Modeling and Forecasting Volatility of the Malaysian and the Singaporean stock indices using Asymmetric GARCH models and Non-normal Densities

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Abstract

This paper examines and estimate the three GARCH(1,1) models (GARCH, EGARCH and GJR-GARCH) using the daily price data. Two Asian stock indices KLCI and STI are studied using daily data over a 14-years period. The competing Models include GARCH, EGARCH and GJR-GARCH used with three different distributions, Gaussian normal, Student-t, Generalized Error Distribution. The estimation results show that the forecasting performance of asymmetric GARCH Models (GJR-GARCH and EGARCH), especially when fat-tailed asymmetric densities are taken into account in the conditional volatility, is better than symmetric GARCH. Moreover, its found that the AR(1)-GJR model provide the best out-of-sample forecast for the Malaysian stock market, while AR(1)-EGARCH provide a better estimation for the Singaporean stock market.

Keywords: ARCH-Models, Asymmetry, Stock market indices and volatility modeling
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1. Introduction

Traditional regression tools have shown their limitation in the modeling of high-frequency (weekly, daily or intra-daily) data, Assuming that only the mean response could be changing with covariates while the variance remains constant over time often revealed to be an unrealistic assumption in practice. This fact is particularly obvious in series of financial data where clusters of volatility can be detected visually. Indeed, it is now widely accepted that high frequency financial returns are heteroskedastic.

Modeling financial time series is not an easy task because they possess some special characteristics (see Ruey S. Tasy (2002)). They often exhibit volatility clustering (i.e. large changes tend to be followed by large changes and small changes by small changes), often exhibit leptokurtosis (i.e., the distribution of their returns is fat tailed) and often show leverage effect (i.e. changes in stock prices tend to be negatively correlated with changes in volatility which implies volatility is higher after negative shocks than after positive shocks of the same magnitude). In order to capture the first two characteristics of financial time series, Engle (1982) propose to model time-varying conditional variance with the Auto-Regressive Conditional Heteroskedasticity (ARCH) processes that use past disturbances to model the variance of the series. Early empirical evidence shows that high ARCH order has to be selected in order to catch the dynamic of the conditional variance. The Generalized ARCH (GARCH) model of Bollerslev (1986) is an answer to this issue. It is based on an infinite ARCH specification and it allows reducing the number of estimated parameters from ∞ to only 2. Both models allow taking the first two characteristics into account, but their distributions are symmetric and therefore fail to model the third stylized fact, namely the "leverage effect". To solve this problem, many nonlinear extensions of the GARCH model have been proposed. Among the most widely spread are the Exponential GARCH (EGARCH) of Nelson (1991), the so-called GJR of Glosten, Jagannathan, and Runkle (1993).

Unfortunately, GARCH models often do not fully capture the thick tails property of high frequency financial time series. This has naturally led to the use of non-normal distributions to better model this excess kurtosis, such as Student-t distribution, generalized error distribution, Normal-Poisson, Normal-Lognormal and Bernoulli-Normal distributions. Liu and Brorsen (1995) introduced the use of an asymmetric stable density to capture the skewness property well. However, since the variance of such a distribution rarely exists, it is not popular in practice.

Fernandez and Steel (1998) introduced the skewed Student-t distribution, which captures both the skewness and kurtosis. Lambert and Laurent (2000, 2001) extended this to the GARCH model.

In this paper, we compare the performance of the GARCH, EGARCH and GJR-GARCH models and we also introduce different densities (Normal, Student-t and GED).

2- Empirical Methodology

2.1 ARCH-Models

Over the past two decades, enormous effort has been devoted to modeling and forecasting the movement of stock returns and other financial time series. Seminal work in this area of research can be attributed to Engle (1982), who introduced the standard Autoregressive Conditional Heteroskedasticity (ARCH) model. Engle's process proposed to model time-varying conditional volatility using past innovations to estimate the variance of the series as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (1)$$

where ε_t denotes a discrete-time stochastic taking the form of $\varepsilon_t = z\sigma_t$ where $z_t \sim iid\ (0,1)$, and σ_t is the conditional standard deviation of return at time t, assuming that market returns follow AR(p) process as follows:

$$R_t = \varphi_0 + \sum_{i=1}^{q} \phi_i R_{t-i} + \varepsilon_t \qquad (2)$$

2.1.1 GARCH

Further extension introduced by Bollerslev (1986) known as the Generalized ARCH (GARCH) model which suggests that the time-varying volatility process is a function of both past disturbances and past volatility. The GARCH model is an infinite order ARCH model generated by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (3)$$

where α_0, α and β are non-negative constants. For the GARCH process to be defined, it is required that $\alpha > 0$.

2.1.2 EGARCH

The first asymmetric GARCH model that is looked at is the EGARCH model of Nelson (1991), which looks at the conditional variance and tries to accommodate for the asymmetric relation between stock returns and volatility changes. Nelson implements that by including an adjusting function *g(z)* in the conditional variance equation, it in turn becomes expressed by:

$$\ln\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i g(z_{t-i}) + \sum_{j=1}^{p}\beta_j \ln(\sigma_{t-j}^2) \qquad (4)$$

where $z_t = \varepsilon_t / \sigma_t$ is the normalized residual series.

The value of $g(z_t)$ is a function of both the magnitude and sign of z_t and is expressed as:

$$g(z_t) = \underbrace{\theta_1 z_t}_{sign\ \ effect} + \underbrace{\theta_2[|z_t| - E|z_t|]}_{magnitude\ \ effect} \qquad (5)$$

Notice moreover that $E|z_t|$ depends on the assumption made on the unconditional density. This point will be clarified in Section 3. The EGARCH model differs from the standard GARCH model in two main respects. First, it allows positive and negative shocks to have a different impact on volatility. Second, the EGARCH model allows big shocks to have a greater impact on volatility than the standard GARCH model.

