns have asymmetric and leverage effects of shocks.

Table 5 summarizes the estimations from the long memory models consisting of FIGARCH(1,*d*,1), FIEGARCH(1,*d*,1), ARFIMA-GARCH(1,*d*,1), ARFIMA-EGARCH (1,*d*,1), ARFIMA-FIGARCH(1,*d*,1), and ARFIMA-FIEGARCH(1,*d*,1) models, estimated under the normal distributional assumptions and *t*-distribution. The results show that most estimates of FIGARCH(1,*d*,1) and FIEGARCH(1,*d*,1) models are highly statistically significant at 1% level. In long memory models estimated under *t*-distribution perform far better, same as the single-index models, judged by AIC and SIC. The maximum likelihood estimates of *d* from FIGARCH(1,*d*,1) and FIEGARCH(1,*d*,1) with *t*-distribution are 0.23 and 0.04 respectively, less than 0.25 which indicate the intermediate-memory in volatility of the portfolio returns. The parameters θ_1 and θ_2 in FIEGARCH(1,*d*,1) models which are significantly different from zero indicate that the volatility of portfolio returns also have asymmetric and leverage effects of shocks. Most estimates of ARFIMA-GARCH(1,*d*,1), ARFIMA-EGARCH(1,*d*,1), ARFIMA-FIGARCH(1,*d*,1), and ARFIMA-FIEGARCH(1,*d*,1) models are highly statistically significant at 1% level, especially in variance equation. The maximum likelihood estimates of *d** from ARFIMA-FIGARCH(1,*d*,1) and ARFIMA-FIEGARCH(1,*d*,1) with *t*-distribution are 0.23 and 0.04 respectively, less than 0.25 which indicate the intermediate-memory in volatility of the portfolio returns, the same results in FIGARCH and FIEGARCH models. However, differencing parameter *d* in long-memory filter ARFIMA in ARFIMA-GARCH(1,*d*,1) and ARFIMA-EGARCH(1,*d*,1) are not significantly different from zero. The parameters θ_1 and θ_2 in both ARFIMA-EGARCH(1,*d*,1) and ARFIMA-FIEGARCH(1,*d*,1) models which are significantly different from zero indicate that the volatility of portfolio returns also have asymmetric and leverage effects of shocks.

From the goodness of fit criteria, AIC and SIC, the long memory models are preferred to short memory for volatility estimation in this portfolio returns. The ARFIMA-FIEGARCH model performs far better for volatility modelling.

4.2 VaR, Daily capital charge and Violation magnitude

We consider the application of the volatility models to Value-at-Risk. We use the estimated coefficients in the previous in single-index models and long memory models to forecast VaR. We use the VaR forecasts to identify the number of violations from the negative returns exceed the VaR forecasts. These numbers of violations can indicate the Basel Accord violation penalty (k) to optimize the daily capital charges. Table 3 gives the mean daily capital charges for each model. The worst-performing model that gives average daily capital charges of 16.68% is the FIGARCH with t-distribution model. The best-performing model which gives average daily capital charges of 6.64% is the ARCH model under a normal distribution.

We have the same results as McAleer and da Veiga (2008b) in the context of distributional assumptions of the estimations. We find that apart from Riskmetrics^{TM} model, both the single-index models and the long memory models which are estimated assuming a t-distribution tend to give higher capital charges than the parallel models estimated under a normal distribution. Therefore, the penalties imposed under the Basel Accord may not be severe enough, as all of models with the normally distributed give a higher number of violations. In conclusion, the Basel Accord prefers models which give an excessive number of violations.

Table 3 also reports the maximum and average absolute deviations of violations from the VaR forecasts. The worst-performing model that gives the largest maximum absolute deviations at 5.304 is the GARCH model under a normal distributed assumption. The best-performing model that gives the lowest maximum absolute deviations at 0.779 is the long memory model ARFIMA-FIGARCH model under a t-distributed assumption. While, for the average absolute deviation values, the worst-performing model that gives the highest average absolute deviations at 1.294 is the ARCH model under a normal distributed assumption. On the contrary, the best-performing model that gives the basis average absolute deviations at 0.409 is the GJR model.

