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Forecasting the Stock Exchange of Thailand uses Day of the Week Effect and Markov Regime Switching GARCH

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Abstract: Problem statement: We forecast return and volatility of the Stock Exchange of Thailand (SET) Index. **Approach:** In this study, we modeled the SET Index returns using mean equation with day of the week effect and autoregressive moving-average. Next we forecast the volatility of the SET Index by using the GARCH-type model and the Markov Regime Switching GARCH (MRS-GARCH) model. **Results:** When we model the SET Index by the ARMA (3, 3) process, we find that Friday is the day of the effect of the SET Index. The empirical analysis demonstrates that the MRS-GARCH models outperform all GARCH-type models in forecasting volatility at long term horizons (two weeks and a month). **Conclusion:** The ARMA (3, 3) and the Friday is the day of the effect of the SET Index return. The MRS-GARCH models outperform at long term horizons.

Key words: Volatility forecasting, SET index, GARCH models, Markov regime switching, stock exchange, models outperform, empirical analysis

INTRODUCTION

In the time series, the stock price is transformed to return series for stationary process which looked like white noise and forecasting was possible using the mean equation. The forecasting of daily returns has led to additional research in financial literature, specifically extending the analysis of the seasonal behavior to include the day of the week effect. This seasonality has been the subject of different studies which detected empirical evidence of abnormal yield distributions based upon the day of the week. The pioneering work was carried out as used in the analysis of seasonality and can be specifically seen in Miralles and Quiros (2000), they included five dummy variables, one for each day of the week.

Nevertheless two serious problems arise with this approach. The first problem is that the residuals obtained from the regression model can be autocorrelated, thus creating errors in the inference. The second problem is that the variances of the residuals are not constant and possibly time-dependent.

A solution to the first type of problem can be solved by introducing the returns with a one week delay into the regression model, as used in the works by Easton and Faff (1994) and Kyimaz and Berument (2001).

Moreover, Apolinario *et al*. (2006) and Ulussever *et al*. (2011) try to solve the second problem by modeling the residuals with the ARCH model in order to correct the variability in the variance of the residuals. In this study, we reconsidered the two problems again. For the first problem, we modeled the SET Index returns by mean equation with the day of the week effect and the autoregressive moving-average order p and q (ARMA (p, q)). For the second problem, we model the residuals by the GARCH, EGARCH, GJR-GARCH and MRS-GARCH models. Finally, we compare their performance by one day, one week, two weeks and one month.

Next, we present forecasting returns with the mean equation. Then we forecast volatility of returns and estimate parameters within-sample evaluation results. Moreover, statistical loss functions are described and out-of-sample forecasting performance of various models is discussed.

MATERIALS AND METHODS

Forecasting financial returns: Let $\{P_t\}$ denote the series of the financial price at time t and the returns for each market $\{r_t\}_{t>0}$ be a sequence of random variables

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on a probability space (Ω, F, P). The index t denotes the daily closing R observations with t = -R+1,..,0. The sample period consists of an estimation (or in-sample) period with n observations and an evolution (or out-of-sample) period with n observations (t = 1,…,n), let r_t be the logarithmic return (in percent) on the financial price at time t, i.e. Eq. 1:

$$r_t = 100 \cdot \ln(\frac{P_t}{P_{t-1}}) \quad (1)$$

To put the volatility models in proper perspective, it is informative to consider the conditional mean and variance of given, that is:

$$\begin{aligned} \mu_t &= E(r_t | F_{t-1}) \\ h_t &= Var(r_t | F_{t-1}) = E[(r_t - \mu_t)^2 | F_{t-1}] \end{aligned} \quad (2)$$

where, F_{t-1} refers to information up to time t-1. Typically, F_{t-1} consists of all linear functions of the past returns. Therefore, the equation for μ_t in Eq. 2 should be simple and we assume that r_t follows a simple time series model such as a stationary ARMA(p, q) model which includes five dummy variables, one for each day of the week, such that Eq. 3:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t, \\ \mu_t &= \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_{5t} \\ &+ \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \end{aligned} \quad (3)$$

where, D_{jt} , j = 1,…, 5 are dummy variables which take on the value of 1 if the corresponding return of the day it is a Monday, Tuesday, Wednesday, Thursday or Friday, respectively and 0 otherwise.

Let β_j, j = 1,…, 5 are coefficients which represent the average return for each day of the week ϕ_i, = 1,…,p and θ_i, i = 1,…, q, are coefficients which represent the ARMA (p, q).

Forecasting financial volatility: We allow variance of errors to be time dependent to include a conditional heteroskedasticity that captures time variations of variances in stock returns Eq. 3. The GARCH-type models in our consideration are GARCH (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1) and MRS-GARCH. For notation conveniences, we shall present some basic definitions of these models.

The GARCH (1, 1) model in the series of the returns rt in Eq. 3 can be written as Eq. 4:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t = \mu_t + \eta_t \sqrt{h_t} \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \end{aligned} \quad (4)$$

where, $a_0 > 0, a_1 \geq 0$ and $\beta_1 \geq 0$ are assumed to be non-negative real constants to ensure that $h_t \geq 0$. We assume n_t is an i.i.d. Process with zero mean and unit variances.

The parameters of the GARCH model are generally considered as constants. But, the movement of financial returns between recession and expansion may result in the variation volatility. Gray (1996) extended the GARCH model to the MRS-GARCH model in order to capture regime changes in volatility with unobservable state variables. It was assumed that those unobservable state variables satisfy the first order of the Markov Chain process.

The MRS-GARCH model represented as the variance of the residual term is not constant through time with only two regimes and distributed as ε_t ~i.i.d. (0, $h_{t,s}$) and defined:

$$\begin{aligned} r_t &= \mu_t + \varepsilon_t, \varepsilon_t = \eta_t \sqrt{h_{t,S_t}} \\ h_{t,S_t} &= \alpha_{0,S_t} + \alpha_{1,S_t} \varepsilon_{t-1}^2 + \beta_{1,S_t} h_{t-1} \end{aligned}$$

Where , S_t = 1 or 2, $h_{t,S}$ is the volatility under regime S_t on F_{t-1}. Also μ_t and $h_{t,St}$ are measurable functions of $F_{t-\tau}$ for $\tau \leq t$. In order to ensure the positivity of the conditional variance, we impose the restrictions $\alpha_{0,S_t} > 0$, ,$\alpha_{1,S_t} \geq 0$ and $\beta_{1,S_t} \geq 0$. The sum $\alpha_{1,S_t} + \beta_{1,S_t}$ measures the persistence of a shock to the conditional variance.

