Chapter 4

Long Memory in Volatility of Stock Markets in South-East Asia

The long memory characteristic of financial market volatility is well known and has important implications for volatility forecasting. Some evidences and literatures of long memory are presented in this chapter. There have been a number of researches investigating whether long memory of volatility can improve volatility measures and forecasts.

Fractionally integrated is the simplest linear model which is used and tested in several literatures for capturing long memory in volatility. However, there are several issues with the fractional differencing operator. The application of the fractional differencing operator requires a very long build-up period which results in a loss of many observations. Moreover, these classes of fractionally integrated models are able to reproduce only the unifractal type of scaling.

Another simple model for capturing long memory property in the process is the Heterogeneous Autoregressive (HAR) model by Corsi (2009). This model becomes more preferable due to several advantages, such as its capability of multivariate modelling and apparent economics interpretation.

However, to provide theoretical backgrounds and comparison between the two models, this chapter introduces and estimates both from the original paper 'Long Memory in Volatility of Southeast Asia Stock Markets' by Chaiwan et al. (2009) presented at the 6^{th} International Conference on Business and Information 2009. The full paper is presented in Appendix B.

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 South-East Asian stock markets. 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, ARFIMA-FIEGARCH models are highly considered. The Heterogeneous Autoregressive (HAR) model of Corsi (2009) also used to capture long memory. Those several long memory models then are 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.

4.1 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 in South-East Asian stock exchanges, namely Indonesia, Malaysia, Thailand, and 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.

4.2 Model Specifications

The following section describes the models that we implement in stock market returns of South-East Asian countries. The time series models for the conditional volatility such as the (generalized) autoregressive conditional heteroskedasticity (ARCH and GARCH), the fractionally integrated models (FIGARCH and FIEGARCH) of Baillie, Bollerslev and Mikkelsen (1996), and Bollerslev and Mikkelsen (1996) are discussed below. Furthermore, the alternative long memory conditional mean and conditional volatility such as the Heterogeneous Autoregressive (HAR) model of Corsi (2009), and the ARFIMA-GARCH model of Long and Li

(1997a) are also reviewed by following subsequences; we first review the specifications of the conditional mean equation. Then, some contributions in the conditional variance equation will be presented.

Conditional Mean equation

Considering a univariate return series $\{ y_t \}$

$$y_t = E(y_t | I_{t-1}) + \varepsilon_t \tag{4.1}$$

where I_{t-1} is the information set at time *t*-1. $E(.|.)$ denotes the conditional expectation operator. ε_t is the disturbance term, with $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma_\varepsilon^2$, and $E(\varepsilon_t \varepsilon_s) = 0$ for all $t \neq s$ and for all $\tau \neq 0$.

The mean equation has been modelled in several ways. The most well-known specifications are the Autoregressive (AR) and Moving Average (MA) models.

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 mention in equation (4.1).

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

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \tag{4.2}$$

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

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{4.3}$$

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

$$y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-1} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \tag{4.4}$$

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).

However, literatures also have shown that y_t can exhibit significant autocorrelation between observations widely separated in time. In such a case, y_t has long memory or long-term dependence.

Considering the following process $\{y_t\}$

$$y_t = \phi(L)\varepsilon_t \qquad (4.5)$$

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 equation (4.5) generates a linear process if ε_t is a strict white noise and the nonlinear if not.

The long memory could be modelled by a fractionally integrated ARMA process, so called ARFIMA process.

ARFIMA

Granger (1980) and Hosking (1981) initially developed 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

$$\phi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \qquad (4.6)$$

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

$$Ly_t = y_{t-1}, \quad \phi(L) = 1 - \phi_1 L - ... - \phi_p L^p \tag{4.7}$$

$$\theta(L) = 1 - \theta_1 L - ... - \theta_q L^q \tag{4.8}$$

Equation (4.7) and (4.8) are polynomials of degrees p and q, respectively. $(1-L)^d$ is the fractional difference operator defined by the binomial series which accounts for the long memory of the 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

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + ... \tag{4.9}$$

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

Conditional Variance equation

ARCH

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

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (4.10)$$

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

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 the present period (GARCH)
- Information about volatility during the previous period that is the squared residual (ARCH)

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

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (4.11)$$

where $\omega > 0$ and the constraints $\alpha \geq 0$ and $\beta \geq 0$ 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.

The α is the ARCH effect which indicates the short run persistence of shocks and 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

$$h_t = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma_i I(\varepsilon_{t-i}))\varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (4.12)$$

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.

In the conditional volatility models, the parameters are estimated by the maximum likelihood estimation method to obtain Quasi-Maximum Likelihood Estimators (QMLE) under normality of the conditional shocks or standardized residuals assumption. The QMLE is efficient only if the conditional shocks are normal, or it is the MLE. Ling and McAleer (2003) shows the QMLE for GARCH(*p*,*q*) is consistent if the second moment of ε_t is finite. As mentioned in Ling and Li (1997) and Ling and McAleer (2003), the necessary and sufficient condition for the existence of the second moment of ε_t is $\alpha + \beta < 1$ for GARCH(1,1).

EGARCH

Nelson (1991) introduced the Exponential GARCH (EGARCH) model given by

$$\log(h_t) = \omega + \sum_{i=1}^{q} \alpha_i \left|\eta_{t-i}\right| + \sum_{i=1}^{q} \gamma_i \eta_{t-i} + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) \qquad (4.13)$$

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.

