Chapter 5

Forecasting Value-at-Risk and Optimizing Capital Charges Using Single-Index and Long Memory Models

Value-at-Risk (VaR) has become very popular in portfolio risk management since it illustrates obvious economics interpretation and relevant concepts. VaR can be defined as “a worst case scenario on a typical day”. Since volatility changes over time, to manage risk this change that can cause losses. VaR forecasts need to be provided to the appropriate regulatory authority before and after planing investment strategies and adopting their risk management systems. This chapter introduces the models used to measure and forecast VaR. The class of univariate GARCH, the fractionally integrated, and the simple long memory -- HAR -- models are employed.

In order to evaluate performance of the models, a back-testing procedure is applied to the VaR forecasts from those models. The number of violations and daily capital charges are considered. The penalty structure for violations arising from risk taking is imposed by the Basel Accord.

This chapter illustrates how to apply volatility into economics problems and demonstrates its significance. The invention of this chapter is inspired by ‘Value-at-Risk in Single-Index of Southeast Asia Stock Markets’ by Chaiwan et al. (2009) presented at the 6th International Conference on Business and Information 2009. The original paper is included in Appendix C.

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), the fractionally integrated and the long memory HAR 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.

5.1 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 and the long memory models.

5.2 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

$$y_t = \mu_t + \varepsilon_t \tag{5.1}$$

$$\varepsilon_t = \sigma_t z_t \tag{5.2}$$

$$\mu_t = c(\eta | I_{t-1}) \tag{5.3}$$

$$\sigma_t = h(\eta | I_{t-1}) \tag{5.4}$$

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 (*iid*) 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

$$\phi L(y_t - \mu) = \theta(L)\varepsilon_t \qquad (5.5)$$

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 equation (5.6) as

$$\mu_t + \sum_{i=1}^{p} \phi_i (y_{t-i} - \mu) \qquad (5.6)$$

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, the long memory models; FIGARCH, FIEGARCH, ARFIMA-GARCH, ARFIMA-EGARCH, ARFIMA-FIGARCH, ARFIMA-FIEGARCH, and HAR models.

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

$$\sigma_t^2 = 0.06\varepsilon_{t-1}^2 + 0.94\sigma_{t-1}^2 \qquad (5.7)$$

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

ARCH

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

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{5.8}$$

The parameters $\omega > 0, \alpha > 0$ 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.

GARCH

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

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{5.9}$$

where the parameters $\omega > 0, \alpha > 0$ and $\beta \geq 0$ are sufficient conditions to ensure positive in the conditional variance, $h_t > 0$. The coefficient α is the ARCH effect which indicates the short run persistence of shocks and the coefficient β is the GARCH effect which indicates the long run persistence of shocks, namely $\alpha + \beta$.

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

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I(\varepsilon_{t-i}))\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}, \qquad (5.10)$$

where the parameters $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0$ and $\beta \geq 0$ are sufficient conditions to ensure positive in the conditional variance, $h_t > 0$. $I(\varepsilon_{t-i})$ is an indicator function which equals 1 if $\varepsilon_{t-i} < 0$ and 0 otherwise. The coefficient γ indicates the asymmetric effects, the positive shocks and negative shocks on conditional variance. In practical, the expected value of γ for financial time series data is greater than or equals to 0 ($\gamma \geq 0$) because negative shocks (decreases in returns) increase volatility (risk), namely $\alpha + \gamma \geq \alpha$. The parameter γ can measure the short run persistence of shocks by $\alpha + \frac{\gamma}{2}$ and the long run persistence of shocks by $\alpha + \beta + \frac{\gamma}{2}$. It is important that the GJR model does not present leverage which negative shocks increase volatility and positive shocks decrease volatility in the same size effects.

EGARCH

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

$$\log(h_t) = \omega + \sum_{i=1}^{q} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{q} \gamma_i \eta_{t-i} + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) \qquad (5.11)$$

where the parameters α, β, and γ are different from those of GARCH and GJR models. The $\left|\eta_{t-i}\right|$ and η_{t-i} capture the size and sign effects of the standardized shocks, respectively. The asymmetry is indicated by γ, if $\gamma = 0$ there is no asymmetry, if $\gamma < 0$, and $\gamma < \alpha < -\gamma$ leverage is exist which negative shocks increase volatility and and positive shocks decrease volatility in the same size effects. This model allows asymmetric and leverage effects.

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

$$h_t = \omega + [1 - \beta_1 L - (1 - \phi_1 L)(1 - L)^d]\varepsilon_t^2 + \beta_1 h_{t-1} \qquad (5.12)$$

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

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \ldots \qquad (5.13)$$

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

$$\log(h_t) = \omega_t + \phi(L)^{-1}(1-L)^d[1+\alpha(L)]g(z_{t-1}) \qquad (5.14)$$

$$g(z_{t-1}) = \theta_1 z_{t-1} + \theta_2(|z_{t-1}| - E[|z_{t-1}|]) \qquad (5.15)$$

where ω_t and h_t denote conditional means and conditional variance respectively. θ_1 is a sign effect and θ_2 is a size effect. And the standardized residuals are

$$z_t = e_t / \sqrt{h_t} \qquad (5.16)$$

ARFIMA-GARCH

Ling and Li (1997) proposed a fractionally integrated autoregressive model with conditional heteroskedasticity, ARFIMA(*p*,*d*,*q*)-GARCH(*r*,*s*). The specifications in the conditional mean equation, y_t displays long memory, or long-term dependence which could be modelled by a fractionally integrated ARMA process, or ARFIMA process initially introduced by Granger (1980) and Granger and Joyeux (1980). The ARFIMA(*p*,*d*,*q*) is given by

$$\phi(L)(1-L)^d(y_t-\mu_t)=\theta(L)\varepsilon_t \tag{5.17}$$

This is discrete time process y_t with standard normal distribution z_t and the GARCH model as

$$h_t=\omega+\sum_{i=1}^{r}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{s}\beta_j h_{t-j} \tag{5.18}$$

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.