These results seem to be contradictory between those values of absolute deviations and the mean capital charges. It is not clear which model is appropriate for capital optimization. However, the numbers of violations should be highly considerable in the sense of accuracy forecast. The long memory models seem to lead to lower the numbers of violations.

5. Conclusion

In conclusion, we investigate (1) the performance of VaR forecasts in between the single-index models and the long memory models for portfolio returns. (2) the daily capital charges and VaR models in order to reach the preferable model.

In the empirical example, the portfolio comprised four stock market indexes in South-East Asia, namely the JKSE, KLCI, SETI, and STI, for the period from October 1, 2007 to April 27, 2009, giving a total of 2,519 return observations. On the basis of the empirical results, the estimation results show that the long memory models yield superior in portfolio volatility forecasts based on the goodness of fit criteria, AIC and SIC. However, in this study we exclude the multivariate volatility models that should be used to forecast the conditional variance and the conditional correlations between all index pairs, in order to capture the spillover effects. In the context of daily capital charges, it was found that the conditional volatility models under the normal distributional assumptions lead to lower daily capital charges by taking into account the Basel Accord penalties. Finally, the results suggest that penalties imposed under the Basel Accord are too relaxed, and tend to favour models that had an excessive number of violations.

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Appendix

Figure 1: The proportion of the Stock Markets in South-East Asia

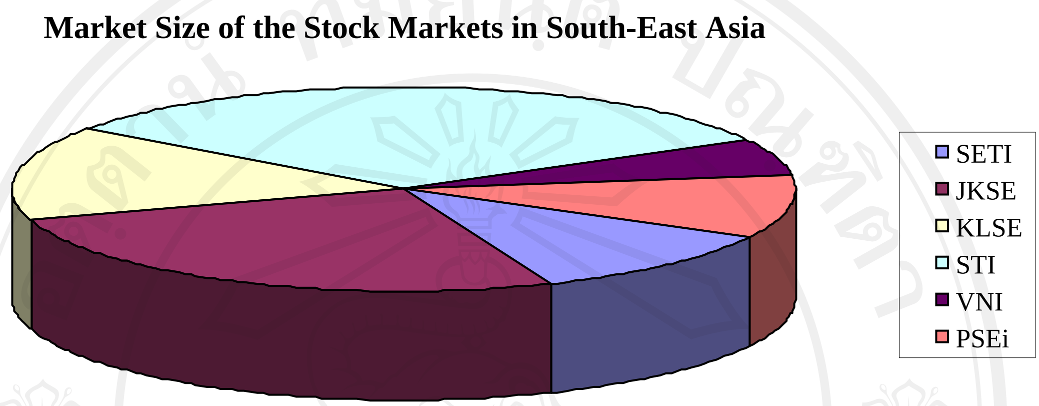

Figure 2: Daily returns for all series

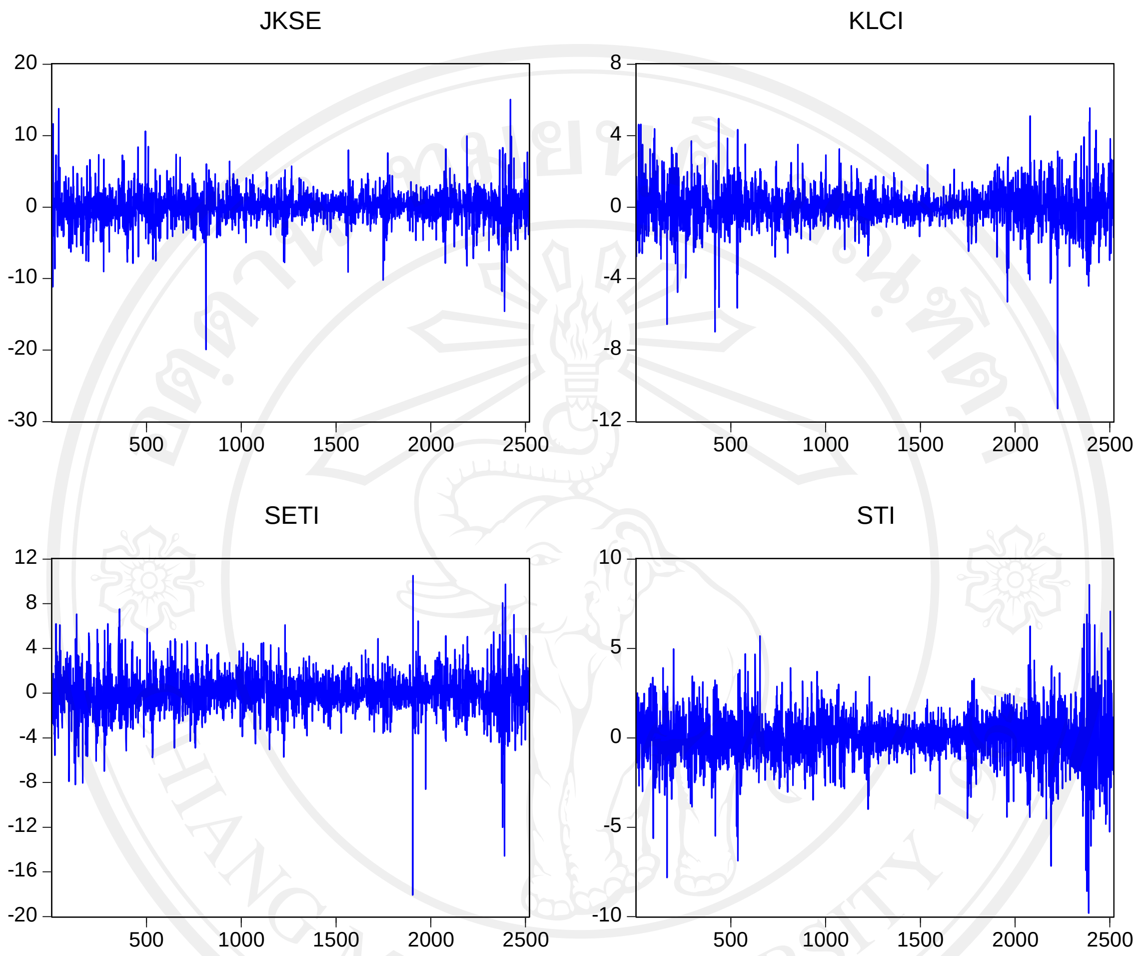

Figure 3: Volatility of returns for all series

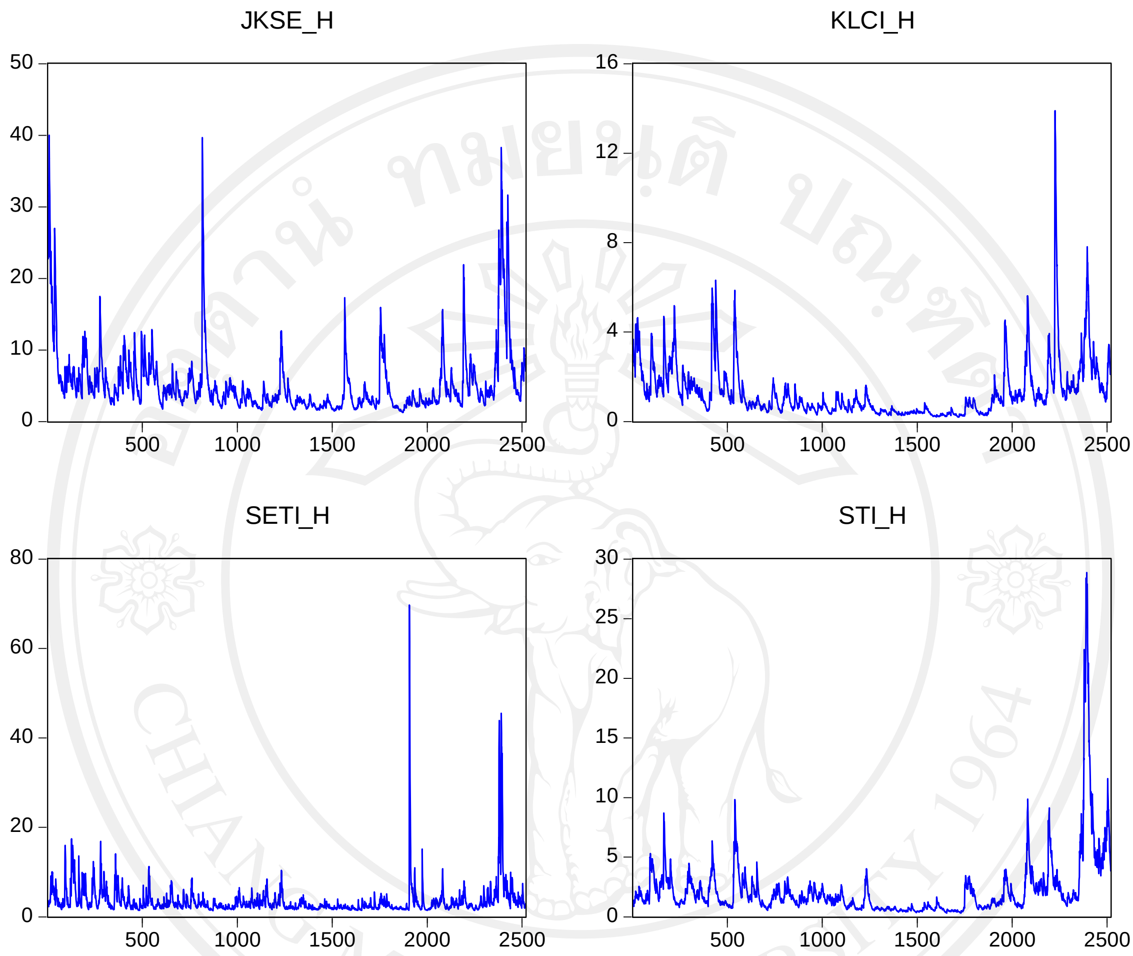

Figure 4: Portfolio Returns and VaR Threshold Forecasts

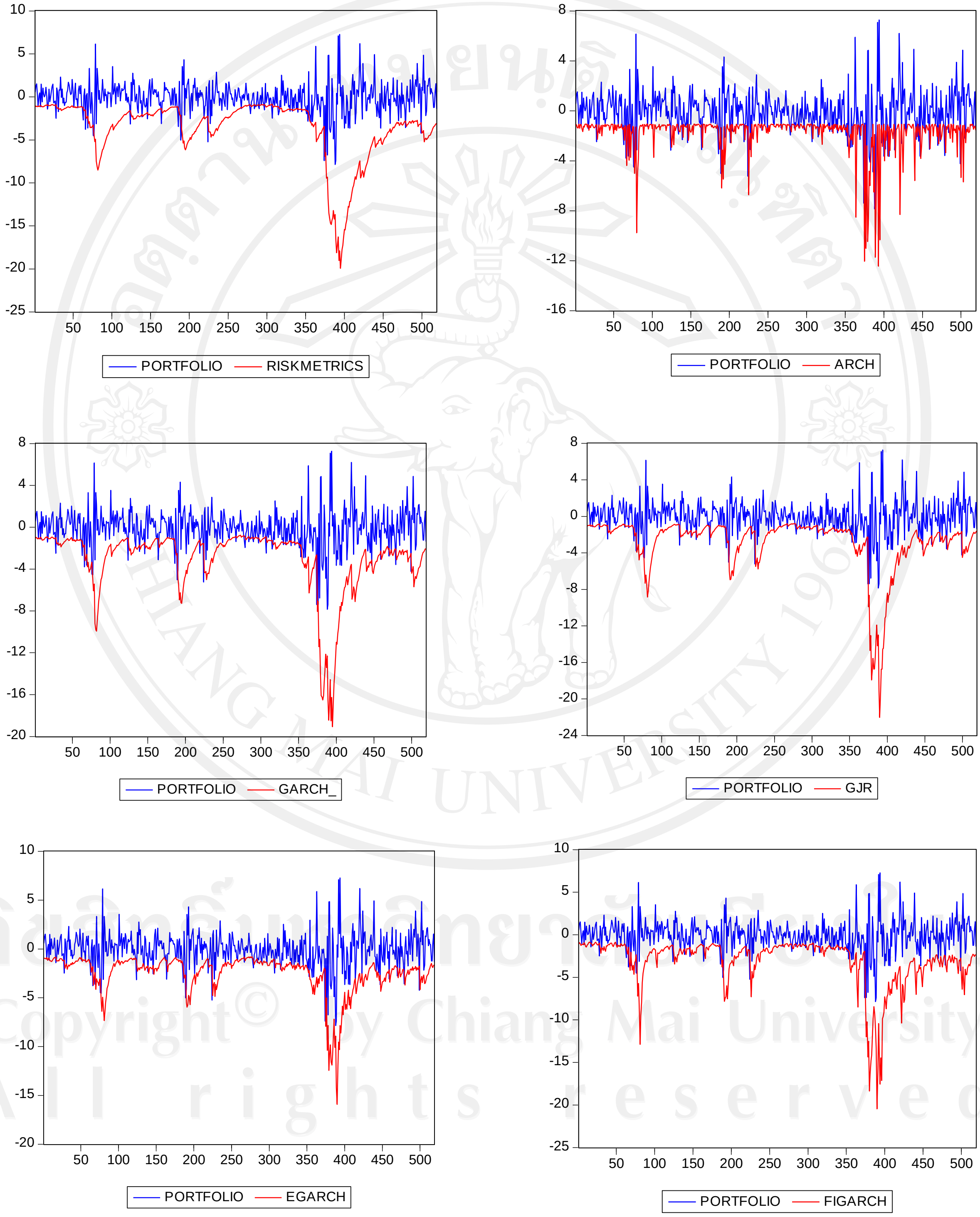

Figure 4: Portfolio Returns and VaR Threshold Forecasts (Continued)