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.

At this instant, a number of specifications for the long memory process are reviewed 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

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

$$h_t = \omega + [1 - \beta_1 L - (1 - \phi_1 L)(1 - L)^d]\varepsilon_t^2 + \beta_1 h_{t-1} \qquad (4.14)$$

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

$$\log(h_t) = \omega_t + \phi(L)^{-1}(1-L)^d[1+\alpha(L)]g(z_{t-1}) \qquad (4.15)$$

$$g(z_{t-1}) = \theta_1 z_{t-1} + \theta_2(|z_{t-1}| - E[|z_{t-1}|]) \qquad (4.16)$$

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

$$z_t = e_t / \sqrt{h_t} \qquad (4.17)$$

Short-memory input, long-memory filter

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

$$\phi(L)(1-L)^d(y_t-\mu_t)=\theta(L)\varepsilon_t \tag{4.18}$$

This is discrete time process with $\phi(L)$ as in equation (4.5), z_t as in equation (4.17) with standard normal distribution and the GARCH model as

$$h_t=\omega+\sum_{i=1}^{r}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{s}\beta_j h_{t-j} \tag{4.19}$$

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.

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)).

$$y_{t,h}=\frac{y_t+y_{t-1}+y_{t-2}+\ldots+y_{t-h+1}}{h} \tag{4.20}$$

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

$$y_t = \phi_1 + \phi_2 y_{t-1} + \varepsilon_t \tag{4.21}$$

$$y_t = \phi_1 + \phi_2 y_{t-1} + \phi_3 y_{t-1,5} + \varepsilon_t \tag{4.22}$$

$$y_t = \phi_1 + \phi_2 y_{t-1} + \phi_3 y_{t-1,5} + \phi_4 y_{t-1,20} + \varepsilon_t \tag{4.23}$$

Long-memory input, long-memory filter

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.

4.3 Data and Estimations

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

4.3.1 Data

The time-series data used in this paper are daily closing prices for four stock markets in South-East Asia, namely JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore) available on DataStream. The variable names are summarized in Table 4.1. We select these stock markets from the index values. Those are very high values and potential investment alternatives compared with other markets among South-East Asian countries. The index values of each market from Bloomberg are shown in Figure 4.1. 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.

4.3.2 Estimations

First, we adjust the closing price to obtain the returns for each market by taking logarithmic different. The daily returns are employed in modelling volatility of index returns because the yesterday information would 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)). There are several reasons to use daily data and the rationale to employ daily data in modelling volatility transmission are mentioned in McAleer (2009), and McAleer and da Veiga (2008a). The continuously compounded returns at time *t* are calculated as follow:

$$r_t = \log(\frac{p_t}{p_{t-1}})*100 \qquad (4.24)$$

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 4.3.

The plots show that all returns have constant mean but the time-varying variance. The dramatic changes in JKSE and SETI from up trend to down trend evidence by the plots of the price changes in Figure 4.2 imply that the returns of JKSE and STI are more volatile than those of the KLCI and SETI. However, all stock markets have practically the same trend over a period of time since 1998 and changing overtime. Then, an appropriate model is necessary to estimate.

Second, we test all daily time-series returns for the stationary by using Augmented Dickey-Fuller (ADF) test from the econometric software package EViews 6.0. Table 4.2 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 -3.4327. These empirical results allow the use of all return series data to estimate the conditional volatility models.

Third, we investigate the standard descriptive statistics of the daily time-series data, provided in Table 4.3. From Table 4.3, 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 models described in the previous section. We take into account as to compare how the performance of those several models for volatility measures. The univariate long memory conditional mean and conditional volatility 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)). 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. The empirical results which evidence the correlogram of all series in Table 4.4 – 4.7 allow to model the returns as a stationary ARMA(1, 1) process as the basis in the univariate long memory conditional mean and conditional volatility models. McAleer and Medeiros (2008) reviews the fact that different autoregressive structures are present at each time scale. In this paper, the alternative long memory HAR(*h*) models are estimated together with the univariate conditional volatility models including GARCH, GJR, and EGARCH models to capture long run persistence of shocks.

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 as

$$\text{AIC} = -2\frac{LogL}{n} + 2\frac{k}{n} \tag{4.25}$$

$$\text{SIC} = -2\frac{LogL}{n} + 2\frac{\log(k)}{n} \tag{4.26}$$

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.

4.4 Empirical Results

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 4.8, 4.9, 4.10, and 4.11 summarize the estimations from GARCH, FIGARCH, FIEGARCH and ARFIMA-GARCH type models using 2,519 daily return observations of stock market indexes in South-East Asia, namely JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore), respectively. Furthermore, Table 4.12, 4.13, and 4.14 summarize the estimations from the alternative long memory HAR(*h*) models -- HAR(1), HAR(1,5), and HAR(1,5,20) for those of stock market indexes, respectively. The parameters are typically estimated using the 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 4.8 – 4.14, they are significantly different from zero at 5% level. The empirical results are divided into three subsequences as follows:

4.4.1 FIGARCH 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 properties 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. All over again, these empirical results clearly show a stationary and the long memory property of 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.

4.4.2 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 4.4 – 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.