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 $\{\varepsilon_t\}$ 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 $0<d_\varepsilon,d_y<0.5$.

HAR

Corsi (2009) proposed the Heterogeneous Autoregressive (HAR) model as an alternative model for realized volatilities. The HAR(h) model is based on the following process in the mean equation (see Chang et al. (2009)).

$$y_{t,h} = \frac{y_t + y_{t-1} + y_{t-2} + \ldots + y_{t-h+1}}{h} \tag{5.19}$$

where typical values of h in financial time series are 1 for daily, 5 for weekly, and 20 for monthly data that referred to HAR(1), HAR(1,5), and HAR(1,5,20), respectively. The models of HAR(1), HAR(1,5), and HAR(1,5,20) are given by

$$y_t = \phi_1 + \phi_2 y_{t-1} + \varepsilon_t \tag{5.20}$$

$$y_t = \phi_1 + \phi_2 y_{t-1} + \phi_3 y_{t-1,5} + \varepsilon_t \tag{5.21}$$

$$y_t = \phi_1 + \phi_2 y_{t-1} + \phi_3 y_{t-1,5} + \phi_4 y_{t-1,20} + \varepsilon_t \tag{5.22}$$

5.3 Data and Estimations

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

5.3.1 Data

The daily closing price indexes are employed based on four stock markets in South-East Asia. 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 South-East Asia. The index values of each market from Bloomberg are shown in Figure 5.1. 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).

5.3.2 Volatility forecasts

To forecast the conditional volatility, we first adjust the closing price to obtain the returns for each market by taking logarithmic different. Several reasons to use daily data are mentioned in McAleer (2009). In addition, the rationale to employ daily data in modelling volatility transmission is mentioned in McAleer and da Veiga (2008a, 2008b). The continuously compounded returns for each index i at time t are calculated as

$$r_{it} = \log(\frac{p_{i,t}}{p_{i,t-1}}) * 100 \tag{5.23}$$

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 portfolio are shown in Figure 5.2 and of the volatility for porfolio in Figure 5.3.

Figure 5.2 shows that portfolio returns exhibit the clustering. The descriptive statistics of each series is provided in Table 5.2. The results show the excess kurtosis in all series that indicates a fat-tailed distribution compared to a standard normal distribution with a kurtosis of 3. Then, an appropriate model to model volatility 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 maximum value of percentage changes of portfolio returns is 0.08%. The minimum values of percentage changes of index returns range approximately between -20.0% and -9.8%. The minimum value of percentage changes of portfolio returns is -0.08%. Finally, The Jarque-Bera test strongly rejects the null hypothesis of normally distributed returns.

Then, the univariate conditional volatility models are estimated, forecasted, and fitted 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. The portfolio returns are modelled as a stationary ARMA(1,1) process for both the univariate GARCH models and the long memory models. In addition, the alternative HAR(*h*) models are used together with the univariate conditional volatility models including GARCH(1,1), GJR(1,1), and EGARCH(1,1) models to capture long run persistence of shocks.

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.

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

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 VaR can be measured with various methods. The VaR threshold for y_t can be calculated by

$$VaR_t = E(y_t | I_{t-1}) - \alpha \sigma_t \tag{5.24}$$

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).

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).

$$\underset{\{k,VaR\}}{Minimize}\, DCC_t = \sup\left\{-(3+k)\overline{VaR}_{60}, -VaR_{t-1}\right\} \qquad (5.25)$$

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 (5.24),

$\overline{VaR}_{60}$ = 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 5.1.

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.

5.4 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 follows:

5.4.1 Model Estimations

We report the estimations for the single-index models and the long memory -- the fractionally integrated and the HAR --, models in Table 5.5, 5.6, and 5.7, respectively. Table 5.5 summarizes the estimations from Riskmetrics™, 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 as

$$\text{AIC} = -2\frac{LogL}{n} + 2\frac{k}{n} \tag{5.26}$$

$$\text{SIC} = -2\frac{LogL}{n} + 2\frac{\log(k)}{n} \tag{5.27}$$

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 effects for GJR and the asymmetric and leverage effects of shocks for EGARCH which negative shocks increase volatility and positive shocks decrease volatility.

Table 5.6 summarizes the estimations from the fractionally integrated 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 the 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 size effect, ϕ, being insignificant and the sing effect, θ_1, being negative, in FIEGARCH(1,*d*,1) models indicate the volatility of portfolio returns have asymmetric effects ,but no 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 size effect, α, being insignificant and the sing effect, θ_1, being negative, in ARFIMA-EGARCH(1,*d*,1) and ARFIMA-FIEGARCH(1,*d*,1) models indicate that the volatility of portfolio returns have asymmetric effects, but no leverage effects of shocks.

Overall, from the goodness of fit criteria, AIC and SIC, the fractionally integrated models are preferred to conditional volatility GARCH-type models for volatility estimations in this portfolio returns. However, from the highly statistically significant estimations, the FIGARCH model performs far better for volatility modelling.

Table 5.7 summarizes the estimations from the long memory HAR models consisting of HAR(1), HAR(1,5), and HAR(1,5,20) models, estimated under the normal distributional assumptions and *t*-distribution. The results show that most estimates of GARCH(1,1) for the HAR(1) and HAR(1,5) are highly highly statistically significant at 1% level. The magnitude of asymmetric effects are evaluated by GJR(1,1) model. The estimated asymmetry coefficients are positive and statistically significant for HAR(1) and HAR(1,5) which the deceases in porfolio increase volatility. Furthermore, the evidences from EGARCH(1,1) for the HAR(1), the HAR(1,5), and the HAR(1,5,20) models, show that the size effect, $\alpha\,(or\phi)$, being insignificant and the sing effect, θ_1, being negative, indicates the asymmetric effects but no leverage as well as the long memory fractionally integrated models. Over all, the estimated under *t*-distribution perform far better, same as the single-index models, judged by AIC and SIC.

