Chapter 3

Multivariate GARCH volatility models for financial portfolio in Thailand

Asset price volatility is central to this research, which covers volatility measurement, modeling, volatility forecasting and its application.

The volatility of asset prices changes over time. Higher volatility could result from macroeconomic news release such as financial crisis, terrorist attack, plane crash, disaster, etc. This is the reason why it is necessary to simulate volatility conditional on the information in previous returns so called the conditional volatility models. These models are easy to estimate from a time series of returns and provide insights into the movement of volatility through time. To understand how volatility is modelled, models belonging within a general class of ARCH models are discussed first in this chapter. However, FIGARCH and HAR models are not considered, because the short memory of shocks in daily returns is assumed and the extension of the procedure to the multivariate process is far more complex and difficult to achieve.

Furthermore, the volatility spillover relationships are potential sources of information. The application of multivariate volatility is also demonstrated in order to capture volatility spillover that benefits for portfolio risk management. This chapter is developed from the original paper 'Multivariate GARCH volatility models for financial portfolio in Thailand' by Chaiwan et al. (2009) presented at the 2nd Conference of the Thailand Econometric Society. This full paper is also present in Appendix A.

Abstract

The purpose in time-series financial analysis is to determine an appropriate forecasting model for the future values of volatility. The variances are determined using a univariate conditional volatility model and the conditional correlation matrix of a portfolio, namely the multivariate conditional volatility models. Moreover, in order to capture the volatility spillover effects as well as the asymmetric effects on the conditional correlations among assets, the VARMA-GARCH of Ling and McAleer (2003) and VARMA-AGARCH of McAleer et al. (2009) models are estimated. Both univariate and multivariate 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 stocks and the multivariate models give the high and dynamic correlations among those stocks. 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.

3.1 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.

Figure 3.1 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 3.2 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 heteroske-dasticity (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 or 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.

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 CCC and DCC models 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. (2009) develops the VARMA-AGARCH model to capture the asymmetric spillover effects among 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 stock returns. The main purpose of this paper is to estimate the volatility of individual stock returns using univariate GARCH model and multivariate GARCH models to capture the volatility asymmetric and spillovers effects among the assets following the motivation of McAlee et al. (2009).

3.2 Model Specifications

This paper models for the conditional variances of individual stock returns belong to a class of following 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

$$h_t = \omega + (r_{t-1} - \mu)^2 + \beta h_{t-1} \tag{3.1}$$

based on the independently and identically distributed (*iid*) assumption; thus,

$$y_t = \mu + \varepsilon_t, \tag{3.2}$$

$$\varepsilon_t = z_t \sqrt{h_t}, \sim iid(0,1) \tag{3.3}$$

where ε_t is the unconditional shock to the variable of interest, y_t. z_t is the standardized residual, and $\sqrt{h_t}$ denotes volatility or risk.

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

$$r_t = \log(p_t / p_{t-1}) = \mu + z_t \sqrt{h_t} \tag{3.4}$$

$$h_t = \omega + \alpha (r_{t-1} - \mu)^2 + \beta h_{t-1} = \omega + (\alpha z_{t-1}^2 + \beta) h_{t-1} \tag{3.5}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3.6}$$

The four parameters are μ, α, β, and ω. The constraints $\omega > 0, \alpha \geq 0$, and $\beta \geq 0$ are sufficient conditions to ensure nonnegative in the conditional variances, h_t.

GJR

Glosten, Jagannathan, and Runkle (1993) proposed an asymmetry model of conditional variances in order to accommodate asymmetric behaviour. Asymmetry can be introduced by weighting ε_{t-1} differently for negative and positive residuals; thus,

$$h_t = \omega + (\alpha + \gamma I\ (\varepsilon_{t-1}))\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (3.7)$$

where $I(\varepsilon_{t-1})$ is an indicator variable that takes value 1 if $\varepsilon_{t-1} < 0$ and 0 otherwise. $I(\varepsilon_{t-1})$ is defined by

$$I_{t-1} = \begin{cases} 1 & if\ \varepsilon_{t-1} < 0 \\ 0 & if\ \varepsilon_{t-1} \geq 0 \end{cases} \qquad (3.8)$$

The squared residual is multiplied by $\alpha + \gamma$ when the return is below its conditional expectation $(I = 1)$ and by α when the return is above or equal to the expected value $(I = 0)$. The parameters, $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0,$ and $\beta \geq 0$ are sufficient conditions for nonnegative in the conditional variance, $h_t > 0$.