4.4.3 HAR Models

Table 4.12 – 4.14 show the estimations of GARCH(1,1), GJR(1,1), and EGARCH(1,1) for the HAR(1), HAR(1,5), and HAR(1,5,20) of stock indexes in South-East Asia, respectively. In the conditional mean equation of HAR(1,5), the estimates for all series; JKSE, KLCI, SETI, and STI, are statistically significant. However, the estimates of HAR(1) for JKSE, KLCI are statistically significant, those of HAR(1,5,20) for all series are not statistically significant. So, the long memory properties of the data are captured adequately. In the conditional variance equation, the results would be given by dividing into JKSE, KLCI, SETI, and STI as following; the empirical results for JKSE suggest that the short run persistence of shocks lies between 0.156 and 0.210, while the long run persistence is 0.923 for HAR(1) and 0.897 for HAR(1,5). The magnitude of asymmetric effects are evaluated by GJR(1,1) model. The estimated asymmetry coefficients are 0.242 and 0.195 for HAR(1) and HAR(1,5), respectively. They are positive and significant that would indicate the deceases in JKSE (or negative shocks) increase volatility. The results from EGARCH(1,1) show each of the estimates is statistically significant for the HAR(1) and HAR(1,5) models. The size effect, α , being insignificant and the sing effect, θ_1, being negative for both models, indicate the asymmetric effects but no leverage.

The empirical results for KLCI suggest that the short run persistence of shocks lies between 0.118 and 0.166, while the long run persistence is 0.998 for

HAR(1) and 0.991 for HAR(1,5). 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), namely 0.076 and 0.065. This result could be interpreted the deceases in KLCI increase volatility. The results from EGARCH(1,1) show each of the estimates is statistically significant for the HAR(1,5) model. The size effect, α , being insignificant and the sing effect, θ_1, being negative, indicate the asymmetric effects but no leverage.

The empirical results for SETI suggest that the short run persistence of shocks lies between 0.114 and 0.164, while the long run persistence is 0.975 for HAR(1) and 0.959 for HAR(1,5). 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), namely 0.094 and 0.117. So, the deceases in SETI increase volatility. The results from EGARCH(1,1) show each of the estimates is statistically significant for HAR(1) and HAR(1,5,20) models. The size effect, α , being insignificant and the sing effect, θ_1, being negative, indicate the asymmetric effects but no leverage.

Lastly, the empirical results for STI suggest that the short run persistence of shocks lies between 0.096 and 0.115, while the long run persistence is 0.993 for both HAR(1) and HAR(1,5) models. The magnitude of asymmetric effects are evaluated by GJR(1,1) model. The estimated asymmetry coefficient is positive and statistically significant for HAR(1) and HAR(1,5), namely 0.083 and 0.120, respectively. The deceases in STI increase volatility. There are no evidences for the EGARCH(1,1).

Overall, in comparison with the HAR(1) model in all series; JKSE, KLCI, SETI, and STI, the estimated asymmetry coefficients for GJR(1,1) model are extremely statistically significant for the HAR(1,5). Therefore, GARCH(1,1) and GJR(1,1) for HAR(1,5) models are preferable. Therefore, the long memory properties of the data are captured adequately and the conditional volatility is sensitive to the long memory of the conditional mean specifications.

4.5 Concluding Remarks

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 standard conditional volatility model, GARCH model, fractionally integrated models, FIGARCH, FIEGARCH, the ARFIMA with GARCH models including ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-FIEGARCH models and the alternative long memory model, the Heterogeneous Autoregressive (HAR) model. These univariate conditional volatility models are applied in the paper time-series data which are daily closing prices for four stock markets in South-East Asia, namely JKSE (Indonesia), KLCI (Malaysia), SETI (Thailand), and STI (Singapore) from September 1, 1999 to April 27, 2009, giving a total of 2,519 return observations, as available on DataStream.

Our finding can be summarized as follows. First of all, our estimation results show that the fractional integration that apparently show the long run persistence of shocks in volatility of all index returns. Therefore the results show that the volatility has the long memory property.

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 fractionally integrated models for long memory are preferred to conditional volatility models, GARCH models. Especially ARFIMA-FIEGARCH model is superior to ARFIMA-FIGARCH and ARFIMA-GARCH models.

Third, the HAR model is used to confirm the long memory properties in the data. The empirical estimates indicate the GARCH, and GJR models are fit the data very well. Typically in financial time series, short and long run persistence of shocks are established in all index returns. In addition, the estimates in stock indexes, GARCH(1,1) and GJR(1,1) for the HAR(1,5) models are preferable. Therefore, the long memory properties of the data are captured adequately and the conditional volatility is sensitive to the long memory of the conditional mean specifications.

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

Table 4.1 Summary of stock index names

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

Table 4.2 ADF Test of a Unit Root in all series

Returns	**Coefficient**	**t-statistic**
JKSE	-0.8708	-44.0375
KLCI	-0.8532	-43.2910
SETI	-0.9287	-46.7129
STI	-0.9799	-49.1349

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

Table 4.3 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 4.4 Correlogram of JKSE (Indonesia)

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 4.5 Correlogram of KLCI (Malaysia)

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 4.6 Correlogram of SETI (Thailand)

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 4.7 Correlogram of STI (Singapore)

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 4.8 Estimation Results for JKSE (Indonesia)