5.4.2 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 the single-index, the fractionally integrated and the alternative HAR 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 5.3 and 5.4 give the mean daily capital charges for each model. The worst-performing model that gives average daily capital charges of 16.68% is the FIGARCH under 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™ model, both the single-index and the long memory including fractionally integrated and HAR 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 5.3 and Table 5.4 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 1.334 is the GARCH for HAR(1) model under a *t*-distributed assumption. On the contrary, the best-performing model that gives the basis average absolute deviations at 0.402 is the GARCH for HAR(1,5) model under a normal distributed assumption.

These results seem to be contradictory between those values of absolute deviations and the mean capital charges. Table 5.3 and Table 5.4 make it clear that increasing the number of violations leads to lower mean daily capital charges. Therefore, there is a trade-off between the number of violations and daily capital charges, with a higher number of violations leading to a higher penalty and lower daily capital charges through lower VaR. Also, 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.

5.5 Concluding Remarks

In conclusion, we investigate (1) the performance of VaR forecasts in between the single-index 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. So, it is necessary to change the penalty structure under the Basel Accord, otherwise there is likely to take high risk excessively.

Table 5.1 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 5.2 Descriptive Statistics of all return series and portfolio

	JKSE	**KLCI**	**SETI**	**STI**	**PORT**
Mean	0.0269	0.0132	0.0046	-0.0048	0.0003
Maximum	15.0419	5.5463	10.5206	8.5634	0.0755
Minimum	-19.9468	-11.2789	-18.0844	-9.8093	-0.0753
Std. Dev.	2.2704	1.1254	1.8869	1.4619	0.0126
Skewness	-0.3595	-0.5422	-0.5770	-0.2981	-0.4297
Kurtosis	9.9880	10.5374	10.4319	7.8136	8.4083
Jarque-Bera	5179.63	6086.52	5937.10	2469.29	3146.23

Table 5.3 DCC and AD of Violations for Single-Index and Long Memory Models

Model	Number of Violations	Mean Daily Capital Charge	AD of Violations	
			Maximun	Mean
Riskmetrics^{TM}	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 5.4 DCC and AD of Violations for HAR Models

Model	Number of Violations	Mean Daily Capital Charge	AD of Violations	
			Maximun	Mean
HAR(1)-GARCH	24	11.333	1.833	0.592
HAR(1)-GARCH-*t*	4	14.511	1.935	1.334
HAR(1)-GJR	22	9.796	1.342	0.466
HAR(1)-GJR-*t*	4	12.575	1.481	0.907
HAR(1)-EGARCH	20	9.255	1.372	0.471
HAR(1)-EGARCH-*t*	4	12.087	1.033	0.851
HAR(1,5)-GARCH	41	8.756	1.982	0.402
HAR(1,5)-GARCH-*t*	16	14.766	3.000	0.910
HAR(1,5)-GJR	44	8.748	1.897	0.446
HAR(1,5)-GJR-*t*	16	14.805	2.979	0.957
HAR(1,5)-EGARCH-*t*	15	13.347	2.651	0.884
HAR(1,5,20)-GARCH	39	7.863	4.524	0.820
HAR(1,5,20)-GARCH-*t*	24	12.699	3.478	1.125
HAR(1,5,20)-GJR	54	7.499	2.841	0.646
HAR(1,5,20)-GJR-*t*	24	12.805	3.195	1.069
HAR(1,5,20)-EGARCH-*t*	24	12.117	2.401	0.956

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 5.5 Estimation Results for Single-Index Models

Model	**Mean equation**			**Variance equation**								LL	
	μ	AR(1)	MA(1)	ω	α	β	γ	θ_1	θ_2	α+β	*df*	AIC	SIC
Riskmetrics™	**0.063**	**0.463**	**-0.313**		**0.06**	**0.94**						-2878.566	
	3.248	**4.928**	**-3.076**									2.883	2.879
ARCH	0.035	**0.444**	**-0.249**	**0.928**	**0.182**					0.1818		-2920.413	
	1.041	**6.135**	**-3.127**	**43.31**	**7.039**							2.925	2.921
ARCH-*t*	**0.071**	**0.454**	**-0.307**	**0.917**	**0.233**					0.2325	**4.290**	-2803.167	
	2.790	**0.454**	**-2.922**	**13.61**	**4.363**						**9.772**	2.809	2.804
GARCH	**0.076**	**0.468**	**-0.317**	**0.041**	**0.093**	**0.875**				0.9671		-2844.226	
	2.868	**4.052**	**-2.494**	**6.932**	**9.536**	**87.53**						2.850	2.845
GARCH-*t*	**0.092**	**0.461**	**-0.334**	**0.041**	**0.090**	**0.876**				0.9657	**5.377**	-2755.761	
	3.878	**3.670**	**-2.479**	**3.365**	**5.378**	**40.13**					**9.228**	2.763	2.757
GJR	**0.051**	**0.457**	**-0.299**	**0.059**	**0.035**	**0.864**	**0.094**					-2833.757	
	1.787	**3.894**	**-2.348**	**8.191**	**3.461**	**82.74**	**6.426**					2.841	2.835
GJR-*t*	**0.077**	**0.460**	**-0.330**	**0.056**	0.026	**0.866**	**0.106**				**5.537**	-2746.806	
	3.201	**3.751**	**-2.506**	**4.170**	1.449	**37.97**	**3.852**				**9.232**	2.755	2.748
EGARCH	0.043	**0.487**	**-0.343**	**0.166**	-0.150	**0.945**		**-0.077**	**0.205**			-2828.989	
	1.518	**4.075**	**-2.609**	**3.287**	-1.079	**124.7**		**-5.830**	**6.934**			2.837	2.830
EGARCH-*t*	**0.070**	**0.465**	**-0.339**	**11.980**	-0.110	**0.950**		**-0.081**	**0.187**		**5.642**	-2744.389	
	2.935	**3.699**	**0.135**	**3.938**	-0.4784	**74.15**		**-3.178**	**3.941**		**9.127**	2.753	2.745