2.1.3 GJR-GARCH

This model is proposed by Glosten, Jagannathan, and Runkle (1993). Its generalized form is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}(\alpha_i\varepsilon_{t-1}^2 + w_i S_{t-i}^{-}\varepsilon_{t-1}^2) + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \qquad (6)$$

where S_t^- is a dummy variable.

In this model, it is assumed that the impact of ε_t^2 on the conditional variance σ_t^2 is different when ε_t is positive or negative. That is why the dummy variable S_t^- takes the value '0' (respectively '1') when ε is positive (negative). Note that the TGARCH model of Zakoian (1994) is very similar to GJR but models the conditional standard deviation instead of the conditional variance.

3. Densities Assumptions

The GARCH models are estimated using a maximum likelihood (ML) methodology[3]. The logic of ML is to interpret the density as a function of the parameters set, conditional on a set of sample outcomes. This function is called the likelihood function.

Failure to capture fat-tails property of high-frequency financial time series has led to the use of non-normal distributions to better model excessive third and fourth moments. The most commonly used are the normal distribution ,Student *t*- distribution[4], Skewed student-*t* distribution[5] and the Generalized Error Distribution (GED)[6].

Since it may be expected that excess kurtosis and skewness displayed by the residuals of conditional heteroscedasticity models will be reduced when a more appropriate distribution is used, we consider three distributions in this study: the Normal, the Student-t (including a “tail” parameter) and the Skewed Student-t (including a “tail” parameter and an asymmetric parameter).

3.1. Gaussian

The normal distribution is the most widely used when estimating GARCH models. The log-likelihood function for the standard normal distribution for the stochastic process of innovations given by (1) is given by:

$$L_{normal} = -\frac{1}{2}\sum_{t=1}^{T}[\ln(2\pi) + \ln(\sigma_t^2) + z_t] \qquad (7)$$

where T is the number of observations.

3.2. Student-t

For a Student-t distribution, the log-likelihood is:

$$L_{student-t} = \ln\left[\Gamma\left(\frac{v+1}{2}\right)\right] - \ln\left[\Gamma\frac{v}{2}\right] - \frac{1}{2}\ln[\pi(v-2)] - \frac{1}{2}\sum_{t=1}^{T}\left[\ln\sigma_t^2 + (1+v)\ln\left(1+\frac{z_t^2}{v-2}\right)\right] \qquad (8)$$

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[3] GARCH models can also be estimated by Quasi Maximum Likelihood (QML) method introduced by Bollerslev and Wooldridge (1992) and by Generalized Method of Moments (GMM) suggested and implemented by GJR (1991).

[4] Suggested by Bollerslev (1987); Baillie and Bollerslev (1989); Kaiser (1996); and Beine, Laurent, and Lecourt (2000).

[5] Suggested by Fernandez and Steel (1998) and Lambert and Laurent (2000, 2001) for better capture of skewness.

[6] Suggested by Nelson (1991) and Kaiser (1996).

where ν is the degrees of freedom, $2 < \nu \leq \infty$ and $\Gamma(\cdot)$ is the gamma function. When $\nu \to \infty$, we have the Normal distribution, so that the lower ν the fatter the tails.

3.3. Generalized Error Distribution (GED)

Skewness and kurtosis are important in financial applications in many respects (in asset pricing models, portfolio selection, option pricing theory or Value-at-Risk among others). Therefore, a distribution that can model these two moments is appropriate, the GED log-likelihood function of a normalized random error is:

$$L_{GED} = \sum_{t=1}^{T}\left[\ln\left(v/\ \lambda_v\right) - 0.5\left|\frac{z_t}{\lambda_v}\right|^{v} - \left(1+v^{-1}\right)\ln(2) - \ln\Gamma\left(1/v\right) - 0.5\ln\left(\sigma_t^2\right)\right] \qquad (9)$$

Where $\lambda_v = \sqrt{\frac{\Gamma\left(1/v\,2^{-2/v}\right)}{\Gamma\left(3/v\right)}}$

and ν is a positive parameter governing the thickness of the tails of the distribution. Note that for ν=2, constant λ=1, and the GED is the standard normal distribution. For more details about the generalized error distribution, see Hamilton (1994).

4. Data and Methodology

4.1 Data

All data are the daily data obtained from DataStream. In the database, the daily return R_t consisted of daily stock closing price P_t, which is measured in local currency[7]. Our measurements include Strait Times Index in Singapore (STI) and Kuala Luampur Composite Index in Malaysia (KLCI).

The sample consists of 3652 daily observations on stock returns of the KLCI and the STI indices. It covers a fourteen-year period, beginning on January 2, 1991 and ending on December 31, 2004[8]. For illustrative purposes, Figure (1) compares the two used indices' daily closing values taken across the sample period. Furthermore, Figure (2) looks at the behavior of the KLCI

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[7] I measure the stock returns in local currency just as Base and Karolyi (1994) and Karolyi (1995) do in their studies. On the other hand, the stock returns in Karolyi (1995) and Ng (2000) is denominated in US dollars. Note that when market returns are denominated in US dollars, international investors are assumed to be unhedged against foreign exchange risk. However, Dumas and Solnik (1995) and De Santis and Ge´rard (1998) insist the importance of currency risk on stock markets. Thus, we assume that the investors are hedged against it.