The GJR (*p*, *q*) model is defined as

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I(\varepsilon_{t-i}))\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (3.9)$$

This paper estimates 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. (2009) to incorporate volatility spillover effects and asymmetric effects among the asset pairs.

CCC

The Constant Conditional Correlation or CCC model of Bolersllev (1990) is suggested as a multivariate GARCH model in which all conditional correlation are constant and the conditional variances are modelled by univariate GARCH models. The CCC(1,1) model is given by

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i h_{ii,t-1}, \quad (3.10)$$

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}} \quad (3.11)$$

where 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. However, the assumption of constant correlation is possibly quite restrictive. To relax this restriction, Engel (2002) proposed a model called the Dynamic Conditional Correlation or DCC model, which providing the time-varying correlations on the correlation matrix.

DCC

Engel (2002) proposed a method of handling time-varying correlations called the Dynamic Conditional Correlation. Considering the following process:

$$y_t \middle| F_{t-1} \sim (0, Q_t), \qquad t = 1,...,T \tag{3.12}$$

$$Q_t = D_t \Gamma_t D_t, \tag{3.13}$$

where $D_t = diag(h_{1t},...,h_{kt})$ is a diagonal 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. The DCC model is given by

$$Q_t = (1 - \phi_1 - \phi_2)S + \phi_1 \eta_{t-1} \eta'_{t-1} + \phi_2 Q_{t-1} \tag{3.14}$$

$$\Gamma_t = \left\{(diag(Q_t)^{-1/2}\right\} Q_t \left\{(diag(Q_t)^{-1/2}\right\} \tag{3.15}$$

where *S* is the unconditional correlation matrix of the ε. θ_1 and θ_2 are scalar parameters. The specification does not guarantee that the elements along the main diagonal are all unity, and all of the off-diagonal terms lie between -1 and 1. Engle (2002), therefore, standardizes the matrix estimated in equation (3.14) by equation (3.15), the elements satisfy the definition of a conditional correlation. In financial time series, $\theta_1 = 0$ and $\theta_2 = 1$ imply the long run conditional correlation matrix is constant which news has little practical effect in changing the purportedly dynamic conditional correlations.

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 between the assets to the others called the VARMA-GARCH model. Considering the vector of returns:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \tag{3.16}$$

$$\varepsilon_t = D_t \eta_t \tag{3.17}$$

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

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-1} + \sum_{j=1}^{s} B_j H_{t-j} \tag{3.18}$$

where $H_t = (h_{1t},...,h_{mt})', \vec{\varepsilon}_t = (\varepsilon_{1t}^2,...,\varepsilon_{mt}^2)'$, and W, $A_i \; \forall i = 1,...,r$, and $B_j \forall j = 1,...,s$ are $m \times m$ matrices. As in the univariate GARCH model, VARMA-GARCH assumes that negative and positive shocks have identical impacts on the conditional variance.

VARMA-AGARCH

In order to accommodate asymmetric impacts of positive and negative shocks on the conditional correlations, McAleer et al. (2008) in the Econometric Theory proposed the following specification for the conditional variance. The VARMA-AGARCH model is given by

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-1} + \sum_{i=1}^{r} C_i I_{t-i} \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \qquad (3.19)$$

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

$$I = \begin{cases} 0, & \varepsilon_{i,t} > 0 \\ 1, & \varepsilon_{i,t} \le 0 \end{cases} . \qquad (3.20)$$

The VARMA-AGARCH model reduces to the VARMA-GARCH model when $C_i = 0$ for all *i*. Furthermore, if $C_i = 0$, with A_i and B_j being diagonal matrices for all *i*, *j*, then the VARMA-AGARCH reduces to the CCC model.

3.3 Description of the studied market, Data and Estimations

3.3.1 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.

Figure 3.1 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.

3.3.2 Data

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

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 stocks in SET based on December 24, 2008, consisting of BANPU, PTT, and PTTEP in Energy and Utilities sector, KBANK and SCB in Banking sector, ADVANC in Information and Communication Technology sector, ITD in Property Development sector, PTTCH in Petrochemicals and Chemicals sector, SCC in Construction Materials sector, and TTA in Transportation and Logistic sector, namely BANPU Public Company Limited, 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 3.2 and the variable names are summarized in Table 3.1.