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 5.6 Estimation Results for 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	**0.074**		**0.506**	**-0.352**	**0.244**	**0.253**	**-0.384**	**-0.231**				-2837.883	
	2.646		**4.460**	**-2.829**	**5.150**	**8.612**	**-3.068**	**-1.674**				2.845	2.839
FIGARCH-*t*	**0.089**		**0.468**	**-0.338**	**0.239**	**0.235**	**-0.352**	-0.232			**5.472**	-2750.240	
	3.726		**3.701**	**-2.493**	**2.772**	**5.527**	**-1.422**	-0.870			**9.390**	2.758	2.751
FIEGARCH-*t*	**0.071**		**0.462**	**-0.338**	**8.227**	**0.042**	-0.063	**0.911**	**-0.087**	**0.161**	**5.771**	-2738.299	
	2.967		**3.599**	**-2.460**	**4.240**	**2.870**	-0.242	**33.20**	**-3.241**	**3.645**	**8.675**	2.748	2.739
					ω		α	β		α+β			
ARFIMA-GARCH	**0.077**	0.005	**0.458**	**-0.313***	**0.041**		**0.092**	**0.874**		0.9670		-2844.221	
	2.788	0.119	**2.834**	**-2.147***	**6.636**		**9.201**	**82.43**				2.851	2.845
ARFIMA-GARCH-*t*	0.101	0.039	0.361	-0.2721	**0.041**		**0.090**	**0.875**		0.9652	**5.358**	-2755.313	
	3.201	0.935	1.440	-1.162	**3.375**		**5.363**	**39.77**			**9.254**	2.763	2.756
					ω		α	β	θ_1	θ_2			
ARFIMA-EGARCH	0.039	0.044	0.392	-0.290	**0.171**		-0.161	0.946	-0.080	0.204		-2828.538	
	1.082	0.985	1.727	-1.365	**3.292**		-1.158	126.3	-5.760	**6.851**		2.837	2.829
ARFIMA-EGARCH-*t*	**0.073***	0.050	0.315	-0.238	**12.134**		-0.122	**0.952**	**-0.084**	**0.186**	**5.633**	-2743.637	
	0.031*	1.227	1.049	-0.839	**3.924**		-0.539	**75.53**	**-3.210**	**3.932**	**9.142**	2.754	2.745
					ω	*d*	ϕ	β	θ_1	θ_2			
ARFIMA-FIGARCH	**0.078***	0.029	**0.453***	-0.327	**0.246**	**0.252**	**-0.385**	-0.234				-2837.733	
	2.339*	0.583	**2.440***	-1.923	**5.141**	**8.538**	**-3.008**	-1.672				2.846	2.839
ARFIMA-FIGARCH-*t*	**0.099**	0.047	0.328	-0.244	**0.243**	**0.234**	-0.363	-0.245			**5.444**	-2749.569	
	3.025	1.170	1.167	-0.920	**2.802**	**5.526**	-1.470	-0.922			**9.406**	2.758	2.750
ARFIMA-FIEGARCH-*t*	**0.073***	0.047	0.324	-0.245	**8.303**	**0.042**	-0.075	**0.913**	**-0.090**	**0.160**	**5.762**	-2737.618	
	2.372*	1.146	1.089	-0.876	**4.229**	**2.862**	-0.2913	**34.09**	**-3.267**	**3.632**	**8.657**	2.749	2.739

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, and bold * are significant at the 99% level, and the 95% level, respectively.

Table 5.7 Estimation Results for HAR Models

Model	**Mean equation**			**Variance equation**								LL	
	ϕ_1	ϕ_2	ϕ_3	ω	α	β	γ	θ_1	θ_2	*df*	$\alpha+\beta$	AIC	SIC
HAR(1)-GARCH	**0.065**	**0.160**		**0.041**	**0.092**	**0.875**					0.967	-2845.235	
	3.119	**6.611**		**3.984**	**6.776**	**49.99**						2.852	2.847
HAR(1)-GARCH-*t*	**0.081**	**0.137**		**0.040**	**0.089**	**0.877**				**5.371**	0.966	-2756.675	
	4.225	**6.043**		**3.159**	**5.210**	**38.40**				**8.571**		2.764	2.759
HAR(1)-GJR	**0.047***	**0.168**		**0.060**	**0.035***	**0.863**	**0.093**					-2834.645	
	2.199	**6.886**		**4.575**	**2.324**	**43.91**	**4.048**					2.842	2.837
HAR(1)-GJR-*t*	**0.070**	**0.139**		**0.057**	0.027	**0.866**	**0.103**			**5.517**		-2747.887	
	3.602	**6.182**		**3.744**	1.546	**35.99**	**3.594**			**8.370**		2.756	2.750
HAR(1)-EGARCH	**0.043***	**0.154**		**0.161***	-0.100	**0.942**		**-0.073**	**0.198**			-2831.853	
	1.989	**6.272**		**1.959**	-0.563	**72.11**		**-3.848**	**5.354**			2.840	2.834
HAR(1)-EGARCH-*t*	**0.066**	**3.475**		**11.98**	-0.096	**0.949**		**-0.076**	**0.189**	**5.661**		-2745.676	
	3.475	**5.975**		**3.776**	-0.431	**69.24**		**-3.361**	**3.938**	**8.312**		2.755	2.746
HAR(1,5)-GARCH	-0.016	**-0.208**	**1.225**	**0.051**	**0.145**	**0.802**					0.946	-2535.650	
	-0.932	**-8.441**	**27.00**	**4.149**	**6.743**	**28.31**						2.547	2.541
HAR(1,5)-GARCH-*t*	-0.002	**-0.181**	**1.132**	**0.052**	**0.137**	**0.804**				**6.782**	0.941	-2478.572	
	-0.135	**-7.638**	**24.62**	**3.113**	**5.201**	**20.60**				**7.156**		2.491	2.484
HAR(1,5)-GJR	-0.023	**-0.204**	**1.208**	**0.046**	**0.110**	**0.816**	0.049					-2534.727	
	-1.295	**-8.146**	**25.57**	**3.914**	**3.542**	**27.57**	1.413					2.547	2.541
HAR(1,5)-GJR-*t*	-0.010	**-0.176**	**1.109**	**0.044**	**0.084**	**0.828**	**0.075**			**6.817**		-2476.787	
	-0.609	**-7.406**	**23.64**	**3.111**	**2.647**	**23.42**	**1.990**			**7.153**		2.490	2.483
HAR(1,5)-EGARCH-*t*	-0.015	**-0.175**	**1.111**	**17.08**	-0.015	**0.943**		-0.049	**0.244**	**7.000**		-2473.444	
	-0.959	**-7.474**	**24.14**	**4.002**	-0.068	**52.40**		-1.824	**4.546**	**7.077**		2.487	2.479