[8] All the data were supplied by Datastream.

and STI returns, respectively, over the sample period. The data of stock price exhibit large fluctuations during the whole period. The indices prices are transformed into their returns so that we obtain stationary series. The transformation is;

$$R_t = 100 * [ln(R_t) / ln(R_{t-1})]$$

Table 1

Summary Statistics for daily returns 1 January 1991-31 December 2004

	Sample	Mean	St.Dev.	Skewness	Ex-Kurtosis	Q(20)	$Q^2(20)$	J.Bera	ARCH(2)
KLCI	3652	0.0163	1.5731	0.5156	40.7437	105.69	1826.321	25255	580.8460
STI	3652	0.0216	1.2908	0.2884	11.2086	101.39	952.0316	19150	101.1180

The descriptive statistics of both indices in Table (1) over the sample period highlights the following:

- Mean returns for the STI Index is slightly larger than the KLCI, whereas, the non-conditional variance for the KLCI Index is larger than the STI. Furthermore, there is evidence of volatility clustering (See figure (2)) and that large or small asset price changes tend to be followed by other large or small price changes of either sign (positive or negative). This implies that stock return volatility changes over time. Furthermore, the figures indicate a sharp increase in volatility starting from the year 1997.
- The returns for both indices are positively skewed. The null hypothesis for skewness coefficients that conform with a normal distribution's value of zero has been rejected at the 5 percent significance level.
- The returns for both indices also display excess kurtosis. The null hypothesis for kurtosis coefficients that conform to the normal value of three is rejected for both indices.
- The high values of Jarque-Bera test for normality decisively rejects the hypothesis of a normal distribution;

- Moreover, Engle (1982) LM test indicates the presence of ARCH processes in the conditional variance. Both indices show signs of heteroskedasticity in sample, indicating the legitimacy of using ARCH/GARCH type models.

The statistical results for both indices appear to have very similar characteristics. They both display positive skewness, were found to be deviating from normality, and display a degree of serial correlation. These stylized results are consistent with previous empirical work on the Asian-Pacific markets [9] and similar to a number of previous empirical works on matured markets[10].

Finally, if we look at the sample, given the fact that the return series exhibited some excess kurtosis, it can also be predicted that a fatter-tailed distribution such as the student-*t*, or maybe a GED, should generate better results than just simply a normal distribution or a more complex asymmetric student-*t*.

To estimate and forecast these indices, we use SAS 9.1 software; SAS/ETS a package dedicated to the estimation and the forecasting for time series data. It is written in the SAS programming language, it offers a lot of features that are not available in traditional econometric software.

To assess the performance of the GARCH models candidate in forecasting the conditional variance, we compute 9 measures of statistic fit:

1. Mean Squared Errors (MSE)
2. Mean Absolute Error (MAE)
3. Mean Absolute Percentage Error (MAPE)
4. Theil Inequality Coefficient (TIC)
5. Akaike Information Criterion (AIC)
6. Schwarz Bayesian Criterion (BIC)
7. Amemiya Prediction Criterion (APC)
8. Adjusted R^2 ($AJDR^2$)
9. Amemiya Adjusted R^2 (AR^2)

The measures above may require some brief additional explanations. The MSE is:

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[9] See, S.-J. Kim (2003), K. Nam et al.(2003) , Ng. A. (2000) and T. Miyakoshi (2003).

[10] Fama (1976) showed that the distribution of both daily and monthly returns for the Dow Jones departs from normality, and are skewed, leptokurtic, and volatility clustered. Furthermore, Kim and Kon (1994) found the same for the S&P 500. Finally, Peters (2001) showed similar results for two major European stock indices (FTSE 100 and DAX 30).

$$\frac{1}{h+1}\sum_{t=s}^{s+h}(\hat{\sigma}_t^2-\sigma_t^2)^2$$

where h is the number of steps ahead, in this paper h is equal to 1(one step ahead), S the sample size, $\hat{\sigma}^2$ the forecasted variance and σ^2 the actual variance.

The MAE is:

$$\frac{1}{h+1}\sum_{t=s}^{s+h}|\hat{\sigma}_t^2-\sigma_t^2|$$

The MAPE is:

$$\frac{1}{h+1}\sum_{t=s}^{s+h}\left|\left(\hat{\sigma}_t^2-\sigma_t^2\right)/\sigma_t^2\right|$$

The TIC is:

$$TIC=\frac{\sqrt{MSE}}{\sqrt{1/h+1\sum_{t=s}^{s+h}\sigma^2}+\sqrt{1/h+1\sum_{t=s}^{s+h}\hat{\sigma}^2}}$$

Theil inequality coefficient is a scale invariant measure that always lies between zero and one, where zero indicates a perfect fit.

The AIC is:

$$AIC=s\ln(SSE/s)+2k$$

where $SSE=\sum_{t=0}^{s}(\sigma_t-\hat{\sigma}_t)^2$, where is the one step predicted value for the series, k is the number of estimated parameters.

The BIC is:

$$AIC=s\ln(SSE/s)+k\ln(s)$$

The APC, Amemiya prediction criterion is defined as:

$$APC=\left(\frac{s+k}{s-k}\right)\frac{1}{s}SSE$$

The AJDR^2 is:

$$AJDR^2 = 1 - \left(\frac{s-1}{s-k}\right)\left(1 - R^2\right)$$

The AR^2 is:

$$AR^2 = 1 - \left(\frac{s+k}{s-k}\right)\left(1 - R^2\right)$$

The R^2 statistic provides the proportion of variances explained by the forecast (i.e., the higher the R^2, the better the forecasts).

4.2 Empirical Results

A maximum likelihood approach is used to estimate the three models (3), (4) and (6), with the three underlying error distributions. Low-order lag lengths were found to be sufficient to model the variance dynamics over very long sample periods[11].