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

$$r_{it} = \log(\frac{p_{i,t}}{p_{i,t-1}}) * 100 \tag{3.21}$$

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

3.3.3 Estimations

The plots of the daily returns for all series used in this study are shown in Figure 3.2. 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 3.2. 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 3.3. 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.

3.4 Empirical Results

3.4.1 Univariate GARCH Models.

The estimations from the class of univariate GARCH models are provided in Table 3.4 - 3.5. The empirical results show the coefficient determining both in conditional mean equation with ARMA(1,1) and condition variance equation. The estimations of the short run persistence of shocks in variance equations of the ARMA(1,1)-GARCH(1,1) model show that all series are significantly different from zero at 5% level. For the long run persistence of shocks, 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 negative shocks increase risk, but no leverage, except SCB.

Figure 3.3 and Figure 3.4 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 3.6. 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.

3.4.2 Multivariate GARCH Models.

Table 3.7 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. Fortunately, the correlation among the ten stocks in portfolio are positive correlations which specialize on the stock with the higher expected returns, however, the portfolio diversification could be inefficient.

The estimated parameters of the conditional correlations for the DCC model are provided in Table 3.8. 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 3.9 shows the estimates of conditional variance of VARMA-GARCH and Table 3.10 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 3.11. 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 3.11 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.

3.5 Concluding Remarks

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 asymmetric effects occur in stock volatility, but no leverage, 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 among stocks are all positive between 0.32 and 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.

In order to accommodate volatility spillover effects, the VARMA-GARCH model is used for the ten stocks. The evidence for the highest volatility spillovers is BANPU which would affect volatility of most stocks. Asymmetric effects are statistically significant in five stocks named KBANK, PTT, PTTCH, SCB, and TTA, means negative shocks increase volatility and positive shocks of equal magnitude decrease volatility or leverage is presented. 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.

Table 3.1 Variable Names

Variables	**Names**
adva	Advanced Info Service Public Company Limited
banpu	BANPU Public Company Limited
itd	Italian-Thai Development Public Company Limited
kbank	Kasikornbank Public Company Limited
ptt	PTT 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

Table 3.2 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 θ = 0 is tested for stationary if reject.

Table 3.3 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

Table 3.4 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**	**21.54**		
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**	**17.53**		
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**	**17.80**		
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**	**22.03**		
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**	**10.65**		
tta	**-0.006**	**-0.864**	**0.942**	**0.001**	**0.471**	-0.068	-3.497	-3.414
	-2.242	**-11.39**	**17.91**	**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 3.5 ARMA(1,1)-GJR(1,1)

	Mean equation			Variance equation				AIC	SIC
	C	AR(1)	MA(1)	ω	α	γ	β		
adva	-0.001	**0.757**	**-0.869**	9.02E-06	-0.004	**0.130**	**0.944**	-4.737	-4.640
	-1.543	**6.527**	**-10.33**	0.758	-0.163	**2.501**	**26.22**		
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**	**21.40**		
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	**12.98**	**-184.2**	**18.19**	**47.59**		
kbank	**-0.003**	**0.913**	**-0.940**	**9.34E-06**	**-0.079**	**0.175**	**0.996**	-4.665	-4.568
	-2.148	**25.114**	**-31.58**	**2.617**	**-3.699**	**5.063**	**46.57**		
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**	**10.11**		
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**	**16.84**		
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	**14.82**		
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.

Table 3.6 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

Table 3.7 CCC-GARCH(1,1)

Returns	banpu	ptt	pttep	kbank	scb	adva	itd	pttch	scc
ptt	**0.633** **13.054**								
pttep	**0.654** **14.208**	**0.792** **30.538**							
kbank	**0.499** **7.807**	**0.704** **17.402**	**0.602** **13.122**						
scb	**0.455** **6.193**	**0.614** **12.479**	**0.545** **11.795**	**0.853** **42.199**					
adva	**0.327** **5.804**	**0.442** **8.675**	**0.365** **6.808**	**0.545** **11.279**	**0.504** **9.656**				
itd	**0.487** **7.390**	**0.554** **10.335**	**0.549** **10.601**	**0.691** **15.902**	**0.617** **13.567**	**0.465** **8.493**			
pttch	**0.493** **9.137**	**0.639** **15.481**	**0.662** **17.759**	**0.620** **15.419**	**0.553** **13.093**	**0.358** **6.533**	**0.603** **12.299**		
rscc	**0.448** **7.169**	**0.551** **10.984**	**0.555** **10.946**	**0.695** **19.905**	**0.648** **16.019**	**0.443** **7.237**	**0.593** **13.112**	**0.593** **12.492**	
rtta	**0.526** **8.670**	**0.599** **13.221**	**0.564** **11.121**	**0.643** **16.849**	**0.574** **12.907**	**0.456** **8.654**	**0.573** **11.145**	**0.583** **12.138**	**0.564** **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 3.8 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 3.9 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 3.9 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 3.10 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 3.10 VARMA-AGARCH(1,1) (Continued)