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, and bold * are significant at the 99% level**,** and the 95% level, respectively.

Table 5.7 Estimation Results for HAR Models (Continued)

Model	Mean equation				Variance equation								LL	
	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ω	α	β	γ	θ_1	θ_2	*df*	$\alpha+\beta$	AIC	SIC
HAR(1,5,20)-GARCH	-0.008	**-0.211**	**1.255**	-0.112	**0.050**	**0.140**	**0.805**					0.944	-2504.814	
	-0.471	**-8.455**	**24.13**	-1.407	**4.028**	**6.627**	**27.96**						2.536	2.530
HAR(1,5,20)-GARCH-*t*	0.0001	**-0.182**	**1.139**	-0.030	**0.054**	**0.134**	**0.802**				**6.659**	0.936	-2446.052	
	0.0076	**-7.684**	**22.11**	-0.379	**3.018**	**5.063**	**19.44**				**7.263**		2.478	2.470
HAR(1,5,20)-GJR	-0.015	**-0.207**	**1.238**	-0.100	**0.047**	**0.111**	**0.816**	0.041					-2504.163	
	-0.816	**-8.240**	**22.83**	-1.237	**3.868**	**3.631**	**27.31**	1.183					2.536	2.529
HAR(1,5,20)-GJR-*t*	-0.007	**-0.178**	**1.121**	-0.029	**0.047**	**0.088**	**0.824**	0.065			**6.693**		-2444.582	
	-0.403	**-7.509**	**21.48**	-0.370	**3.030**	**2.804**	**22.02**	1.804			**7.257**		2.477	2.469
HAR(1,5,20)-EGARCH-*t*	-0.013	**-0.178**	**1.122**	-0.031	**14.97**	0.082	**0.931**		-0.045	**0.237**	**6.994**		-2440.790	
	-0.768	**-7.574**	**21.60**	-0.407	**3.859**	0.327	**38.81**		-1.707	**4.378**	**7.089**		2.474	2.465

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, and bold * are significant at the 99% level, and the 95% level, respectively.