Var. JKSE	**Mean equation**				**Variance equation**							LL	
Model	μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*	AIC	SIC
GARCH (1, 1)	**0.121**				**0.192**		**0.151**	**0.777**	0.928		**4.1234**	-4256.78	
	5.456				**2.144**		**3.318**	**10.36**			**11.15**	3.384	3.380
							ϕ	β	θ_1	θ_2			
FIGARCH (1,*d*,1)	**0.123**				**0.382**	**0.322**	-0.053	0.093			**4.1096**	-4252.27	
	5.602				**3.382**	**4.338**	-0.362	0.5358			**10.82**	3.381	3.377
FIEGARCH (1,*d*,1)	**0.108**				**6.754**	**0.036***	-0.114	**0.863**	**-0.147**	**0.2827**	**4.1888**	-4240.28	
	5.021				**4.534**	**1.782**	-0.477	**15.04**	**-4.229**	**5.230**	**10.81**	3.373	3.367
ARFIMA-	**0.121**	0.021	-0.235	**0.307***	**0.198**		**0.157**	**0.766**				-4245.78	
GARCH (1,1)	**4.503**	0.9380	-1.228	**1.702**	**2.119**		**3.378**	**9.700**				3.377	3.372
ARFIMA-	**0.135**	**0.059**			**0.463**	**0.233**					**4.3969**	-4248.68	
FIGARCH (0,*d*,0)	**3.981**	**3.239**			**5.774**	**7.115**					**10.98**	3.377	3.374
ARFIMA-	**0.126**	0.022	-0.222	**0.301***	**0.455**	**0.235**					**4.4381**	-4243.78	
FIGARCH (0,*d*,0)	**4.607**	0.9716	-1.245	**1.799**	**5.801**	**7.163**					**10.86**	3.375	3.370
ARFIMA-	**0.123**	0.022	-0.223	**0.297***	**0.381**	**0.314**	-0.082	0.052			**4.2773**	-4240.54	
FIGARCH (1,*d*,1)	**4.532**	1.004	-1.216	**1.725**	**3.471**	**4.488**	-0.563	0.2998			**10.33**	3.374	3.368
ARFIMA-	**0.089**	**0.067**			**7.382**	**0.033***	-0.134	**0.879**	**-0.158**	**0.2726**	**4.3601**	-4230.773	
FIEGARCH (1,*d*,1)	**2.390**	**3.926**			**4.485**	**1.813**	-0.606	**17.56**	**-4.570**	**5.367**	**10.30**	3.366	3.360
ARFIMA-	**0.089***	0.034	-0.305	**0.369***	**7.169**	**0.033***	-0.139	**0.871**	**-0.162**	**0.2816**	**4.3807**	-4227.07	
FIEGARCH (1,*d*,1)	**1.861**	1.602	-1.409	**1.807***	**4.543**	**1.792**	-0.651	**16.67**	**-4.704**	**5.434**	**10.14**	3.365	3.357

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 95% level, and the 90% level, respectively.

Table 4.9 Estimation Results for KLCI (Malaysia)

Var. KLCI	**Mean equation**				**Variance equation**							LL	
Model	μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*	AIC	SIC
GARCH(1,1)	**0.027**				**0.014**		**0.115**	**0.884**	0.9991		**4.144**	-3057.02	
	2.153				**2.068**		**4.188**	**31.97**			**11.74**	2.431	2.428
							φ	β	θ_1	θ_2			
FIGARCH(1,*d*,1)	**0.028**				**0.074**	**0.312**	-0.110	0.084			**4.751**	-3039.82	
	2.268				**2.673**	**8.624**	-0.670	0.468			**12.57**	2.418	2.414
FIEGARCH(1,*d*,1)	**0.024**				**14.933**	**0.033**	-0.104	**0.954**	**-0.0553**	**0.231**	**4.269**	-3041.55	
	1.864				**3.478**	**2.250**	-0.438	**45.05**	**-3.062**	**4.448**	**11.70**	2.421	2.416
ARFIMA-	0.026	0.037	-0.150	0.244	**0.014**		**0.117**	**0.881**				-3033.35	
GARCH(1,1)	1.438	0.890	-0.195	0.329	**2.063**		**4.437**	**32.24**				2.415	2.409
ARFIMA-	0.023	**0.091**			**0.114**	**0.228**					**4.910**	-3034.82	
FIGARCH(0,*d*,0)	0.907	**4.599**			**5.005**	**12.83**					**12.29**	2.413	2.410
ARFIMA-	0.027	0.033	-0.024	0.129	**0.113**	**0.227**					**4.923**	-3028.14	
FIGARCH(0,*d*,0)	1.525	0.816	-0.040	0.223	**5.015**	**13.01**					**12.13**	2.410	2.405
ARFIMA-	0.028	0.032	0.001	0.097	**0.069**	**0.316**	-0.104	0.099			**4.975**	-3016.12	
FIGARCH(1,*d*,1)	1.580	0.849	0.002	0.155	**2.560**	**8.313**	-0.622	0.538			**11.62**	2.402	2.395
ARFIMA-	-0.006	**0.203**	**0.786**	**-0.867**	**15.567**	**0.031**	-0.093	**0.953**	**-0.070**	**0.231**	**4.480**	-3016.81	
FIEGARCH(1,*d*,1)	-0.133	**3.901**	**9.933**	**-16.99**	**3.533**	**2.226**	-0.395	**43.62**	**-3.459**	**4.959**	**11.02**	2.404	2.396

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 95% level, and the 90% level, respectively.