The unobserved regime variable S_t is governed by a first order Markov Chain with constant transition probabilities. Given by:

$$\Pr(S_t = i | S_{t-1} = j) = p_{ji} \text{ for } i, j = 1, 2$$

In matrix notation Eq. 5:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix} \quad (5)$$

In the MRS-GARCH model with two regimes, Klaassen (2002) forecast volatility for k-step-ahead. Klaassen used the recursive method as in the standard GARCH model for k = 1,2,…, n. In order to compute the k-step-ahead volatility forecasts, we first compute a weighted average of the k-step-ahead volatility forecasts in each regime and the weights are the prediction probability $\Pr(S_{i+t} = i/F_{t-1})$.

Since there is no serial correlation in the returns, the k-step-ahead volatility forecast at a time depends on information at time t-1. Let $h_{t,\ t+k}$ denotes the time t aggregated volatility forecasts for the next k steps. It can be calculated as follows: where indicates the -step-ahead volatility forecast in the regime i made at time t and can be calculated recursively as follows Eq. 6:

$$\hat{h}_{t,t+k} = \sum_{\tau=1}^{k}\hat{h}_{t,t+\tau} = \sum_{\tau=1}^{k}\left[\sum_{i=1}^{2}\Pr\left(S_{t+\tau}=i\middle|F_{t-1}\right)\hat{h}_{t,t+\tau,S_{t+\tau}=i}\right] \qquad (6)$$

$$\hat{h}_{t,t+\tau,S_{t+\tau}=i}$$

where, $h_{t,t+\tau,St+\tau=\ i}$ indicates the τ-step-ahead volatility forecast in the regime i made at time t and can be calculated recursively as follows Eq. 7:

$$\begin{aligned}
&\hat{h}_{t,t+\tau,s_{t+\tau}=i} = E_{t-1}\left[h_{t+\tau}\middle|S_{t+\tau}=i\right]\\
&= E_{t-1}\left[\alpha_{0,S_{t+\tau}} + \alpha_{1,S_{t+\tau}}\varepsilon^2_{t+\tau-1} + \beta_{1,S_{t+\tau}}h_{t+\tau-1}\middle|S_{t+\tau}=i\right]\\
&=\alpha_{0,S_{t+\tau}=i} + \alpha_{1,S_{t+\tau}=i}E_{t-1}\left[\varepsilon^2_{t+\tau-1}\middle|S_{t+\tau}=i\right]\\
&\quad+\beta_{1,S_{t+\tau}=i}E_{t-1}\left[h_{t+\tau-1}\middle|S_{t+\tau}=i\right] \qquad (7)\\
&=\alpha_{0,S_{t+\tau}=i} + \alpha_{1,S_{t+\tau}=i}E_{t-1}\left[E_{t-1}[\varepsilon^2_{t+\tau-1}|S_{t+\tau-1}]\middle|S_{t+\tau}=i\right]\\
&\quad+\beta_{1,S_{t+\tau}=i}E_{t-1}\left[h_{t+\tau-1}\middle|S_{t+\tau}=i\right]\\
&=\alpha_{0,S_{t+\tau}=i} + \left(\alpha_{1,S_{t+\tau}=i}+\beta_{1,S_{t+\tau}=i}\right)E_{t-1}\left[h_{t,t+\tau-1}\middle|S_{t+\tau}=i\right]
\end{aligned}$$

Also, in general the prediction probability in Eq. 6 is computed as:

$$\begin{bmatrix}\Pr\left(S_{t+\tau}=1\middle|F_{t-1}\right)\\ \Pr\left(S_{t+\tau}=2\middle|F_{t-1}\right)\end{bmatrix} = P^{\tau+1}\begin{bmatrix}\Pr\left(S_{t-1}=1\middle|F_{t-1}\right)\\ \Pr\left(S_{t-1}=2\middle|F_{t-1}\right)\end{bmatrix}$$

where, P defined in Eq. 4 and Pr (S_{t-1} = i/F_{t-1}) will be calculated in Eq. 12. Lastly, we compute expectation part $E_{t-1}[h_{t,t+\tau-1}|S_{t+\tau} = i]$ as appeared in Eq. 7 as follows Eq. 8:

$$\begin{aligned}
&E_{t-1}[h_{t,t+\tau-1}|S_{t+\tau}=i]\\
&=E_{t-1}\begin{bmatrix}E_{t-1}[r^2_{t+\tau-1}|S_{t+\tau-1}=j]\\ -\left[E_{t-1}[r_{t+\tau-1}|S_{t+\tau-1}=j]\right]^2|S_{t+\tau}=i\end{bmatrix} \qquad (8)\\
&=E_{t-1}\left[E_{t-1}[r^2_{t+\tau-1}|S_{t+\tau-1}=j]\middle|S_{t+\tau}=i\right]\\
&\quad-E_{t-1}\left[\left[E_{t-1}[r_{t+\tau-1}|S_{t+\tau-1}=j]\right]^2\middle|S_{t+\tau}=i\right]
\end{aligned}$$

The first on the right hand side of Eq. 11 can be calculated as follows Eq. 9 and 10:

$$\begin{aligned}
&E_{t-1}\left[E_{t-1}[r^2_{t+\tau-1}|S_{t+\tau-1}=j]\middle|S_{t+\tau}=i\right]\\
&=\sum_{j=1}^{2}E_{t-1}[r^2_{t+\tau-1}|S_{t+\tau-1}=j]\cdot\Pr\left(S_{t+\tau-1}=j\middle|S_{t+\tau}=i,F_{t-1}\right)\\
&=\sum_{j=1}^{2}E_{t-1}[\left(\mu_t+\varepsilon_{t+\tau-1}\right)^2|S_{t+\tau-1}=j]\\
&\quad\cdot\Pr\left(S_{t+\tau-1}=j\middle|S_{t+\tau}=i,F_{t-1}\right) \qquad (9)\\
&=\sum_{j=1}^{2}E_{t-1}[\mu_t{}^2+2\mu_t\varepsilon_{t+\tau-1}+\varepsilon^2_{t+\tau-1}|S_{t+\tau-1}=j]\\
&\quad\cdot\Pr\left(S_{t+\tau-1}=j\middle|S_{t+\tau}=i,F_{t-1}\right)\\
&=\sum_{j=1}^{2}\tilde{p}_{ji,t-1}\left[\mu^2_{t,S_{t+\tau-1}=j}+h_{t+\tau-1,S_{t+\tau-1}=j}\right]
\end{aligned}$$