This section presents the estimation results and the validity, post estimation tests, of the estimated model. Table 2, 3 and 4 presents the estimation results for the parameters for the GARCH, EGARCH and GJR-GARCH models while Tables 5-10 reports some useful in-sample statistics. Forecasting ability is reported by the different models. Table11 compares the models based on the GARCH specifications for both series. Some comments can be made on these results:

Several conclusions can be drawn when analyzing these results:

- The use of asymmetric GARCH models seems to be justified. All asymmetric coefficients are significant at standard levels. Moreover, the Akaike information criteria (henceforward AIC) and the log-likelihood values highlight the fact that EGARCH or GJR models better estimate the series than the traditional GARCH.

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[11] French, Schwert, and Stambaugh (1987) analyze daily S&P stock index data for 1928-1984 for a total of 15,369 observations and require only four parameters in the conditional variance equation (including the constant).

- As, is typical of GARCH model estimates for financial asset returns data, the sum of the coefficients on the lagged squared error and the lagged conditional variance is close to unity 0.99 and .98 for KLCI and STI respectively, this implies that shocks to the conditional variance well be highly persistent indicating that large changes and small changes tend to be followed by small changes, this mean volatility clustering is observed in both KLCI and STI financial returns series.
- Regarding the densities (tables 5-7), the Student-t distributions clearly outperform the Gaussian and (GED). Indeed, the log-likelihood function strongly increases when using the Student-t, leading to BIC criteria of 3.09 and 3.04 with the Gaussian versus 2.98 and 2.97 with the non-normal densities, for the KLCI and the STI respectively using AR(1)-GARCH, similar result for both AR(1)-EGARCH and AR(1)-GJR .
- All the models seem to do a good job in describing the dynamic of the first two moments of the series as shown by the Box-Pierce statistics for the squared residuals which are all non-significant at 5% level.
- LM test for presence of ARCH effects at lag 2, indicate that the conditional hetroskedasity that existed when the test was performed on the pure return series (see table 1) are removed for GARCH but remains for EGARCH and GJR using the Gaussian distribution. EGARCH and GJR models with student-t and GED distributions shows that the conditional hetroskedasity are successfully removed which are all non-significant at 5% level. From the previous, GARCH model perform better with Gaussian distribution however, EGARCH and GJR models give better results with student-t distribution.
- Similar to the results found in various markets, the leverage effect term $\boldsymbol{w_1}$ ($\boldsymbol{g_1}$) in the GJR (EGARCH) is statistically significant at levels (p-value equal 0.01 and 0.05 respectively) with negative sign, as expected that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, indicating that the existence of leverage effect is observed in returns of the KLCI and STI stock market index.
- However, the comparison between models with each density (normal versus non-normal) shows that, according to the different measures used for modeling the volatility, the GJR-GARCH model provides the best in-sample estimation for KLCI having slight difference with EGARH and clearly outperforms the symmetric models. The opposite is true for STI where EGARCH provides the best in-sample estimation. Moreover, it is found that the student-t density is more appropriate for modeling KLCI and STI stock market index

volatility in particular; Skewness and excess kurtosis are clearly observed in the return time series.

- Testing the validation of GARCH models different tests are performed to see if the autocorrelation in the squared return has successfully been removed Ljung-Box-Pierce Q-test in the validation part is to test autocorrelations and partial autocorrelations of the squared standardized residuals. The test is made on the squared standardized residuals with lag 20 to test for remaining ARCH in the variance equation and to check the specification of the variance equation. If the variance equation is correctly specified, all Q-statistics should not be significant. The results indicate that no significance correlation exists.
- Moreover, Engle's ARCH-test carries out Lagrange multiplier tests to test whether the standardized residuals exhibit additional ARCH effects. If the variance equation is correctly specified, there should be no ARCH effects left in the standardized residuals. The result from Engle's ARCH-test is presented in table (5) to (10). This indicates that we have successfully removed the conditional heteroskedasticity that existed when the test was performed on the pure return series in section 4.1 (data description)
- For out-sample, the comparison between models strongly supports the use of asymmetric GARCH models. Among these three models, GJR outperforms EGARCH for the KLCI while the opposite is true for the STI index. GJR provides less satisfactory results while symmetric GARCH clearly gives the poorest forecasts.
- In particular, the R^2 is higher when using asymmetric GARCH. For instance, when using a Student-t distribution, it ranges from 0.927 to 0.946 with the asymmetric GARCH versus 0.925 with the symmetric GARCH for the KLCI and it goes from 0.920 to 0.923 versus 0.893 with the symmetric GARCH for the STI.

5. Conclusion

Stock prices volatility has received a great attention from both academies and practitioners over the last two decades because it can be used as a measure of Risk in financial Markets. Recent portfolio selection, asset pricing, value at risk, option pricing and hedging strategies highlight the importance of modeling and forecasting the conditional volatility of returns.

This paper contributes to the Literature of volatility modeling in two aspects. First, we use a data set from an emerging market. Secondly we estimate the alternative ARCH-type models (symmetric and asymmetric GARCH Models). The comparison was focused on two different aspects: the difference between symmetric and asymmetric GARCH (i.e., GARCH versus EGARCH and GJR-GARCH) and the difference between normal tailed symmetric, fat-tailed symmetric and fat-tailed asymmetric distributions (i.e. Normal versus Student-t and Generalized Error Distribution) for estimating the KLCI and STI stock market index returns volatility.

The results indicate, according to the in-sample statistics that the estimated parameters of the AR(1)-GJR Model, the coefficients of ARCH($\boldsymbol{\alpha_1}$) and GARCH($\boldsymbol{\beta_1}$) in the conditional variance equation of the AR(1)-GJR in the both markets are highly significant with p-value equal 0.016 and 0.019 for KLCI , 0.017 and 0.020 for STI.