Table 4.10 Estimation Results for SETI (Thailand)

Var. SETI	**Mean equation**						**Variance equation**							LL	
Model	μ	*d*	AR(1)	AR(2)	MA(1)	MA(2)	ω	*d*	α	β	α+β		*df*	AIC	SIC
GARCH(1,1)	**0.051**						**0.066**		**0.112**	**0.863**	0.975		**5.156**	-4231.43	
	2.308						**3.158**		**6.741**	**42.48**			**7.601**	3.363	3.360
									ϕ	β	θ_1	θ_2			
FIGARCH(1,*d*,1)	**0.050**						**0.114**	0.522	0.117	**0.542***			**4.961**	-4232.18	
	2.211						**1.895**	1.578	1.610	**1.726**			**6.446**	3.365	3.360
FIEGARCH(1,*d*,1)	**0.044**						**12.24**	**0.034**	0.041	**0.929**	**-0.058**	**0.182**	**5.306**	-4221.89	
	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		**0.068**		**0.114**	**0.860**				-4226.92	
GARCH(1,1)	1.638	**2.482**	-1.393		1.346		**3.176**		**6.818**	**41.69**				3.362	3.356
ARFIMA-	0.043	**0.042**					**0.430**	**0.193**					**5.264**	-4241.66	
FIGARCH(0,*d*,0)	1.375	**2.461**					**5.861**	**9.969**					**7.978**	3.372	3.368
ARFIMA-	0.042	**0.064**	-0.308		0.267		**0.432**	**0.193**					**5.250**	-4240.449	
FIGARCH(0,*d*,0)	1.178	**2.615**	-1.592		1.481		**5.846**	**9.939**					**7.985**	3.372	3.367
ARFIMA-	0.053	**0.062**	-0.317		0.282		**0.117**	**0.515***	0.110	**0.526***			**5.013**	-4227.52	
FIGARCH(1,*d*,1)	1.538	**2.551**	-1.496		1.433		**1.950**	**1.686***	0.071	**1.759**			**6.533**	3.364	3.357
ARFIMA-	0.033	**0.078**	-0.299		0.252		**12.166**	**0.034**	0.051	**0.9275**	**-0.071**	**0.180**	**5.437**	-4214.582	
FIEGARCH(1,*d*,1)	0.660	**3.441**	-1.427		1.267		**4.963**	**3.088**	0.2321	**48.72**	**-3.748**	**5.784**	**7.111**	3.355	3.347
ARFIMA-	0.030	**0.065**	**-1.033**	**-0.670**	**0.998**	**0.6873**	**12.06**	**0.035**	0.0212	**0.926**	**-0.072**	**0.187**	**5.4244**	-4208.68	
FIEGARCH(1,*d*,1)	0.771	**1.964**	**-2.253**	**-2.679**	**2.386**	**3.458**	**4.992**	**3.118**	0.1022	**47.62**	**-3.726**	**5.972**	**7.150**	3.352	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, and bold * are significant at the 95% level, and the 90% level, respectively.

Table 4.11 Estimation Results for STI (Singapore)

Var. STI	**Mean equation**				**Variance equation**							LL	
Model	μ	*d*	AR(1)	MA(1)	ω	*d*	α	β	α+β		*df*	AIC	SIC
GARCH(1,1)	**0.066**				**0.020**		**0.095**	**0.897**	0.993		**6.875**	-3932.83	
	3.446				**2.914**		**6.425**	**59.38**			**7.409**	3.126	3.123
							φ	β	θ_1	θ_2			
FIGARCH(1,*d*,1)	**0.068**				**0.053**	**0.432**	0.1164	**0.498**			**7.225**	-3925.273	
	3.524				**2.321**	**5.826**	1.597	**4.216**			**7.367**	3.121	3.117
FIEGARCH(1,*d*,1)	**0.180**				**1.003**	**0.650**	0.5406		**-0.142**	**0.009**	**3.816**	-4032.90	
	7.891				**3.749**	**7.954**	1.102		**-2.898**	**2.566**	**10.34**	3.208	3.203
ARFIMA-	**0.072**	0.053	0.233	-0.264	**0.020**		**0.0958**	**0.897**				-3930.29	
GARCH(1,1)	**2.666**	1.535	0.895	-0.993	**2.902**		**6.351**	**58.20**				3.127	3.121
ARFIMA-	**0.069**	**0.039**			**0.240**	**0.221**					**6.946**	-3952.81	
FIGARCH(0,*d*,0)	**2.720**	**2.268**			**5.969**	**14.60**					**8.229**	3.142	3.139
ARFIMA-	**0.072**	0.061	0.262	-0.296	**0.241**	**0.220**					**6.869**	-3952.469	
FIGARCH(0,*d*,0)	**2.502**	1.629	0.800	-0.883	**5.971**	**14.47**					**8.201**	3.144	3.139
ARFIMA-	**0.073**	0.0502	0.215	-0.244	**0.054**	**0.427**	0.1171	**0.492**			**7.307**	-3922.823	
FIGARCH(1,*d*,1)	**2.753**	1.458	0.780	-0.864	**2.296**	**5.788**	1.558	**4.055**			**7.097**	3.122	3.115
ARFIMA-	**0.053**	0.019			**3.764**	**0.179**	**1.187**		**-0.118**	**0.240**	**3.274**	-4036.400	
FIEGARCH(0,*d*,1)	**2.853**	1.243			**12.70**	**6.681**	**2.918**		**-2.664**	**4.139**	**12.86**	3.211	3.205
ARFIMA-	**0.0534**	**0.046***		-0.046	**3.777**	**0.180**	**1.238**		**-0.111**	**0.237**	**3.246**	-4035.41	
FIEGARCH(0,*d*,1)	**1.895**	**1.833**		-1.333	**13.03**	**6.867**	**2.781**		**-2.538**	**3.975**	**12.90**	3.211	3.205

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 95% level, and the 90% level, respectively.