Where:

$$\begin{aligned}
\tilde{p}_{ji,t-1} &= \Pr\left(S_{t+\tau-1}=j\middle|S_{t+\tau}=i,F_{t-1}\right)\\
&=\frac{p_{ji}\Pr\left(S_{t+\tau-1}=j\middle|F_{t-1}\right)}{\Pr\left(S_{t+\tau}=i\middle|F_{t-1}\right)}
\end{aligned} \qquad (10)$$

Similarly, the second term on the right hand side in Eq. 8 is equal to:

$$\begin{aligned}
&E_{t-1}\left[\left[E_{t-1}[r_{t+\tau-1}|S_{t+\tau-1}=j]\right]^2\middle|S_{t+\tau}=i\right]\\
&=\sum_{j=1}^{2}\tilde{p}_{ji,t-1}\left[\mu_{t},_{S_{t+\tau-1}=j}\right]^2
\end{aligned} \qquad (11)$$

Substituting Eq. 9 and 11 into Eq. 8, one gets:

$$\begin{aligned}
E_{t-1}(\hat{h}_{t,t+\tau-1}|S_{t+\tau}=i) &= \sum_{j=1}^{2}\tilde{p}_{ji,t-1}\left[\mu_{t},^2_{S_{t+\tau-1}=j}+h_{t+\tau-1,S_{t+\tau-1}=j}\right]\\
&\quad-\sum_{j=1}^{2}\tilde{p}_{ji,t-1}\left[\mu_{t},_{S_{t+\tau-1}=j}\right]^2
\end{aligned}$$

Now we are ready to compute those regime probabilities p_{it} = Pr (S_t = i|F_{t-1}) for i = 1, 2 in Eq. 10. In order to compute the regime probabilities, we denote f_{1t} = f (r_t|S_t = 1, F_{t-1}) f_{2t} = f (r_t|S_t = 2F_{t-1}). Then, the conditional distribution of return series r_t becomes a mixture-of-distribution model. Which the mixing variable is a regime probability p_{it}. That is:

$$r_t|F_{t-1}\sim\begin{cases}f(r_t|S_t=1,F_{t-1}) & \text{with probability } p_{1t}\\ f(r_t|S_t=2,F_{t-1}) & \text{with probability } p_{2t}=1-p_{1t}\end{cases}$$

Here $\Pr(S_{t-1}=j|F_{t-1})$ denotes one of the assumed conditional distributions for errors, i.e. Normal distribution (N), Student-t distribution with single (t) or double (2t) degree of freedom, or Generalized Error Distributions (GED).

We shall compute regime probabilities recursively by following two steps (Kim and Nelson, 1999).

Step 1, given the PR ($S_{t-1} = j|F_{t-1}$) at the end of the time t-1, the regime probabilities p_{it} Pr ($S_{t-1} = j|F_{t-1}$) is computed as:

$$\Pr(S_t = i|F_{t-1}) = \sum_{j=1}^{2}\Pr(S_t = i, S_{t-1} = j|F_{t-1})$$

Since the current regime (S_t) only depends on the regime one period ago (S_{t-1}), then:

$$\begin{aligned}\Pr(S_t = i|F_{t-1}) &= \sum_{j=1}^{2}\Pr(S_t = i, S_{t-1} = j|F_{t-1})\\ &= \sum_{j=1}^{2}\Pr(S_t = i|S_{t-1} = j)\Pr(S_{t-1} = j|F_{t-1})\\ &= \sum_{j=1}^{2}p_{ji}\Pr(S_{t-1} = j|F_{t-1})\end{aligned}$$

Step 2, once r_t observed at the end of time t, we can update the probability term in the following way:

$$\Pr(S_t = i|F_t) = \Pr(S_t = i|r_t, F_{t-1}) = \frac{f(r_t, S_t = i|F_{t-1})}{f(r_t|F_{t-1})}$$

where, $F_t = \{F_{t-1}, r_t\}$.

Let $f(r_t, S_t = i/F_{t-1})$ is the joint density of returns and unobserved at state for i = 1, 2 and it can be written as follows:

$$\begin{aligned}f(r_t, S_t = i|F_{t-1}) &= f(r_t|S_t = i, F_{t-1})f(S_t = i|F_{t-1})\\ &= f(r_t|S_t = i, F_{t-1})\Pr(S_t = i|F_{t-1})\end{aligned}$$

Define $f(r_t/F_{t-1})$ is a marginal density function of returns and can be constructed as follows:

$$\begin{aligned}f(r_t|F_{t-1}) &= \sum_{i=1}^{2}f(r_t, S_t = i|F_{t-1})\\ &= \sum_{i=1}^{2}f(r_t|S_t = i, F_{t-1})\Pr(S_t = i|F_{t-1})\end{aligned}$$

We use Bayesian arguments Eq. 12:

$$\begin{aligned}\Pr(S_t = i|F_t) &= \frac{f(r_t, S_t = i|F_{t-1})}{f(r_t|F_{t-1})}\\ &= \frac{f(r_t|S_t = i, F_{t-1})\Pr(S_t = i|F_{t-1})}{\sum_{i=1}^{2}f(r_t|S_t = i, F_{t-1})\Pr(S_t = i|F_{t-1})}\\ &= \frac{f_{it}p_{it}}{\sum_{i=1}^{2}f_{it}p_{it}}\end{aligned} \quad (12)$$

Then, all regime probabilities (p_{it}) can be computed by iterating these two steps. However, at the beginning of the iteration, Pr ($S_0 = i/F_0$) for i = 1, 2 are necessary to start iterating. We follow the technique of Hamilton (1989; 1990) by setting:

$$\pi_1 = \Pr(S_0 = 1|F_0) = \frac{1-q}{2-p-q},$$

$$\pi_2 = \Pr(S_0 = 2|F_0) = \frac{1-p}{2-p-q}$$

Given initial values for regime probabilities, conditional mean and conditional variance in each regime, the parameters of the MRS-GARCH model can be obtained by maximizing numerically the log-likelihood function Marcucci (2005). The log-likelihood function is constructed recursively similar to that in the GARCH model.