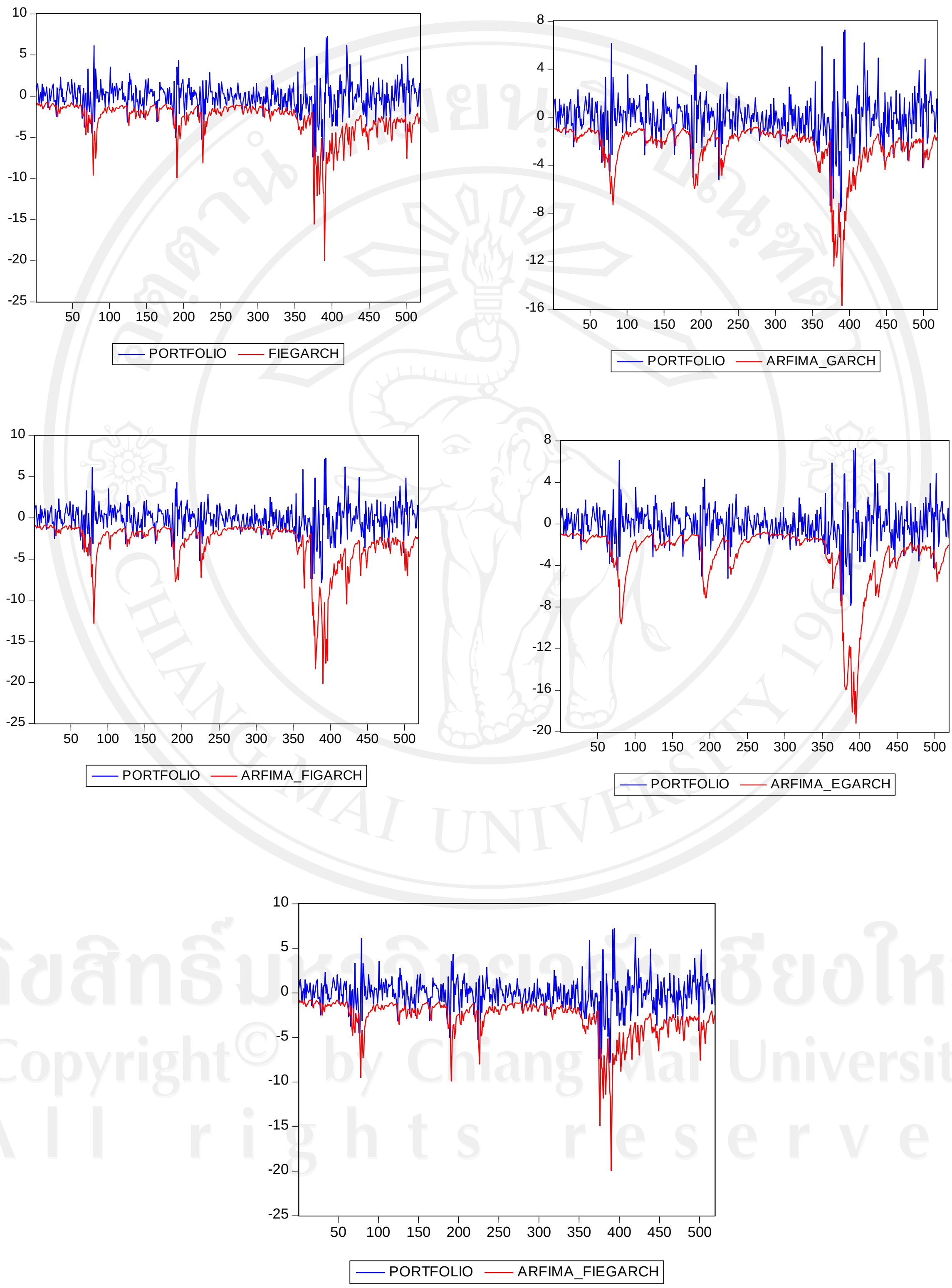

Table 1: Basel Accord penalty zones

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

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

Table 2: Descriptive Statistics of all return series

	JKSE	KLCI	SETI	STI
Mean	0.0269	0.0132	0.0046	-0.0048
Maximum	15.0419	5.5463	10.5206	8.5634
Minimum	-19.9468	-11.2789	-18.0844	-9.8093
Std. Dev.	2.2704	1.1254	1.8869	1.4619
Skewness	-0.3595	-0.5422	-0.5770	-0.2981
Kurtosis	9.9880	10.5374	10.4319	7.8136
Jarque-Bera	5179.63	6086.52	5937.10	2469.29

Table 3: Mean Daily Capital Charge and AD of Violations for the Single-Index and the Long Memory Models

Model	Number of Violations	Mean Daily Capital Charge	AD of Violations	
			Maximun	Mean
Riskmetrics™	21	13.876	4.811	0.854
ARCH	51	6.645	0.967	1.294
ARCH-*t*	19	14.441	2.711	0.597
GARCH	25	11.344	5.304	0.769
GARCH-*t*	4	14.503	1.697	1.220
GJR	20	9.922	1.122	0.409
GJR-*t*	4	12.714	1.404	0.757
EGARCH	22	9.424	3.019	0.582
EGARC-*t*	4	12.153	1.172	0.682
FIGARCH	18	13.142	1.227	0.439
FIGARCH-*t*	2	16.684	0.797	0.797
FIEGARCH	10	13.583	1.347	0.583
FIEGARCH-*t*	6	11.619	0.925	0.611
ARFIMA-GARCH	25	11.085	5.172	0.749
ARFIMA-GARCH-*t*	4	14.461	1.665	1.193
ARFIMA-EGARCH	22	9.339	2.979	0.572
ARFIMA-EGARCH-*t*	3	12.031	0.916	0.611
ARFIMA-FIGARCH	18	13.124	1.217	0.434
ARFIMA-FIGARCH-*t*	2	16.669	0.779	0.779
ARFIMA-FIEGARCH	10	13.421	1.301	0.559
ARFIMA-FIEGARCH-*t*	7	13.142	0.877	0.535