As expected with the results found in various markets, the leverage effect term ($\boldsymbol{w_1}$) in both markets KLCI and STI the AR(1)-GJR Model is statistically significant at levels (p-value equal 0.014 and 0.015 respectively) with a negative sign, which indicate that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, indicating that the existence of leverage effect is observed in returns of the KLCI and STI stock market index.

However, the comparison between models with each density (normal versus non-normal) shows that, according to the different measures used for the performance of volatility forecast, the GJR-GARCH model provides the best out-sample estimation for KLCI and EGARCH model provides the best out-sample estimation for STI and clearly those asymmetric models outperforms symmetric models. Our results show that noticeable improvements can be made when using an GARCH models in the conditional variance (and, among the tested models, EGARCH and GJR seem to outperform GARCH). Moreover, non-normal distributions provide better in-sample results than the Gaussian distribution. Out-of-sample results show however less evidence of superior forecasting ability.

Briefly, looking at the overall results, we can argue that the asymmetric models (GJR and EGARCH model) coupled with a Student-t distribution for the innovations performs very well with the dataset we have investigated. The models seems to capture the dynamics of the first and second moments of the KLCI and STI stock market index returns series

Finally, several directions for future researches could be investigated to forecast the volatility of the KLCI and STI financial time series. First, “true volatility” could be better estimated by selecting shorter time intervals (for instance, intra-day trading). Second, introducing long run persistence of shocks in the volatility with fractionally integrated models (FIGARCH, FIEGARCH, FIAPARCH) would certainly allow better catch the dynamic of the series.

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Table 2:

Estimation Statistics-Distributions Comparison AR(1)-GARCH Model

$$R_t = \varphi_0 + \sum_{i=1}^{q} \phi_i R_{t-i} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
φ_0	0.04563 (0.0156)	0.018806 (0.013)	0.005157 (0.0152)	0.03876 (0.0159)	0.019358 (0.0147)	0.015127 (0.0140)
φ_1	0.176251 (0.0179)	0.150871 (0.0170)	0.112706 (0.0237)	0.135218 (0.0181)	0.127392 (0.0173)	0.090214 (0.0195)
α_0	0.021963 (0.00407)	0.02101 (0.0049)	0.036622 (0.00767)	0.037439 (0.00657)	0.030273 (0.00713)	0.051645 (0.0104)
α_1	0.10164 (0.00972)	0.078454 (0.0107)	0.132121 (0.0169)	0.127884 (0.0125)	0.084825 (0.0121)	0.137722 (0.0175)
β_1	0.88967 (0.00967)	0.842576 (0.0194)	0.85267 (0.0165)	0.854878 (0.0128)	0.842505 (0.0209)	0.833316 (0.0191)
ν		4.241789 (0.3307)	1.096725 (0.0361)			1.24425 (0.0396)

Asymptotic heteroskedasticity-consistent standard errors are given in parentheses.

Table 3:

Estimation Statistics-Distributions Comparison AR(1)-EGARCH Model

$$R_t = \varphi_0 + \sum_{i=1}^{q} \phi_i R_{t-i} + \varepsilon_t$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_j \ln(\sigma_{t-j}^2)$$

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
φ_0	0.039446 (0.0155)	0.007716 (0.0137)	0.001398 (0.0124)	0.009178 (0.0160)	-0.00026 (0.0429)	0.000639 (0.0139)
φ_1	0.167528 (0.0171)	0.148854 (0.0165)	0.110731 (0.0233)	0.136472 (0.0174)	0.128629 (0.0176)	0.092575 (0.0148)
α_0	0.011857 (0.00220)	-0.04131 (0.00707)	0.01857 (0.00425)	0.014674 (0.00285)	-0.03072 (0.0113)	0.016111 (0.00403)
α_1	0.160061 (0.0126)	0.176339 (0.0197)	0.198965 (0.0232)	0.198497 (0.0163)	0.188372 (0.0245)	0.211591 (0.0233)
β_1	0.990215 (0.00188)	0.974307 (0.00574)	0.982273 (0.00421)	0.978938 (0.00367)	0.966408 (0.00751)	0.973411 (0.00597)
g	-0.28794 0.0453	-0.28878 (0.0523)	-0.27707 (0.0544)	-0.31462 (0.0448)	-0.28956 (0.0570)	-0.28998 (0.0543)
ν		4.181703 (0.3161)	1.107278 (0.0365)		5.798267 (1.6173)	1.261971 (0.0396)

Asymptotic heteroskedasticity-consistent standard errors are given in parentheses.

Table 4:

Estimation Statistics-Distributions Comparison AR(1)-GJR Model

$$R_t = \varphi_0 + \sum_{i=1}^{q} \phi_i R_{t-i} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-1}^2 + w_i S_{t-i}^- \varepsilon_{t-1}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
φ_0	0.019303 (0.0160)	0.003455 (0.0142)	5.653E-6 (0.00165)	0.013754 (0.0163)	0.004819 (0.0151)	0.00199 (0.0140)
φ_1	0.18286 (0.0178)	0.1566 (0.0167)	0.116387 (0.0234)	0.141688 (0.0178)	0.12999 (0.0171)	0.095103 (0.0181)
α_0	0.021062 (0.00374)	0.022501 (0.00507)	0.036813 (0.00751)	0.036575 (0.00628)	0.03107 (0.00703)	0.050256 (0.00982)
α_1	0.13262 (0.0134)	0.116718 (0.0161)	0.185545 (0.0255)	0.166968 (0.0169)	0.120471 (0.0177)	0.186991 (0.0242)
β_1	0.899607 (0.00922)	0.843183 (0.0199)	0.858273 (0.0163)	0.866336 (0.0121)	0.845867 (0.0202)	0.841952 (0.0179)
ω_1	-0.08089 (0.0125)	-0.07259 (0.0142)	-0.11386 (0.0232)	-0.10247 (0.0157)	-0.07149 (0.0156)	-0.11188 (0.0223)
ν		4.329078 (0.3285)	1.111723 (0.0366)		5.829943 (0.5414)	1.265056 (0.0404)

Asymptotic heteroskedasticity-consistent standard errors are given in parentheses.