RESULTS

The data set was used the daily closing prices of the SET Index P_t over the period 3/01/2007 through 30/03/2011 (t = 1,…, 1,038 observations). The data set is obtained from the Stock Exchange of Thailand. The data set is divided into in-sample (R 977 observations) and out-of-sample (n = 61 observations). The plot p_t of and its log returns series r_t (Eq. 1) are given in Fig. 1. Plot p_t and r_t display the usual properties of financial data series. As expected, volatility is not constant over that period of time and exhibit volatility clustered with large changes in the index often followed by large changes and small changes often followed by small changes.

Descriptive statistics of r_t are presented in Table 1. As Table 1 shows, overall, r_t has a quite small positive average return (about 0.0436%). Standard deviation of r_t is 1.5525%. The lowest average return is observed on Monday and the highest average return occurs on Friday.

Moreover, we tested for the normality of r_t by using the Jarque-Bera test (The Jarque-Bera Normality test is a goodness-of-fit measure of departure from normality and can be used to test which has a x^2distribution with 2 degrees of freedom under the null hypothesis that the data is from a normal distribution. The 5% critical value is, therefore, 5.99) under the null hypothesis r_t is normally distributed and we find that the test statistic value is 1,758.1080 which lead us to reject the null hypothesis. So r_t is not normally distributed. Also, the skewness and kurtosis of r_t are -0.7189 (not equal zero) and 6.2605 (greater than 3) respectively. These values confirm that the returns are not normally distributed, namely, it has fatter tails.

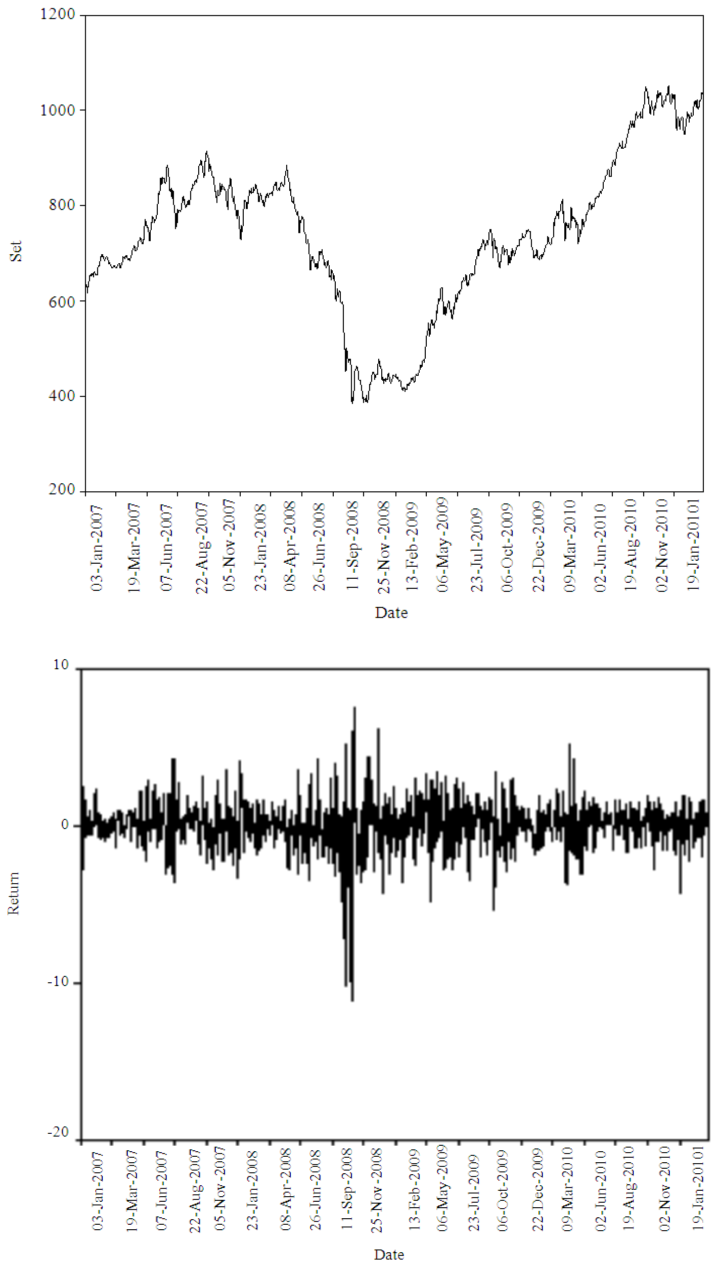

Fig. 1: Graph of (a) SET Index closing prices (P_t) and (b) logs returns series (r_t) for the period 3/01/2007 through 31/03/2011

Table 1: Descriptive statistics of SET Index log returns series (r_t)

Statistic	All day	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0. 04%	-0.04%	-0.02%	0.03%	0.03%	0.22%
Std. Deviation	1. 55%	1.98%	1.46%	1.37%	1.43%	1.48%
Minimum	-11. 09%	-11.09%	-4.28%	-7.13%	-5.44%	-10.10%
Maximum	7. 55%	7.55%	5.29%	3.28%	6.10%	4.19%
Skewness	-0.7189	-0.5511	0.2214	-1.0215	-0.2429	-1.9876
Kurtosis	6.2605	5.8511	1.7362	3.2096	2.7026	13.7500
Jarque-Bera Normality test	1758. 1080					
Augmented Dickey-Fuller test	-30.0801					

Table 2: Day of the week effect and ARMA (p, q) in mean equation of return

Panel A: Day of the week effect in mean equation of return

	Monday	Tuesday	Wednesday	Thursday	Friday
β	-0.064	-0.038	0.02	0.014	0.2210**
Std. error	0. 109	0.106	0.105	0.106	0.107

** refer the significance at 95%confidence

Panel B: ARMA models parametric estimates in mean equation of return

Variable	Coefficient	Std. Error	t-Statistic	P-value
AR (1)	2.5855	0.0579	44.6244	0.0000***
AR (2)	-2.4248	0.1121	-21.6289	0.0000***
AR (3)	0.8289	0.0617	13.4318	0.0000***
MA (1)	2.5059	0.0732	34.2502	0.0000***
MA (2)	-2.2667	0.1436	-15.7891	0.0000***
MA (3)	0.7459	0.0799	9.3413	0.0000***

*** refer the significance at 99%confidence

Moreover, we test for the stationary of r_t by using the Augmented Dickey-Fuller test (The Augmented Dickey-Fuller test is a test for a unit root in a time series sample, the null hypothesis of ADF test is that the series is non-stationary. The 1, 5 and 10% critical value are -3.44, -2.86 and -2.57 respectively). The test statistic value is -30.0801 which indicates the stationary of r_t.