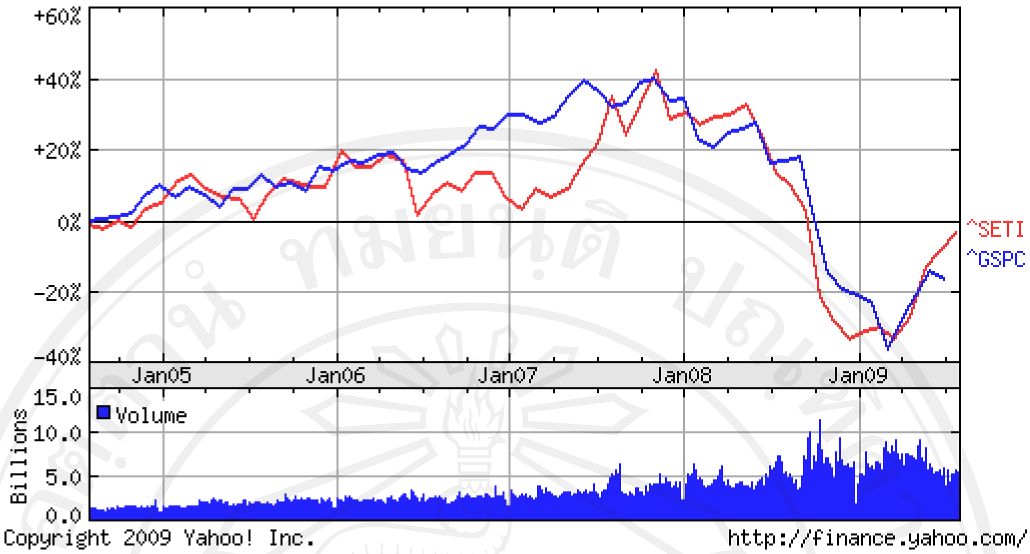
Returns	γ	β_{adva}	β_{banpu}	β_{itd}	β_{kbank}	β_{ptt}	β_{pttch}	β_{pttep}	β_{scb}	β_{scc}	β_{tta}
adva	0.0445	**0.8401**	**0.2383**	**0.0694**	**-0.3372**	-0.0493	-0.0700	**0.1688**	-0.0068	-0.1607	0.0318
banpu	0.0039	**-0.3450**	**0.8262**	**-0.2908**	**0.3096**	**0.2369**	**-0.1939**	**-0.3270**	**0.2859**	-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 3.11 Spillovers and asymmetric effects of negative and positive shocks

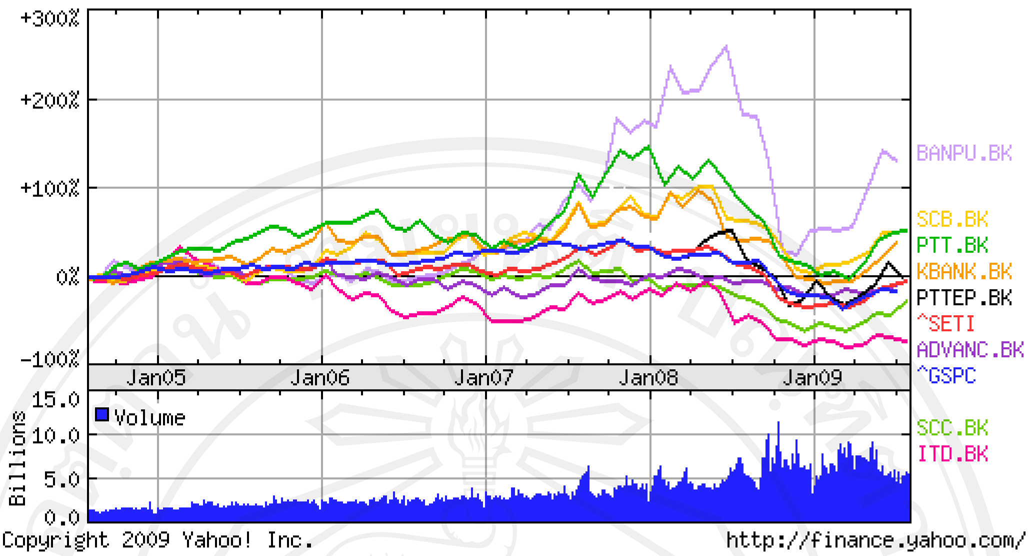
Returns	Number of volatility spillovers		Asymmetric effects
	VARMA-GARCH	VARMA-AGARCH	
adva	5	4	N
banpu	7	8	N
itd	3	-	N
kbank	1	2	Y
ptt	4	2	Y
pttch	2	2	Y
pttep	-	2	N
scb	2	2	Y
scc	5	2	N
tta	2	1	Y