Table 4.12 Estimation Results of Conditional Mean (HAR(1)) and Conditional Variance Models

Var.	**Model**	**Mean equation**		**Variance equation**								LL	
		ϕ_1	ϕ_2	ω	α	β	γ	θ_1	θ_2	*df*	$\alpha+\beta$	AIC	SIC
JKSE	GARCH(1,1)	**0.106**	**0.091**	**0.197**	**0.156**	**0.767**				**4.303**	0.923	-4245.397	
		4.722	**4.422**	**3.274**	**4.845**	**15.74**				**10.53**		3.377	3.373
	GJR(1,1)	**0.078**	**0.100**	**0.257**	**0.040***	**0.727**	**0.242**			**4.550**		-4222.768	
		3.416	**4.901**	**4.882**	**1.987**	**17.46**	**4.913**			**10.11**		3.360	3.355
	EGARCH(1,1)	**0.081**	**0.097**	**7.363**	-0.139	**0.897**		**-0.158**	**0.292**	**4.410**		-4229.720	
		3.554	**4.813**	**4.974**	-0.855	**34.53**		**-5.083**	**6.070**	**10.31**		3.366	3.360
KLCI	GARCH(1,1)	0.023	**0.129**	**0.014**	**0.118**	**0.880**				**4.391**	0.998	-3033.174	
		1.802	**6.459**	**2.779**	**5.851**	**46.15**				**10.87**		2.414	2.410
	GJR(1,1)	0.016	**0.131**	**0.017**	**0.086**	**0.872**	**0.076**			**4.453**		-3027.849	
		1.214	**6.570**	**2.967**	**4.741**	**44.78**	**2.882**			**10.72**		2.411	2.406
	EGARCH(1,1)	0.014	**0.133**	**22.21**	-0.125	**0.973**		**-0.061**	**0.245**	**4.493**		-3021.008	
		1.367	**6.227**	**3.754**	-0.660	**112.6**		**-3.243**	**5.224**	**10.82**		2.406	2.400
SETI	GARCH(1,1)	**0.049***	0.037	**0.066**	**0.114**	**0.862**				**5.216**	0.975	-4227.845	
		2.208	1.852	**3.624**	**6.894**	**46.29**				**9.236**		3.363	3.359
	GJR(1,1)	0.035	0.038	**0.090**	**0.074**	**0.842**	**0.094**			**5.321**		-4220.631	
		1.558	1.915	**3.884**	**4.510**	**39.76**	**3.296**			**9.078**		3.358	3.353
	EGARCH(1,1)	0.042	0.038	**14.82**	0.055	**0.951**		**-0.055**	**0.196**	**5.284**		-4225.030	
		1.849	1.923	**4.846**	0.273	**80.95**		**-3.319**	**5.747**	**9.321**		3.362	3.356
STI	GARCH(1,1)	**0.064**	0.025	**0.020**	**0.096**	**0.896**				**7.036**	0.993	-3930.922	
		3.334	1.242	**3.086**	**7.022**	**64.92**				**7.376**		3.127	3.123
	GJR(1,1)	**0.046***	0.029	**0.025**	**0.043**	**0.901**	**0.083**			**7.377**		-3920.259	
		2.316	1.408	**3.621**	**3.234**	**63.81**	**4.378**			**7.105**		3.119	3.114

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 4.13 Estimation Results of Conditional Mean (HAR(1,5)) and Conditional Variance Models

Var.	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
JKSE	GARCH(1,1)	-0.017	**-0.202**	**1.187**	**0.184**	**0.210**	**0.688**				**5.504**	0.897	-3896.283	
		-0.859	**-9.647**	**27.40**	**4.419**	**6.178**	**14.55**				**8.746**		3.104	3.099
	GJR(1,1)	-0.038	**-0.189**	**1.134**	**0.135**	**0.084**	**0.751**	**0.195**			**5.644**		-3886.561	
		-1.871	**-9.032**	**25.89**	**4.057**	**2.743**	**17.49**	**4.384**			**8.540**		3.097	3.091
	EGARCH(1,1)	**-0.041**	**-0.191**	**1.144**	**14.363**	-0.026	**0.919**		**-0.112**	**0.325**	**5.661**		-3888.532	
		-2.054	**-9.252**	**27.01**	**4.729**	-0.144	**35.73**		**-3.344**	**6.203**	**8.614**		3.099	3.093
KLCI	GARCH(1,1)	-0.004	**-0.168**	**1.109**	**0.017**	**0.166**	**0.826**				**5.366**	0.991	-2709.168	
		-0.401	**-7.954**	**26.19**	**3.320**	**6.514**	**33.72**				**9.619**		2.160	2.155
	GJR(1,1)	-0.010	**-0.164**	**1.095**	**0.016**	**0.129**	**0.832**	**0.065**			**5.409**		-2707.684	
		-0.897	**-7.787**	**25.57**	**3.204**	**4.291**	**33.28**	**1.733**			**9.551**		2.159	2.154
SETI	GARCH(1,1)	-0.010	**-0.255**	**1.238**	**0.076**	**0.164**	**0.795**				**7.319**	0.959	-3853.321	
		-0.513	**-12.49**	**28.94**	**3.958**	**7.140**	**28.94**				**7.836**		3.070	3.065
	GJR(1,1)	-0.028	**-0.251**	**1.211**	**0.070**	**0.099**	**0.808**	**0.117**			**7.461**		-3848.247	
		-1.454	**-12.34**	**28.54**	**4.049**	**4.037**	**31.95**	**3.186**			**7.700**		3.067	3.061
STI	GARCH(1,1)	-0.005	**-0.262**	**1.281**	**0.016**	**0.115**	**0.878**				**9.081**	0.993	-3521.148	
		-0.336	**-13.29**	**30.87**	**3.101**	**7.191**	**54.61**				**5.799**		2.806	2.801
	GJR(1,1)	-0.027	**-0.258**	**1.246**	**0.014**	**0.048**	**0.890**	**0.120**			**9.497**		-3512.966	
		-1.599	**-13.17**	**30.34**	**3.062**	**2.656**	**59.70**	**4.113**			**5.653**		2.799	2.794