Table 2 reports the day of the week effects and ARMA (p, q) for returns. Panel A of Table 2 displays the first estimated coefficients of the day of the week effect (β_I: I = 1,…, 5). From Table 2 (Panel A), we found the estimated coefficients of β_i are almost zero. Then we test under the null hypothesis that each coefficient (β_I: I = 1,…, 5) is zero. We find that the coefficient of Fridays' dummy variable is not zero significant at the 95% level and other days are insignificant. These observations suggest that only Friday is the day of the effect of the SET Index.

Panel B displays the estimated coefficients of the ARMA process and P-values. By using t-test under the null hypothesis that each coefficient AR (p) and MA (q) is zero, we found that the P-values are all zero then each coefficient is not zero significant at the 99% level. Hence the SET Index return can be modeled by the ARMA (3,3) process.

The autocorrelation functions (ACF) are presented in Table 3, when we apply Ljung-Box to test serial correlation in P_t and r_t. We use the specified lag from the first to the tenth lags and the twenty-second lag. Serial correlation in P_t (column 2) confirmed as non-stationary but r_t is stationary because of ACF values (column 5) decrease very fast when the lag increases and is confirmed by the Augmented Dickey-Fuller test in Table 1. We analyze the significance of autocorrelation in the squared mean adjusted $(r_t-\mu_t)^2$ return series by using the Ljung-Box Q-test (The Ljung-Box Q-test is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero. The test is also distributed as a x^2 (q), where q is the number of lags). Since the P - value in column 10 is equal to zero then the squared mean adjusted return is non-stationary. Next, we apply Engle's ARCH test (The ARCH test is a test with the null hypothesis that, in the absence of ARCH components, we have α_i = 0 for all $i = 1, 2, ..., q$. The test is also distributed as a x^2 (q), where *q* is the number of lags). The test is also distributed as a x^2 (q), where q is the number of lags) (1982) to test ARCH effects of the squared mean adjusted return. The P-value in column 12 suggests the conditional heteroskedasticity.

Empirical methodology: This empirical part adopts the GARCH type and MRS-GARCH (1,1) models to estimate the volatility of the P_t. The GARCH type models that will be considered are GARCH (1,1), EGARCH (Model of EGARCH (1,1) is):

$$\ln(h_t) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \beta_1 \ln(h_{t-1}) + \xi \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$$

(where ξ is the asymmetry parameter to capture leverage effect) and GJR-GARCH (Model of GJR-GARCH(1,1) is:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 (1 - I_{\{\varepsilon_{t-1} > 0\}}) + \beta_1 h_{t-1} + \xi \varepsilon_{t-1}^2 (I_{\{\varepsilon_{t-1} > 0\}})$$

(where $I_{\{\varepsilon t-1\}} > 0$ is equal to one when ε_{t-1} is greater than zero and another is zero) (Klaanssen, 2002) (1,1). In order to account for the fat tails feature of financial returns, we consider three different distributions for the innovations: Normal (N), Student-t (t) and Generalized Error Distributions (GED).

Garch type models: Table 4, presents and estimation of the results for GARCH type models. It is clear from the table that almost all parameter estimates are highly significant at 1%. However, the asymmetry effect term ξ in EGARCH models is significantly different from zero, which indicates unexpected negative returns implying higher conditional variance as compared to the same size positive returns.

All models display strong persistence in volatility ranging from 0.8950 to 0.9521, that is, volatility is likely to remain high over several price periods once it increases.

Markov regime switching garch models: Estimation results and summary statistics of MRS-GARCH models are presented in Table 5. Most parameter estimates in MRS-GARCH are significantly different from zero at least at the 95% confidence level.

Table 3: ACF of SET Index closed price (P_t), log returns series (r_t), squared mean adjusted return and results for Engle's ARCH Test

	ACF of P_t			ACF of r_t			ACF of $(r_t-\mu_t)^2$			Engle's ARCH test	
Lag	ACF	LBQ Test	P-value	ACF	LBQ Test	P-value	ACF	LBQ Test	P-value	ARCH Test	P-value
1	0.9962	0.1033	0.0000	0.0672	4.69380	0.0303	0.2872	85.71260	0.0000	85.48390	0.0000
2	0.9922	0.2059	0.0000	0.0639	8.94150	0.0114	0.3126	187.3116	0.0000	145.2592	0.0000
3	0.9881	0.3077	0.0000	0.0111	9.06890	0.0284	0.2141	235.0199	0.0000	152.0515	0.0000
4	0.9839	0.4088	0.0000	-0.0175	9.38790	0.0521	0.1656	263.5800	0.0000	152.5688	0.0000
5	0.9798	0.5091	0.0000	-0.0261	10.0980	0.0725	0.2031	306.5847	0.0000	162.1801	0.0000
6	0.9758	0.6087	0.0000	-0.0844	17.5358	0.0075	0.1170	320.8663	0.0000	161.9628	0.0000
7	0.9723	0.7077	0.0000	0.0106	17.6543	0.0136	0.0808	327.6824	0.0000	162.9380	0.0000
8	0.9688	0.8061	0.0000	-0.0447	19.7439	0.0113	0.1018	338.5187	0.0000	164.0005	0.0000
9	0.9656	0.9039	0.0000	0.0634	23.9630	0.0044	0.1991	380.0243	0.0000	187.2375	0.0000
10	0.9621	1.0011	0.0000	0.0870	31.8949	0.0004	0.2701	456.4668	0.0000	217.0212	0.0000
22	0.9113	2.1086	0.0000	-0.0038	64.5758	0.0000	0.0168	726.4272	0.0000	256.9269	0.0000