Notes: (1) The daily capital charge, $DCC_t = -(3+k)*\overline{VaR}_{60}$ where $\overline{VaR}_{60}$ is the average VaR over the last 60 business days, or replace by the greater of the previous day's VaR. *k* is the penalty.

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

Table 4: Estimation Results for the Single-Index Models

Model	Mean equation			Variance equation								LL	
	μ	AR(1)	MA(1)	ω	α	β	γ	θ_1	θ_2	$\alpha+\beta$	*df*	AIC	SIC
Riskmetrics™	**0.0633**	**0.4629**	**-0.3127**		**0.06**	**0.94**						-2878.566	
	3.248	**4.928**	**-3.076**									2.8835	2.8792
ARCH	0.0348	**0.4444**	**-0.2490**	**0.9279**	**0.1818**					0.1818		-2920.413	
	1.041	**6.135**	**-3.127**	**43.31**	**7.039**							2.9254	2.9211
ARCH-*t*	**0.0710**	**0.4536**	**-0.3068**	**0.9167**	**0.2325**					0.2325	**4.2898**	-2803.167	
	2.790	**0.4536**	**-2.922**	**13.61**	**4.363**						**9.772**	2.8091	2.8039
GARCH	**0.0764**	**0.4681**	**-0.3174**	**0.0411**	**0.0925**	**0.8745**				0.9671		-2844.226	
	2.868	**4.052**	**-2.494**	**6.932**	**9.536**	**87.53**						2.8502	2.8450
GARCH-*t*	**0.0924**	**0.4615**	**-0.3339**	**0.0408**	**0.0901**	**0.8756**				0.9657	**5.3766**	-2755.761	
	3.878	**3.670**	**-2.479**	**3.365**	**5.378**	**40.13**					**9.228**	2.7627	2.7566
GJR	**0.0515**	**0.4572**	**-0.2989**	**0.0585**	**0.0352**	**0.8641**	**0.0938**					-2833.757	
	1.787	**3.894**	**-2.348**	**8.191**	**3.461**	**82.74**	**6.426**					2.8407	2.8346
GJR-*t*	**0.0769**	**0.4603**	**-0.3296**	**0.0559**	0.0262	**0.8663**	**0.1058**				**5.5369**	-2746.806	
	3.201	**3.751**	**-2.506**	**4.170**	1.449	**37.97**	**3.852**				**9.232**	2.7548	2.7477
EGARCH	0.0434	**0.4872**	**-0.3432**	**0.1662**	-0.1503	**0.9453**		**-0.0769**	**0.2052**			-2828.989	
	1.518	**4.075**	**-2.609**	**3.287**	-1.079	**124.7**		**-5.830**	**6.934**			2.8369	2.8298
EGARCH-*t*	**0.0701**	**0.4649**	**-0.3395**	**11.980**	-0.1095	**0.9504**		**-0.0807**	**0.1865**		**5.6418**	-2744.389	
	2.935	**3.699**	**0.1349**	**3.938**	-0.4784	**74.15**		**-3.178**	**3.941**		**9.127**	2.7533	2.7453

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.

(2) Entries in bold are significant at the 99% level.