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 4.14 Estimation Results of Conditional Mean (HAR(1,5,20)) and Conditional Variance Models

Var.	**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
JKSE	GARCH(1,1)	-0.018	**-0.202**	**1.187**	0.003	**0.188**	**0.208**	**0.685**				**5.517**	0.893	-3861.303	
		-0.833	**-9.650**	**24.88**	0.039	**4.470**	**6.201**	**14.43**				**8.736**		3.095	3.090
	GJR(1,1)	-0.037	**-0.190**	**1.139**	-0.007	**0.140**	**0.086**	**0.745**	**0.192**			**5.660**		-3851.823	
		-1.764	**-9.043**	**23.76**	-0.098	**4.117**	**2.835**	**17.23**	**4.329**			**8.530**		3.089	3.082
	EGARCH(1,1)	**-0.041**	**-0.193**	**1.145**	0.012	**13.67**	0.021	**0.910**		**-0.107**	**0.325**	**5.707**		-3853.827	
		-2.008	**-9.302**	**24.46**	0.162	**4.880**	0.113	**34.07**		**-3.357**	**6.146**	**8.655**		3.091	3.084
KLCI	GARCH(1,1)	-0.003	**-0.168**	**1.106**	-0.003	**0.017**	**0.164**	**0.827**				**5.380**	0.991	-2682.259	
		-0.310	**-7.969**	**23.67**	-0.043	**3.288**	**6.422**	**33.26**				**9.524**		2.152	2.146
	GJR(1,1)	-0.009	**-0.165**	**1.094**	-0.004	**0.016**	**0.129**	**0.832**	0.061			**5.421**		-2680.921	
		-0.775	**-7.811**	**23.16**	-0.051	**3.175**	**4.298**	**32.80**	1.646			**9.460**		2.152	2.145
SETI	GARCH(1,1)	-0.008	**-0.254**	**1.242**	-0.036	**0.077**	**0.162**	**0.795**				**7.232**	0.957	-3824.465	
		-0.409	**-12.41**	**25.77**	-0.450	**3.952**	**7.096**	**28.76**				**7.848**		3.066	3.060
	GJR(1,1)	-0.027	**-0.250**	**1.212**	-0.015	**0.071**	**0.102**	**0.806**	**0.111**			**7.352**		-3819.961	
		-1.332	**-12.26**	**25.08**	-0.188	**4.036**	**4.156**	**31.30**	**2.999**			**7.739**		3.063	3.057
	EGARCH(1,1)	-0.018	**-0.246**	**1.215**	-0.013	**16.40**	0.367	**0.916**		**-0.040***	**0.235**	**7.344**		-3821.363	
		-0.888	**-12.41**	**25.57**	-0.178	**5.564**	1.390	**40.79**		**-2.216**	**6.101**	**7.885**		3.065	3.058
STI	GARCH(1,1)	-0.003	**-0.261**	**1.283**	-0.019	**0.016**	**0.116**	**0.877**				**9.130**	0.992	-3498.647	
		-0.240	**-13.21**	**27.47**	-0.240	**3.116**	**7.181**	**53.76**				**5.751**		2.805	2.799
	GJR(1,1)	-0.025	**-0.258**	**1.250**	-0.022	**0.014**	**0.049**	**0.889**	**0.119**			**9.535**		-3490.650	
		-1.468	**-13.09**	**27.04**	-0.288	**3.082**	**2.663**	**58.81**	**4.077**			**5.622**		2.799	2.793

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.