Table 4: Summary results of GARCH type models

	GARCH			EGARCH			GJR-GARCH		
Parameter	N	t	GED	N	t	GED	N	t	GED
a_0	0. 1318***	0.1593***	0.1476***	-0.1605***	-0.1612***	-0.1628***	0.1576**	0.1828***	0.1715***
Std.err.	0.0274	0.0443	0.0425	0.0224	0.0332	0.0323	0.0314	0.0472	0.0465
a_1	0. 1528***	0.1659***	0.1609***	0.2476***	0.2537***	0.2512***	0.2173***	0.2421	2320***
Std. err.	0.0211	0.0357	0.0342	0.0295	0.0463	0.0442	0.0320	0.0527	0.0507
β_1	0.7854***	0.7605***	0.7698***	0.9521***	0.9446***	0.9490***	0.7755***	0.7507***	0.7600***
Std.err.	0.0206	0.0386	0.0361	0.0096	0.0154	0.0147	0.0238	0.0409	0.0391
ξ				-0.0759***	-0.0890***	-0.0823***	0.0749***	0.0757***	0.0758***
Std.err.				0.0159	0.0261	0.0242	0.0217	0.0358	0.0339
v		7. 3375***	1.3861***		7.8523***	1.4351***		7.6961***	1.4074***
Std.err.	1.6342	0.0805	1.9484			0.0872		1.7453	0.0809
Log (L)	-1682.9300	-1667.7000	-1667.1400	-1672.8400	-1660.3800	-1659.9800	-1677.2900	-1662.7900	-1662.6700
Persistence	0.9382	0.9264	0.9307	0.9521	0.9446	0.9490	0.8950	0.9096	0.9139
LBQ (22)	63.3245	63.3245	63.3245	63.3245	63.3245	63.3245	63.3245	63.3245	63.3245
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LBQ^2 (22)	673.3047	673.6150	673.6558	671.9037	672.9447	672.8664	672.0820	672.9410	672.9100
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*** and ** refer the significance at 99% and 95% confidence level respectively, LBQ (22) is Ljung-Box test of innovation at lag 22, LBQ^2 (22) is Ljung-Box test of squared innovation at lag 22 and P-value of the LBQ test in parentheses

Table 5: Summary results of MRS-GARCH models

	MRS GARCH							
	N		t		2t		GED	
Parameters State i	Low volatility	High volatility	Low volatility	High volatility	Low volatility	High volatility	Low volatility	High volatility
$a_0^{(1)}$	0.2163***	0.1850***	0.2350**	0.1898**	0.0000	0.1843**	0.0000	0.1763***
Std.err.	0.0844	0.0651	0.0893	0.1144	0.0926	0.1091	0.1090	0.0467
$A_1^{(i)}$	0.0000	0.0749***	0.0000	0.0763	0.9027***	0.0746	0.9619***	0.0681**
Std.err.	0.0560	0.0180	0.0264	69.2049	0.0270	50.2277	0.3552	0.0351
$\beta_0^{(i)}$	0.6052***	0.8845***	0.5842***	0.8750***	0.0000	0.7613***	0.0000	0.7762***
Std.err.	0.1205	0.0299	0.0456	0.1782	0.0465	0.1771	0.0207	0.0389
p	0.9582***	0.9603***	0.9785***	0.9822***				
Std.err.	0.0179	0.0105	0.0204	0.0066				
q	0.9737***	0.9776***	0.4409***	0.5696***				
Std.err.	0.0100	0.0202	0.0107	0.1093				
$V^{(i)}$			11.2518***	9.1414***	8.3746	1.4692***		
Std.err.			4.4451	4.2972	29.6785	0.0947		
Log(L)	-1658.0700	-1652.6900	-1651.180	-1654.0600				
σ^2	0.5479	1.7128	0.5652	3.8973	0.0000	1.1231	0.0000	0.9955
π	0.3862	0.6138	0.3607	0.6393	0.0370	0.9630	0.0397	0.9603
Persistence	0.6052	0.8919	0.5842	0.9513	0.9027	0.8359	0.9619	0.8229
LBQ(22)	62.6690	57.659	62.2970	55.8980				
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
LBQ^2(22)	678.9360	725.076	677.7940	720.355				
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	

*** and ** refer the significance at 99% and 95% confidence level respectively, LBQ (22) is Ljung-Box test of innovation at lag 22, LBQ^2 (22) is Ljung-Box test of squared innovation at lag 22 and P-value of the LBQ test in parentheses

Table 6: In-sample Evaluation Results

Models	N*	Pers*	Aic	R*	Sbic	R	Logl	R	Mse1	R	Mse2	R	Qlike	R	Mad1	R	Mad2	R	Hmse	R
Garch-N	4	0.9382	3.4533	13	3.4733	13	-1682.93	13	1.1944	13	43.6818	13	1.60764	12	7.4140	12	2.6653	13	0.8357	13
Garch-t	5	0.9264	3.4241	10	3.4491	6	-1667.70	10	1.1790	11	43.1525	8	1.60786	13	7.4197	13	2.6412	10	0.8330	12
Garch-GED	5	0.9307	3.4230	9	3.4480	5	-1667.14	9	1.1830	12	43.3345	10	1.60750	11	7.4045	11	2.6472	12	0.8329	11
Egarch-N	5	0.9521	3.4347	11	3.4597	7	-1672.84	11	1.1294	4	41.4361	3	1.58851	3	7.3832	9	2.5688	4	0.8240	7
EGARCH-t	6	0.9446	3.4112	5	3.4412	2	-1660.38	6	1.1233	1	41.1859	1	1.58958	5	7.3854	10	2.5629	3	0.8239	6
EGARCH-GED	6	0.9490	3.4104	4	3.4404	1	-1659.98	5	1.1244	2	41.2950	2	1.58904	4	7.3713	7	2.5627	2	0.8229	5
GJR-GARCH-N	5	0.8950	3.4438	12	3.4688	12	-1677.29	12	1.1635	10	42.1079	6	1.59727	6	7.3687	6	2.6464	11	0.8302	10
GJR-GARCH-t	6	0.9096	3.4161	8	3.4461	4	-1662.79	8	1.1535	8	41.7429	4	1.59817	8	7.3728	8	2.6378	8	0.8293	9
GJR-GARCH-GED	6	0.9139	3.4159	7	3.4459	3	-1662.67	7	1.1559	9	41.8707	5	1.59759	7	7.3591	5	2.6384	9	0.8287	8
MRS-GARCH-N	10	0.9581	3.4147	6	3.4647	11	-1658.07	4	1.1518	7	43.1296	7	1.58837	2	7.2508	3	2.5784	6	0.8171	3
MRS-GARCH-2t	12	0.8888	3.4047	1	3.4647	10	-1651.18	1	1.1373	5	43.6584	12	1.60437	9	7.1590	2	2.5816	7	0.8095	2
MRS-GARCH-t	11	0.8964	3.4057	2	3.4607	8	-1652.69	2	1.1261	3	43.4001	11	1.60655	10	7.1021	1	2.5568	1	0.8035	1
MRS-GARCH-GED	11	0.9484	3.4085	3	3.4635	9	-1654.06	3	1.1473	6	43.1537	9	1.58770	1	7.2959	4	2.5696	5	0.8185	4