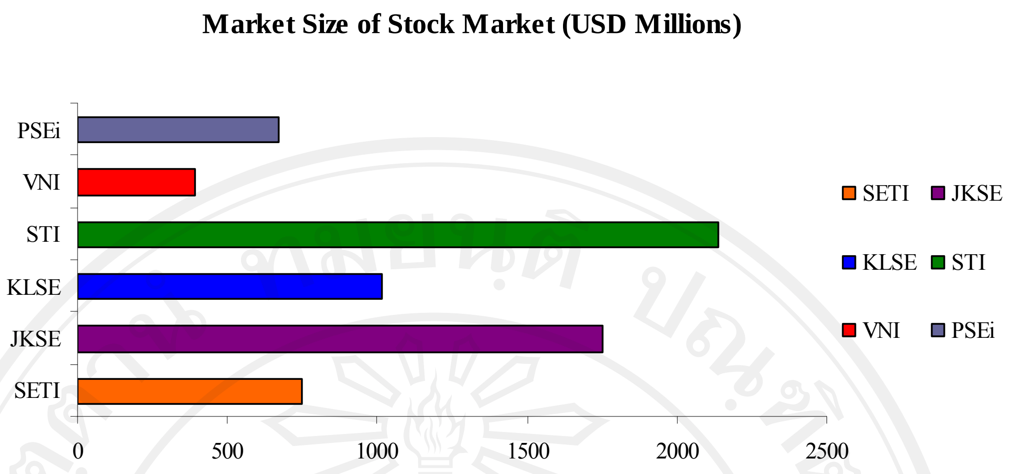

Figure 5.1 The Market Size of Stock Markets in South-East Asia

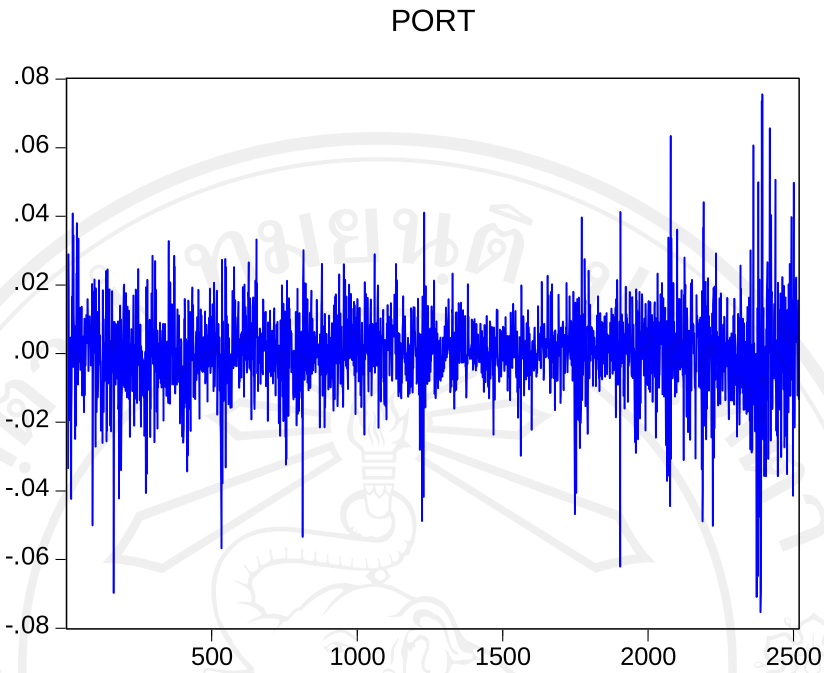

Figure 5.2 Daily returns for portfolio

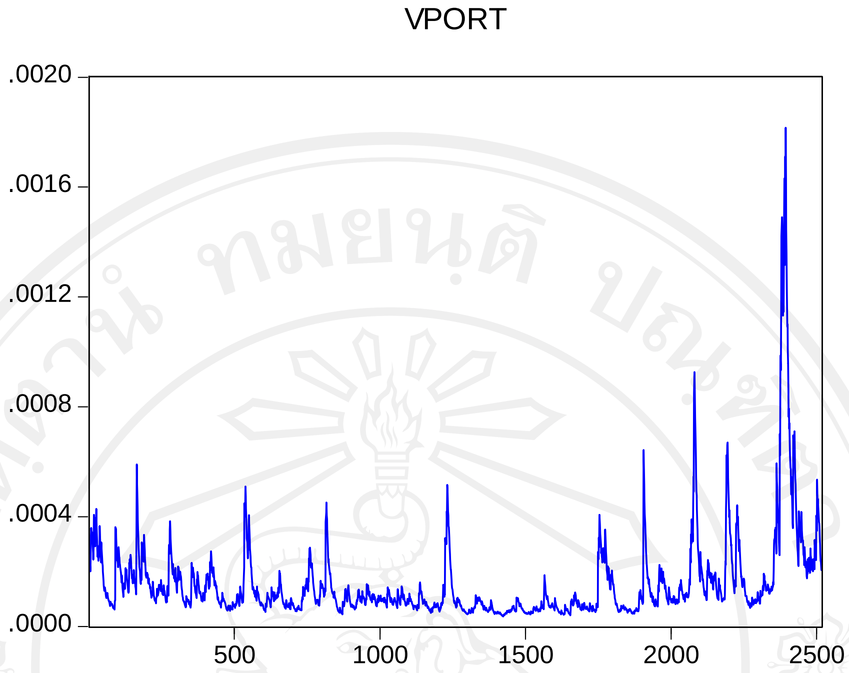