Table 5:

Diagnostics statistics -Distributions Comparison AR(1)-GARCH Model

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
$Q^2(20)$	17.380 (0.628)	14.343 (0.813)	11.673 (0.927)	13.250 (0.866)	13.044 (0.875)	12.801 (0.886)
ARCH(2)	2.924836 (0.053799)	0.549214 (0.577451)	0.032969 (0.967569)	0.815931 (0.442308)	1.128814 (0.323530)	1.046473 (0.351280)
AIC	3.088865	2.976918	2.969216	3.044102	2.968075	2.966946
BIC	3.095661	2.985413	2.977711	3.050898	2.976570	2.975440
Log-Like	-5585	-5389	-5393	-5523	-5385	-5400

$Q^2(20)$ are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 6:

Diagnostics statistics -Distributions Comparison AR(1)-EGARCH Model

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
$Q^2(20)$	30.803 (0.058)	11.960 (0.917)	12.845 (0.884)	12.311 (0.905)	12.666 (0.891)	12.443 (0.900)
ARCH(2)	10.01139 (0.000046)	1.960507 (0.140935)	2.301999 (0.100204)	2.480221 (0.083866)	1.647911 (0.192595)	2.046106 (0.129386)
AIC	3.082735	2.969516	2.961012	3.035179	2.960535	2.960053
BIC	3.091229	2.979709	2.971205	3.043674	2.970728	2.970246
Log-Like	-5575	-5375	-5378	-5503	-5369	-5382

$Q^2(20)$ are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 7:

Diagnostics statistics -Distributions Comparison AR(1)-GJR Model

	Malaysia			Singapore		
	Normal	**Student-t**	**GED**	**Normal**	**Student-t**	**GED**
$Q^2(20)$	20.424 (0.432)	13.503 (0.855)	11.944 (0.918)	12.496 (0.898)	18.124 (0.579)	12.550 (0.896)
ARCH(2)	4.5840 (0.0103)	1.1092 (0.3299)	0.1454 (0.8647)	0.814720 (0.442844)	0.706989 (0.493194)	1.460312 (0.232300)
AIC	3.076357	2.967911	2.962434	3.030473	2.967269	2.958600
BIC	3.086506	2.979803	2.970422	3.040646	2.971731	2.970493
Log-Like	-5561	-5370	-5375	-5497	-5369	-5384

$Q^2(20)$ are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 8:

Diagnostics statistics – Gaussian Distribution

	Malaysia			Singapore		
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
Q^2(20)	17.380 (0.628)	30.803 (0.058)	20.424 (0.432)	13.250 (0.866)	12.311 (0.905)	12.496 (0.898)
ARCH(2)	2.924836 (0.053799)	10.01139 (0.000046)	4.5840 (0.0103)	0.815931 (0.442308)	2.480221 (0.083866)	0.814720 (0.442844)
AIC	3.088865	3.082735	3.076357	3.044102	3.035179	3.030473
BIC	3.095661	3.091229	3.086506	3.050898	3.043674	3.040646
Log-Like	-5585	-5575	-5561	-5523	-5503	-5497

Q^2(20) are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 9:

Diagnostics statistics – Student-t Distribution

	Malaysia			Singapore		
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
Q^2(20)	14.343 (0.813)	11.960 (0.917)	13.503 (0.855)	13.044 (0.875)	12.666 (0.891)	18.124 (0.579)
ARCH(2)	0.549214 (0.577451)	1.960507 (0.140935)	1.1092 (0.3299)	1.128814 (0.323530)	1.647911 (0.192595)	0.706989 (0.493194)
AIC	2.976918	2.969516	2.967911	2.968075	2.960535	2.967269
BIC	2.985413	2.979709	2.979803	2.976570	2.970728	2.971731
Log-Like	-5389	-5375	-5370	-5385	-5369	-5369

Q^2(20) are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 10:

Diagnostics statistics – GED Distribution

	Malaysia			Singapore		
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
$Q^2(20)$	11.673 (0.927)	12.845 (0.884)	11.944 (0.918)	12.801 (0.886)	12.443 (0.900)	12.550 (0.896)
ARCH(2)	0.032969 (0.967569)	2.301999 (0.100204)	0.1454 (0.8647)	1.046473 (0.351280)	2.046106 (0.129386)	1.460312 (0.232300)
AIC	2.969216	2.961012	2.962434	2.966946	2.960053	2.958600
BIC	2.977711	2.971205	2.970422	2.975440	2.970246	2.970493
Log-Like	-5393	-5378	-5375	-5400	-5382	-5384

$Q^2(20)$ are the Box-Pierce statistic at lag 20 of the squared standardized residuals. P-values of are given in parentheses. AIC,BIC and Log-Like are the Akaike Information criterion, Swartz information criterion and Log-Likelihood value respectively.