*N=Number of Parameters, PERS=Persistence, R=Rank

Table 7: Result loss function of out-of-sample

Panel A: Result loss function of out-of-sample with forecasting volatility for one day ahead

Model	MSE1	R	MSE2	R	QLIKE	R	MAD1	R	MAD2	R	HMSE	R	SR	R
Garch-N	0.9307	2	11.4131	6	2.3322	13	1.0260	2	2.178	2	14.9938	13	0.5333	9
Garch-t	0.9386	3	11.4142	7	2.3287	11	1.0269	3	2.1793	3	14.7135	11	0.5333	9
Garch-GED	0.9305	1	11.4087	5	2.3317	12	1.0254	1	2.1763	1	14.8922	12	0.5333	9
Egarch-N	1.2836	8	11.3594	3	2.0482	6	1.1036	6	2.3922	7	3.8081	5	0.5667	3
Egarch-t	1.3391	10	11.4262	8	2.0389	3	1.1123	9	2.4231	10	3.4130	1	0.5833	1
EGARCH-GED	1.3073	9	11.3871	4	2.0423	4	1.1067	8	2.4044	8	3.6081	3	0.5833	1
GJR-GARCH-N	1.3396	11	11.8156	9	2.0448	5	1.1127	10	2.4487	11	3.9283	6	0.5667	3
GJR-GARCH-t	1.3835	13	11.9325	13	2.0333	1	1.1200	13	2.4790	13	3.5696	2	0.5500	7
GJR-GARCH-GED	1.3627	12	11.8783	11	2.0364	2	1.1164	11	2.4653	12	3.6997	4	0.5500	7
MRS-GARCH-N	1.2383	4	11.1717	1	2.1023	8	1.1046	7	2.3802	6	4.4324	8	0.5000	12
MRS-GARCH-2t	1.2827	7	11.8513	10	2.1618	9	1.0748	4	2.3403	4	8.2194	9	0.5667	3
MRS-GARCH-t	1.2797	6	11.2014	2	2.0985	7	1.1178	12	2.4106	9	4.2068	7	0.4833	13
MRS-GARCH-GED	1.2437	5	11.9301	12	2.1635	10	1.0756	5	2.3517	5	8.3499	10	0.5667	3

Panel B: Result loss function of out-of-sample with forecasting volatility for five days ahead. (A week)

Model	MSE1	R	MSE2	R	QLIKE	R	MAD1	R	MAD2	R	HMSE	R	SR	R
Garch-N	1.3612	12	39.236	12	4.3247	12	1.1097	6	5.266	8	1.5169	13	0.7667	11
Garch-t	1.3653	13	39.0978	11	4.3272	13	1.1234	10	5.3199	10	1.4435	11	0.7667	11
Garch-GED	1.3605	11	39.0643	10	4.3243	11	1.1135	8	5.277	9	1.476	12	0.7667	11
Egarch-N	0.9829	3	31.3583	8	4.1335	3	0.8642	3	4.2087	3	0.58	8	0.8833	3
Egarch-t	0.9769	2	29.5375	6	4.1243	1	0.8485	1	4.1154	1	0.5291	6	0.9167	1
Egarch-GED	0.9753	1	30.3812	7	4.1269	2	0.8528	2	4.1483	2	0.5546	7	0.9000	2
Gjr-garch-N	1.0412	6	26.2744	2	4.2308	7	1.1102	7	5.1685	6	0.429	3	0.8500	4
Gjr-garch-t	1.0374	5	26.6931	3	4.2394	9	1.1384	11	5.3234	11	0.4225	1	0.8500	4
Gjr-garch-ged	1.0342	4	26.2502	1	4.2329	8	1.1204	9	5.2264	7	0.4229	2	0.8500	4
Mrs-garch-n	1.2209	7	36.7342	9	4.2182	5	1.206	12	6.044	12	0.4883	4	0.8333	8
Mrs-garch-2t	1.2774	9	28.8287	5	4.2184	6	0.9939	5	4.6311	5	0.6579	10	0.8333	8
Mrs-garch-t	1.2637	8	39.9566	13	4.2505	10	1.2768	13	6.4067	13	0.5125	5	0.8500	4
Mrs-garch-ged	1.2775	10	27.5975	4	4.2139	4	0.9815	4	4.5268	4	0.6421	9	0.8000	10

Panel C: Result loss function of out-of-sample with forecasting volatility for ten days ahead. (Two weeks)

Model	MSE1	R	MSE2	R	QLIKE	R	MAD1	R	MAD2	R	HMSE	R	SR	R
Garch-N	1.9098	7	83.8490	3	5.2852	7	1.6278	6	9.11900	6	0.5595	10	0.7667	12
Garch-t	2.0007	9	90.8608	6	5.3063	10	1.703	9	9.67070	8	0.5519	8	0.7500	13
Garch-ged	1.9512	8	87.5095	5	5.2957	9	1.6645	7	9.38710	7	0.5554	9	0.7833	8
Egarch-N	1.4102	3	95.5747	10	5.2121	2	1.5346	4	8.84040	4	0.8871	13	0.8333	2
Egarch-t	1.3958	1	93.8165	7	5.2106	1	1.5242	3	8.75230	3	0.8556	11	0.8333	2
Egarch-GED	1.4003	2	95.2004	8	5.2136	3	1.5373	5	8.84360	5	0.8859	12	0.8333	2
Gjr-garch-N	2.0831	11	101.1884	11	5.3156	11	1.8032	10	10.62690	10	0.4039	2	0.7833	8
Gjr-garch-t	2.2168	13	113.8863	13	5.3376	13	1.8748	13	11.22480	13	0.4133	5	0.8000	6
Gjr-garch-ged	2.1429	12	107.2969	12	5.3256	12	1.8339	12	10.88700	12	0.4079	4	0.8000	6
Mrs-garch-N	1.9057	6	87.1919	4	5.2639	6	1.6939	8	9.83390	9	0.3783	1	0.8500	1
Mrs-garch-2t	1.6556	5	70.3567	2	5.2385	5	1.3956	1	7.43980	1	0.4352	7	0.7833	8
Mrs-garch-t	2.0646	10	95.3080	9	5.2887	8	1.8076	11	10.65460	11	0.4069	3	0.8333	2
Mrs-garch-ged	1.6434	4	68.9504	1	5.2337	4	1.4007	2	7.53820	2	0.4210	6	0.7833	8