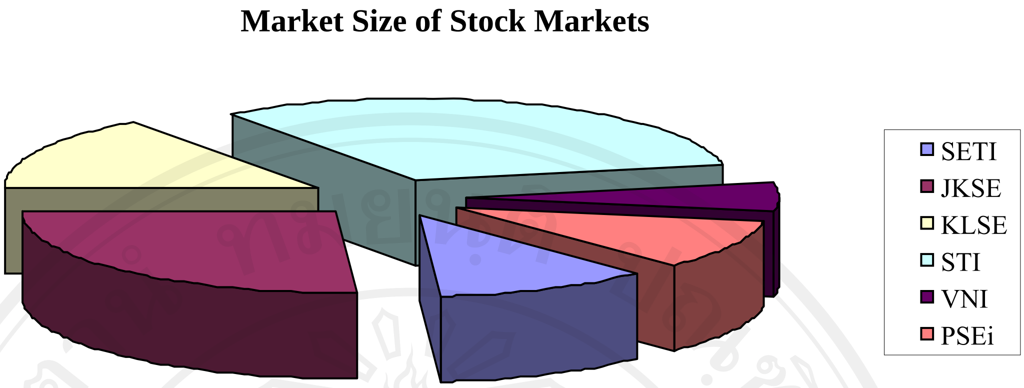
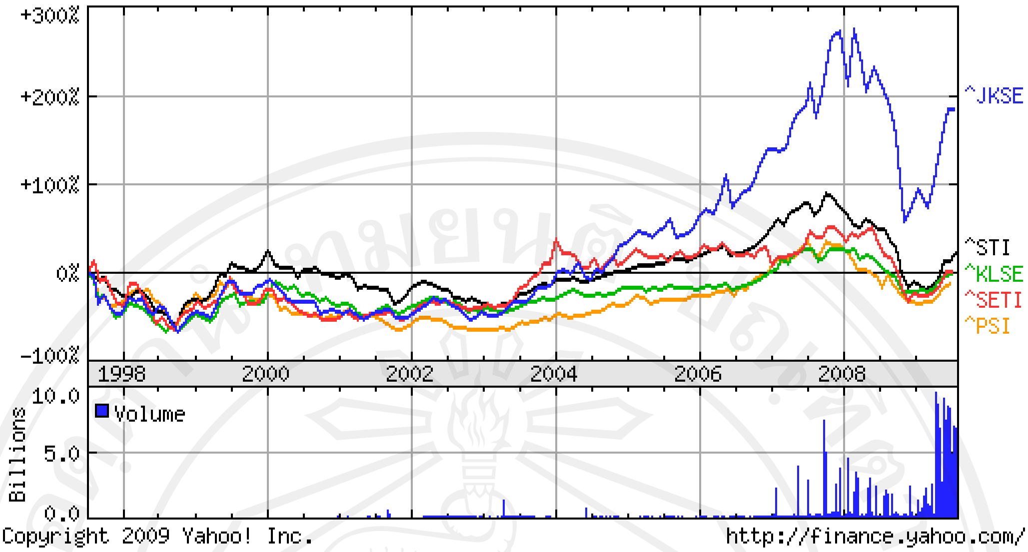


Figure 4.1 Index values of Stock Markets in South-East Asia



Source: Yahoo Finance (July 2009)

Figure 4.2 The percent change in prices of Stock Markets in South-East Asia

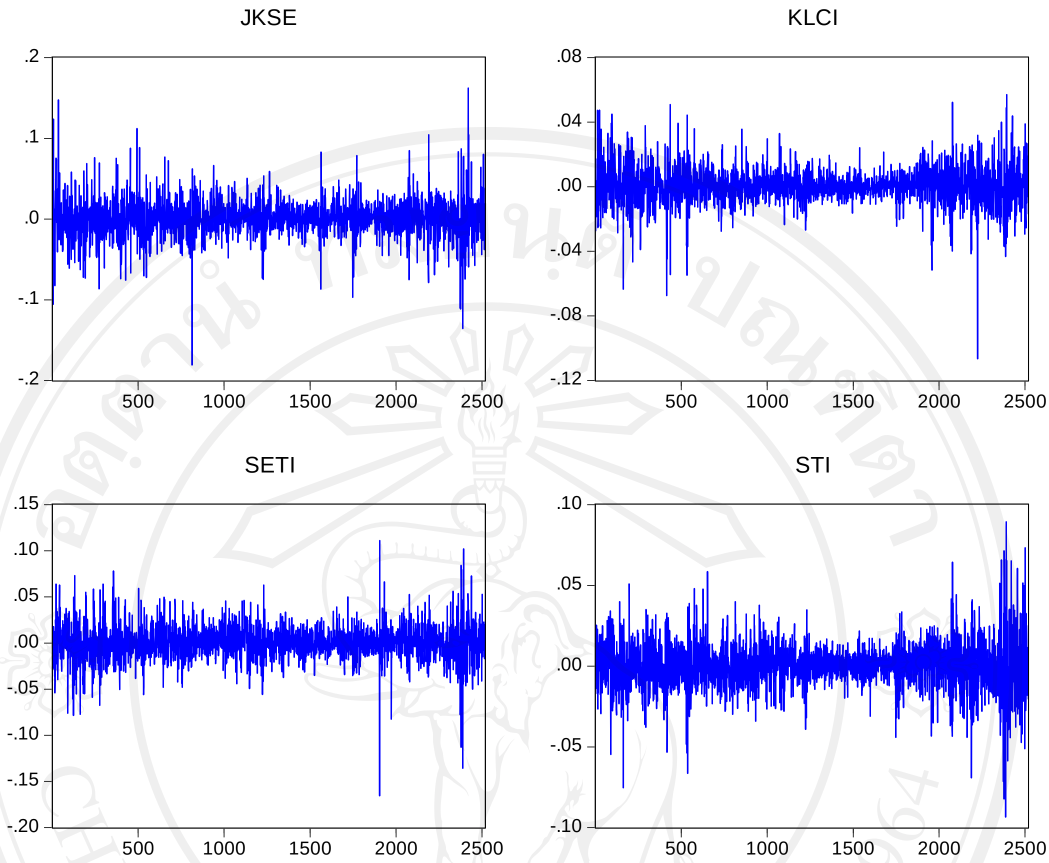


Figure 4.3 Daily returns for all series