Table 11:

Forecast Performance –In Sample

	KLCI			STI		
			Normal			
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
MSE	2.0211	0.5938	0.5625	0.5910583	0.1779	0.2945
MAE	0.2933	0.2113	0.2180	0.2445678	0.1906	0.2116
MAPE	12.50454	9.8018	9.9522	13.413375	11.3728	12.0916
TIC	0.1952	0.1581	0.1485	0.2647	0.1811	0.2088
AIC	3174.90	-1499.3631	-1632.4601	-1930.7351	-6284.3188	-4445.0386
BIC	3181.11	-1493.1603	-1626.2574	-1905.9241	-6259.5078	-4420.2276
APC	2.38595	0.6632	0.6394	0.5892	0.1788	0.2959
AJDR^2	0.94896	0.9646	0.96871	0.89163	0.93590	0.92585
AR^2	0.94893	0.9646	0.96869	0.89148	0.93582	0.92575
			Student-t			
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
MSE	3.9085	1.4998	1.3143	0.5305	0.2066152	0.2821
MAE	0.4081	0.3110	0.3118	0.2317	0.203192	0.2167
MAPE	16.4260	13.9788	13.5583	12.7713	12.177492	12.4356
TIC	0.2391	0.2345	0.2011	0.2608	0.2002378	0.2108
AIC	5528.0063	1748.5998	1389.2326	-2360.1765	-5746.0613	-4604.5757
BIC	5534.2091	1754.8025	1395.4354	-2335.3655	-5721.2502	-4579.7646
APC	4.5453	1.6143	1.4630	0.5239	0.2072	0.2833
AJDR^2	0.92591	0.92669	0.94555	0.89319	0.92053	0.92261
AR^2	0.92587	0.92665	0.94552	0.89304	0.92042	0.92251
			GED			
	GARCH	**EGARCH**	**GJR**	**GARCH**	**EGARCH**	**GJR**
MSE	6.0594	1.3041	1.2848	0.5305	0.1877	0.2805
MAE	0.5086	0.2894	0.3041	0.2317	0.1944	0.2123
MAPE	21.2935	13.6436	13.8632	12.7713	11.7055	12.2234
TIC	0.2931	0.2307	0.2067	0.2608	0.1911	0.2097
AIC	7072.1195	1236.2414	1281.9070	-2326.3503	-6093.1885	-4623.4905
BIC	7078.3223	1242.4442	1288.1098	-2301.5393	-6068.3775	-4598.6794
APC	6.9381	1.4029	1.42064	0.5287	0.1884	0.2818
AJDR^2	0.89192	0.92897	0.94301	0.89277	0.92753	0.92397
AR^2	0.89186	0.92893	0.94298	0.89262	0.92743	0.92387

MSE is Mean Squared Error, MAE is the Mean Absolute Error, MAPE is the Mean Absolute Percentage Error, TIC is the Theil Inequality Coefficient, AIC is Akaike Information Criterion, BIC is Schwarz Bayesian Criterion, APC is Amemiya Prediction Criterion, AJDR^2 is the Adjusted R^2 , AR^2 is the Amemiya Adjusted R^2.