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



Source: Yahoo Finance (July 2009)

Figure 3.1 The SET Index returns of Thailand



Source: Yahoo Finance (July 2009)

Figure 3.2 The returns of ten most active trading stocks in SET

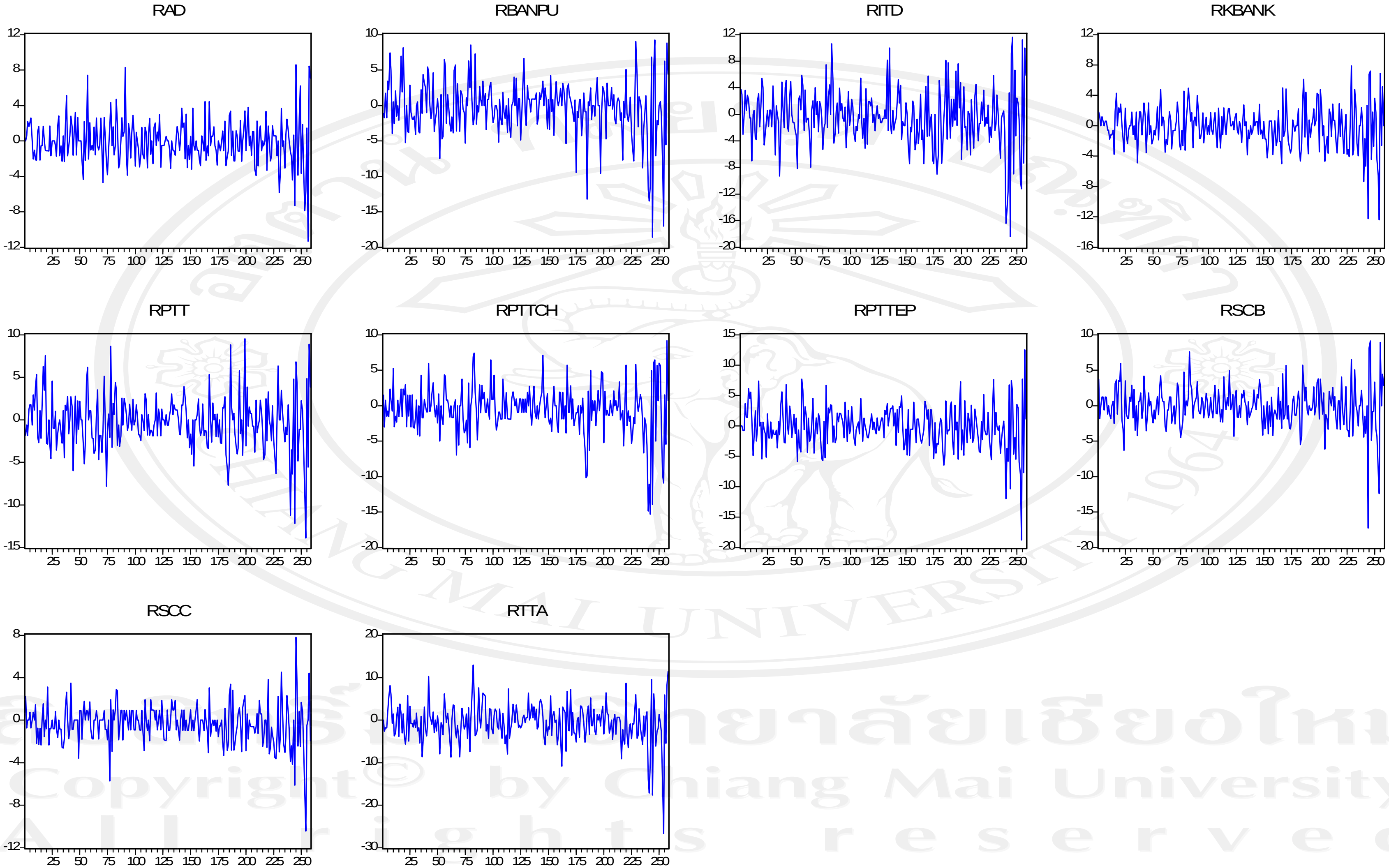


Figure 3.3 Daily returns of all series

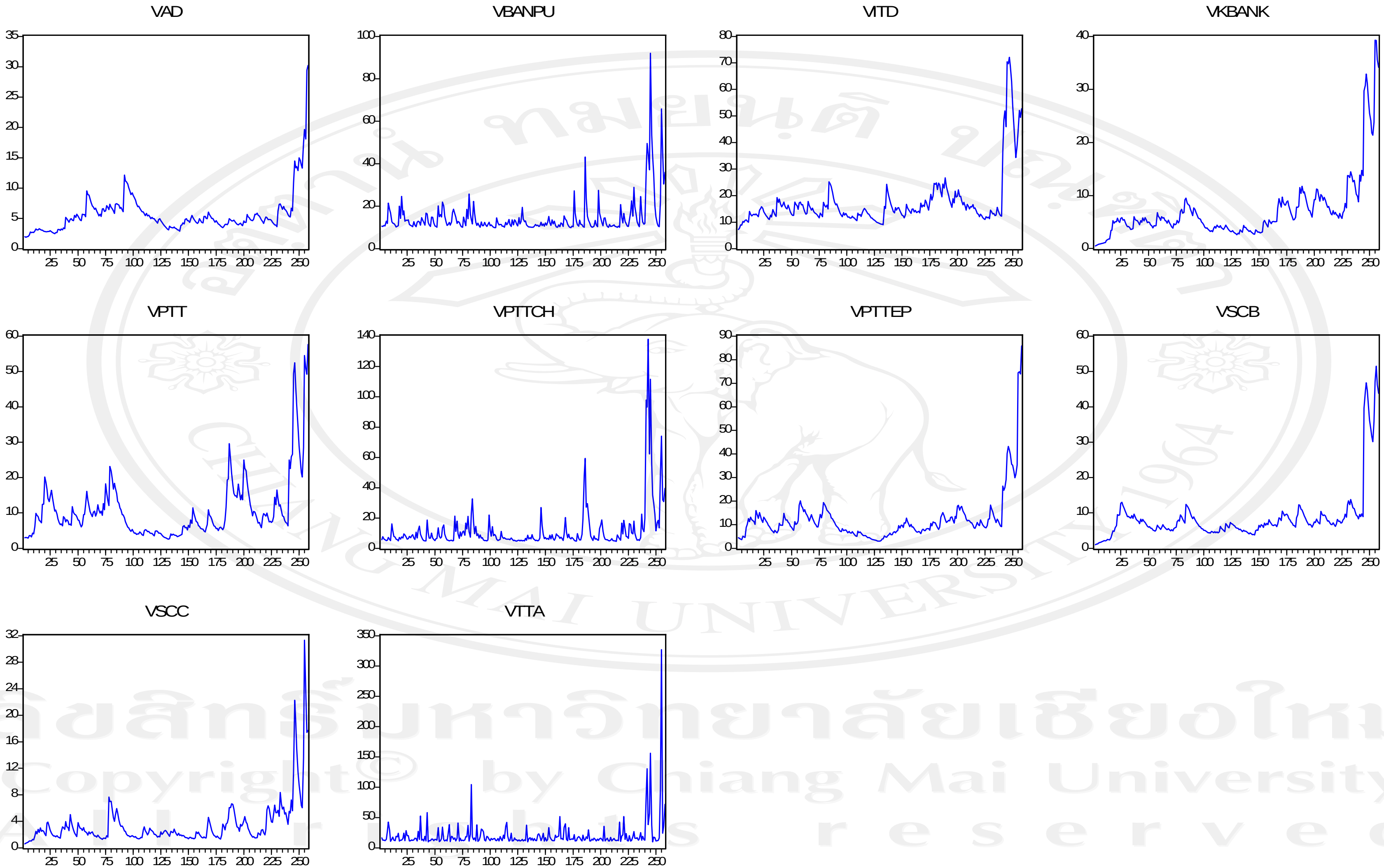


Figure 3.4 Daily volatility of all series