Figure 5.3 Volatility of returns for portfolio

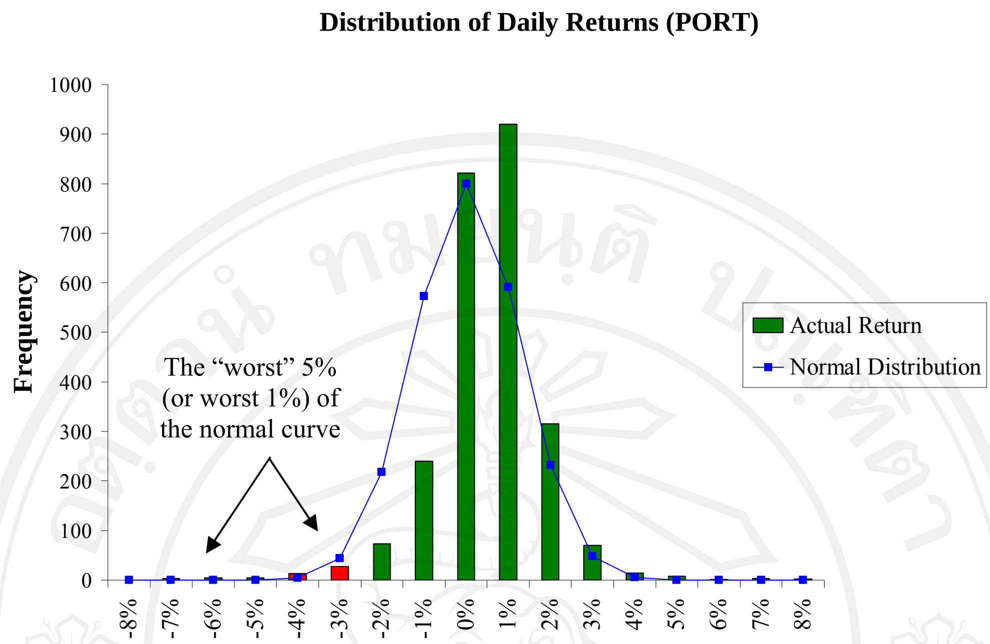

Figure 5.4 The distribution of portfolio returns in South-East Asia

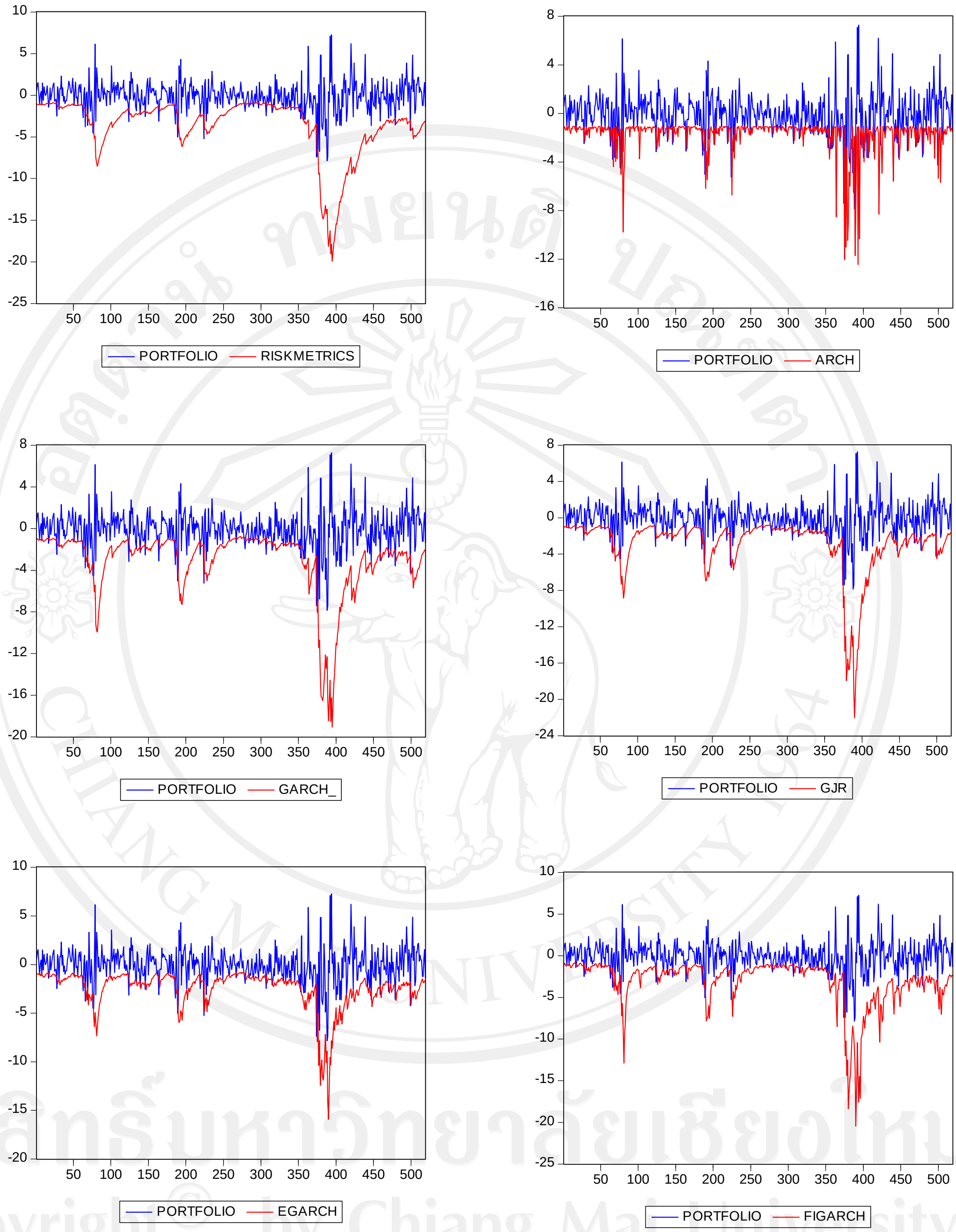

Figure 5.5 Portfolio Returns and VaR Threshold Forecasts