Table 5: Estimation Results for the Long Memory Models

Model	Mean equation				Variance equation							LL	
	μ	d	AR(1)	MA(1)	ω	d	ϕ	β	θ_1	θ_2	df	AIC	SIC
FIGARCH	**0.0744**		**0.5065**	**-0.3524**	**0.2439**	**0.2532**	**-0.3841**	**-0.2308**				-2837.883	
	2.646		**4.460**	**-2.829**	**5.150**	**8.612**	**-3.068**	**-1.674**				2.8448	2.8387
FIGARCH-*t*	**0.0895**		**0.4678**	**-0.3376**	**0.2389**	**0.2346**	**-0.3521**	-0.2317			**5.4721**	-2750.240	
	3.726		**3.701**	**-2.493**	**2.772**	**5.527**	**-1.422**	-0.8696			**9.390**	2.7582	2.7511
FIEGARCH-*t*	**0.0706**		**0.4620**	**-0.3380**	**8.2273**	**0.0425**	-0.0627	**0.9106**	**-0.0875**	**0.1607**	**5.7712**	-2738.299	
	2.967		**3.599**	**-2.460**	**4.240**	**2.870**	-0.2416	**33.20**	**-3.241**	**3.645**	**8.675**	2.7482	2.7392
					ω		α	β		$\alpha+\beta$			
ARFIMA-GARCH	**0.0770**	0.0054	**0.4581**	**-0.3127***	**0.0412**		**0.0925**	**0.8744**		0.9670		-2844.221	
	2.7880	0.1186	**2.834**	**-2.147***	**6.636**		**9.201**	**82.43**				2.8512	2.8450
ARFIMA-GARCH-*t*	0.1008	0.0391	0.3608	-0.2721	**0.0414**		**0.0904**	**0.8747**		0.9652	**5.3580**	-2755.313	
	3.201	0.9348	1.440	-1.162	**3.375**		**5.363**	**39.77**			**9.254**	2.7633	2.7562
					ω		α	β	θ_1	θ_2			
ARFIMA-EGARCH	0.0390	0.0439	0.3917	-0.2905	**0.1709**		-0.1609	0.9464	-0.0797	0.2040		-2828.538	
	1.082	0.9855	1.727	-1.365	**3.292**		-1.158	126.3	-5.760	**6.851**		2.8375	2.8294
ARFIMA-EGARCH-*t*	**0.0735***	0.0500	0.3153	-0.2376	**12.134**		-0.1216	**0.9519**	**-0.0838**	**0.1863**	**5.6333**	-2743.637	
	0.0311*	1.227	1.049	-0.8394	**3.924**		-0.5391	**75.53**	**-3.210**	**3.932**	**9.142**	2.7536	2.7446
					ω	d	ϕ	β	θ_1	θ_2			
ARFIMA-FIGARCH	**0.0777***	0.0286	**0.4533***	-0.3271	**0.2458**	**0.2522**	**-0.3851**	-0.2343				-2837.733	
	2.339*	0.5832	**2.440***	-1.923	**5.141**	**8.538**	**-3.008**	-1.672				2.8457	2.8386
ARFIMA-FIGARCH-*t*	**0.0988**	0.0474	0.3280	-0.2443	**0.2435**	**0.2341**	-0.3628	-0.2451			**5.4439**	-2749.569	
	3.025	1.170	1.167	-0.9204	**2.802**	**5.526**	-1.470	-0.9218			**9.406**	2.7585	2.7505
ARFIMA-FIEGARCH-*t*	**0.0729***	0.0471	0.3238	-0.2454	**8.3029**	**0.0422**	-0.0746	**0.9131**	**-0.0901**	**0.1602**	**5.7620**	-2737.618	
	2.372*	1.146	1.089	-0.8762	**4.229**	**2.862**	-0.2913	**34.09**	**-3.267**	**3.632**	**8.657**	2.7486	2.7386

Notes: (1) The two entries for each parameter are their respective estimate and t-ratios, and *df* indicates *t*-distribution parameter.

(2) Entries in bold are significant at the 99% level.

Entries in bold * are significant at the 95% level.

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