Panel D: Result loss function of out-of-sample with forecasting volatility for twenty-two days ahead. (A month)

Model	MSE1	R	MSE2	R	QLIKE	R	MAD1	R	MAD2	R	HMSE	R	SR	R
Garch-N	14.1768	60	913.3033	60	6.314	30	4.1168	60	29.774	6	0.6512	40	0.5500	20
Garch-t	14.8896	80	969.6524	80	6.346	50	4.2464	80	31.2089	8	0.66	80	0.5500	20
Garch-GED	14.5087	70	933.3108	70	6.3291	40	4.1817	70	30.4736	7	0.6565	60	0.5500	20
Egarch-N	9.5602	10	631.9223	10	6.5527	11	4.0874	30	27.1309	3	4.9652	12	0.5500	20
Egarch-t	9.6971	30	635.4651	20	6.5539	12	4.0956	40	27.212	4	4.9013	11	0.5500	20
Egarch-GED	9.6581	20	637.1163	30	6.5726	13	4.1044	50	27.2486	5	5.0823	13	0.5500	20
Gjr-garch-N	17.9597	11	1377.439	11	6.4293	80	4.5093	11	34.8962	11	0.6511	30	0.5167	90
Gjr-garch-t	18.6557	13	1439.5115	13	6.4532	10	4.6106	13	36.1021	13	0.6587	70	0.5000	10
Gjr-garch-ged	18.2373	12	1392.524	12	6.4384	90	4.5515	12	35.3763	12	0.6547	50	0.5000	10
Mrs-garch-n	16.7158	10	1247.1304	10	6.4006	60	4.3003	90	32.5696	90	0.6279	10	0.5500	20
Mrs-garch-2t	12.2903	40	651.7878	40	6.2225	10	3.6891	10	24.9944	10	0.737	10	0.5000	10
Mrs-garch-t	16.687	90	1224.4922	90	6.4033	70	4.3627	10	33.1213	10	0.6402	20	0.6333	10
Mrs-garch-ged	12.5857	50	686.0672	50	6.2299	20	3.7129	20	25.321	20	0.7226	90	0.5000	10

But a_0, a_1 and β_1 are insignificantly different in some states. All models display strong persistence in volatility ranging from 0.5842-0.9619, that is, volatility is likely to remain high over several price periods once it increases.

In-sample evaluation: We use various goodness-of-fit statistics to compare volatility models. These statistics are Akaike Information Criteria (AIC), Schwarz Bayesian Information Criteria (SBIC) and Log-likelihood (LOGL) values. In Table 6, the results of goodness-of-fit statistics and loss functions:

Loss functions:

$$MSE_1 = \frac{1}{n}\sum_{t=1}^{n}\left(\sigma_{t+K} - \sqrt{h_{t,K}}\right)^2,$$

$$MSE_2 = \frac{1}{n}\sum_{t=1}^{n}\left(\sigma^2_{t+K} - h_{t,K}\right)^2$$

$$,QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left(\ln(h_{t,K}) - \frac{\sigma^2_{t+K}}{h_{t,K}}\right),$$

$$MAD_1 = \frac{1}{n}\sum_{t=1}^{n}\left|\sigma_{t+K} - \sqrt{h_{t,K}}\right|,$$

$$MAD_2 = \frac{1}{n}\sum_{t=1}^{n}\left|\sigma^2_{t+K} - h_{t,K}\right|,$$

$$HMSE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{\sigma^2_{t+K}}{h_{t,K}} - 1\right)^2$$

For all volatility models are presented. According to SBIC, the EGARCH model with GED-distribution performs best in modeling the SET Index volatility. However, the MSE1 and MSE2 suggest that the EGARCH with a t - distribution performs best in SET Index volatility. Also AIC and LOGL suggest that the MRS-GARCH-2t performs best in SET Index volatility. MAD1, MAD2 and HMSE suggest that the MRS-GARCH-t performs best in SET Index volatility and in QLIKE the MRS-GARCH with GED-distribution performs best in SET Index volatility.

Forecasting volatility in out-of-sample: We investigate the ability of MRS-GARCH and GARCH type models to forecast volatility of the SET Index in out-of-sample.

In Table 7, we present the results of loss function of out-of-sample with forecasting volatility for one day ahead, five days ahead (a week), ten days ahead (two weeks) and twenty-two days ahead (a month). We found the GARCH-type models perform best in the short term (one day and a week) for forecasting volatility of the SET Index. Additionally, we have reported a particular sign-test, the Success Ratio (SR), i.e.:

$$SR = \frac{1}{n}\sum_{j=1}^{n} I_{\{\hat{\sigma}^2_{t+j,1}\cdot\hat{h}_{t+j,1}>0\}} \quad \text{where I is indicator function}$$

$$\hat{\sigma}^2_{t+j,1} = \sigma^2_{t+j,1} - \bar{\sigma}^2_{t,1} \text{ and } \hat{h}_{t+j,1} = h_{t+j,1} - \bar{h}_{t,1}$$

The SR test is simply the fraction of volatility forecasts that have the same sign as volatility realizations. From the table we can see that the GARCH-type models do a great job in correctly predicting the sign of the future volatility in the short term.

On the other hand, we found that the MRS-GARCH models perform best in the long term (two weeks and a month) for forecasting the volatility of the SET Index. Also, the SR test MRS-GARCH models do a great job in correctly predicting the future volatility in the long term.

DISCUSSION

For forecasting volatility in the long term in SET Index, the MRS-GARCH models perform best.

CONCLUSION

In this study, we modeled the returns of the SET Index by mean equation with the day of the week effect and the autoregressive moving-average order p and q (ARMA (p, q)) and forecasted the volatility of the SET Index by the GARCH, EGARCH, GJR-GARCH and MRS-GARCH models. Moreover we compared their volatility forecast performance with one day, one week, two weeks and one month returns.

Friday is day effect of the SET Index. Displays the first estimate of return equation with ARMA (3, 3). The GARCH-type models perform best in the short term (one day and a week). On the other hand, the MRS-GARCH models perform best in the long term (two weeks and a month) for forecasting volatility of the SET Index.

For further study, three or four volatility regime settings can be considered rather than two-volatility regimes or using Markov Regime Switching with other volatility models e.g. EGARCH, GJR. In addition, the performance of the MRS-GARCH models can be compared in terms of their ability to forecast Value at Risk (VaR) for long and short positions.

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