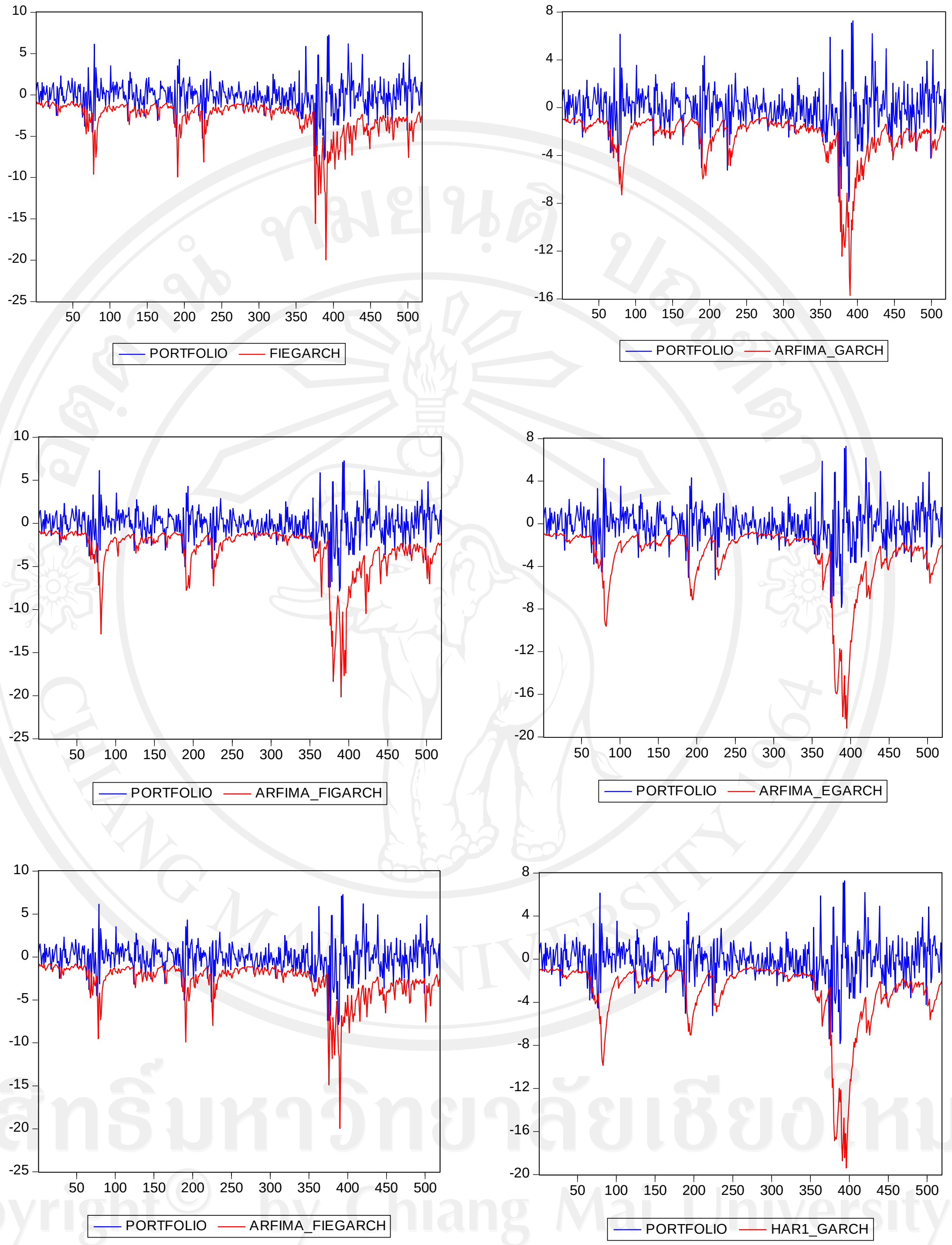

Figure 5.5 Portfolio Returns and VaR Threshold Forecasts (Continued)

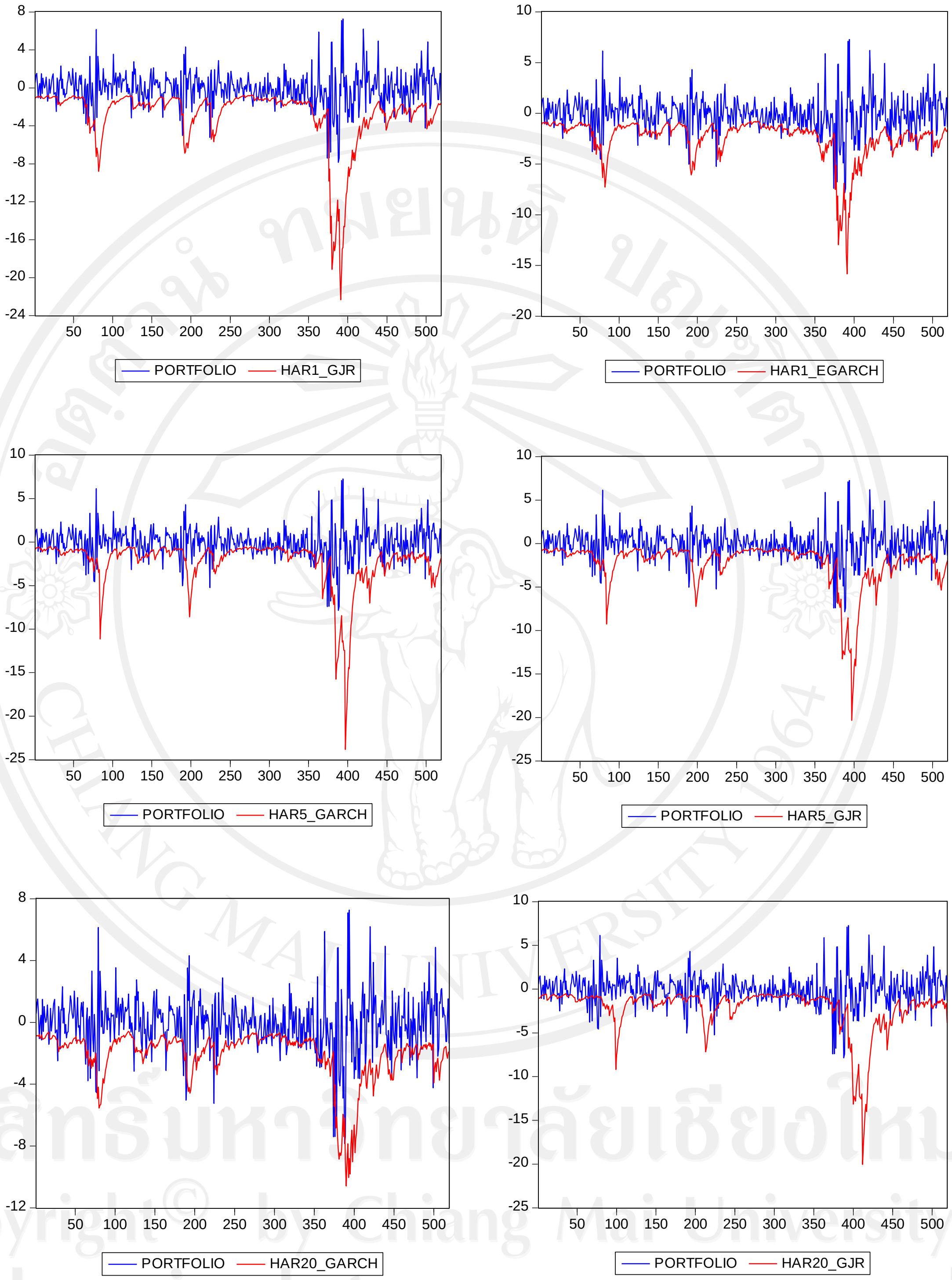

Figure 5.5 Portfolio Returns and VaR Threshold Forecasts (Continued)