Fig. (1): KLCI & STI Daily Closing Prices
2January 1991-31December 2004

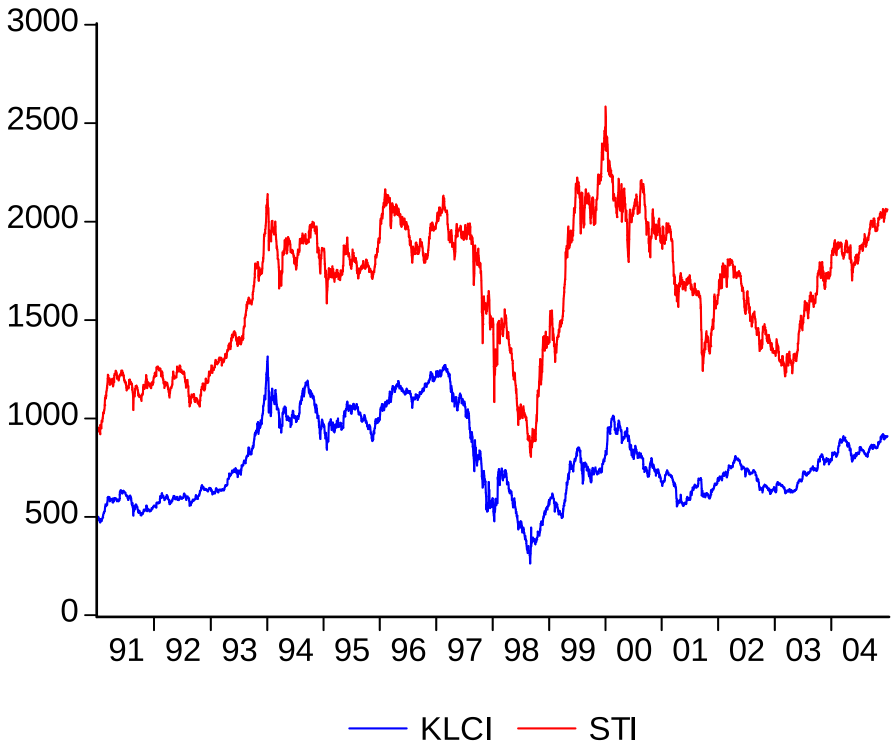

Fig. (2: KLCI & STI Returns
2January 1991-31December 2004

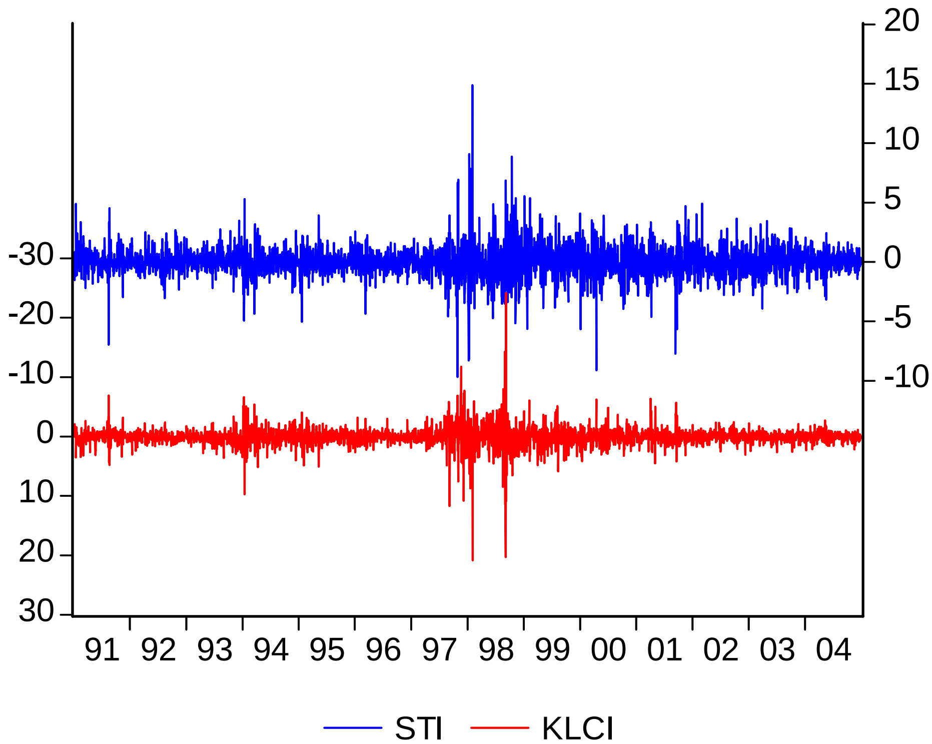

Fig.(3):The STI Returns, Residuals and
Conditional Variance AR(1)-GJR Model

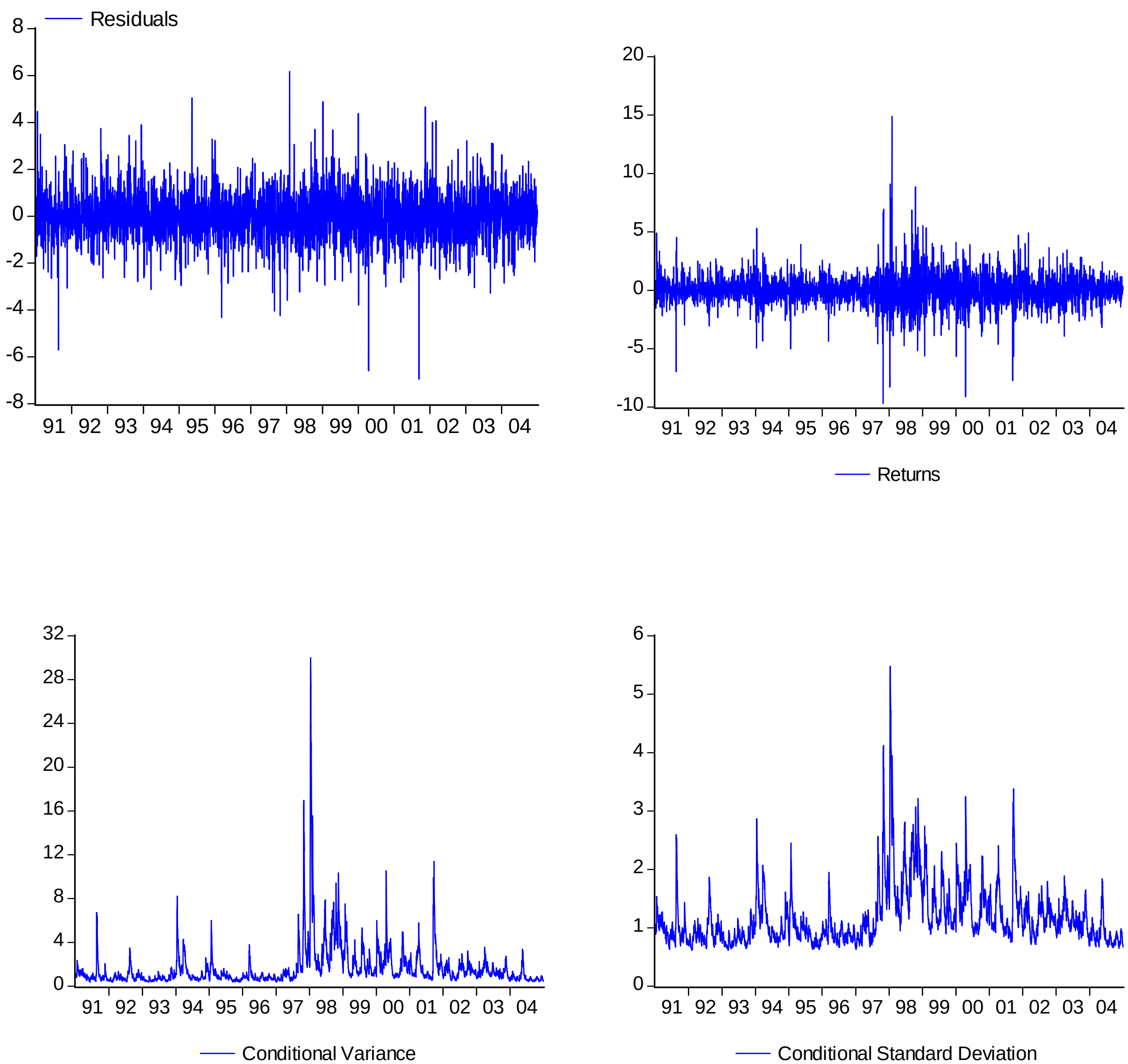

Fig.(4):The KLCI Returns, Residuals and
Conditional Variance AR(1)-GJR Model

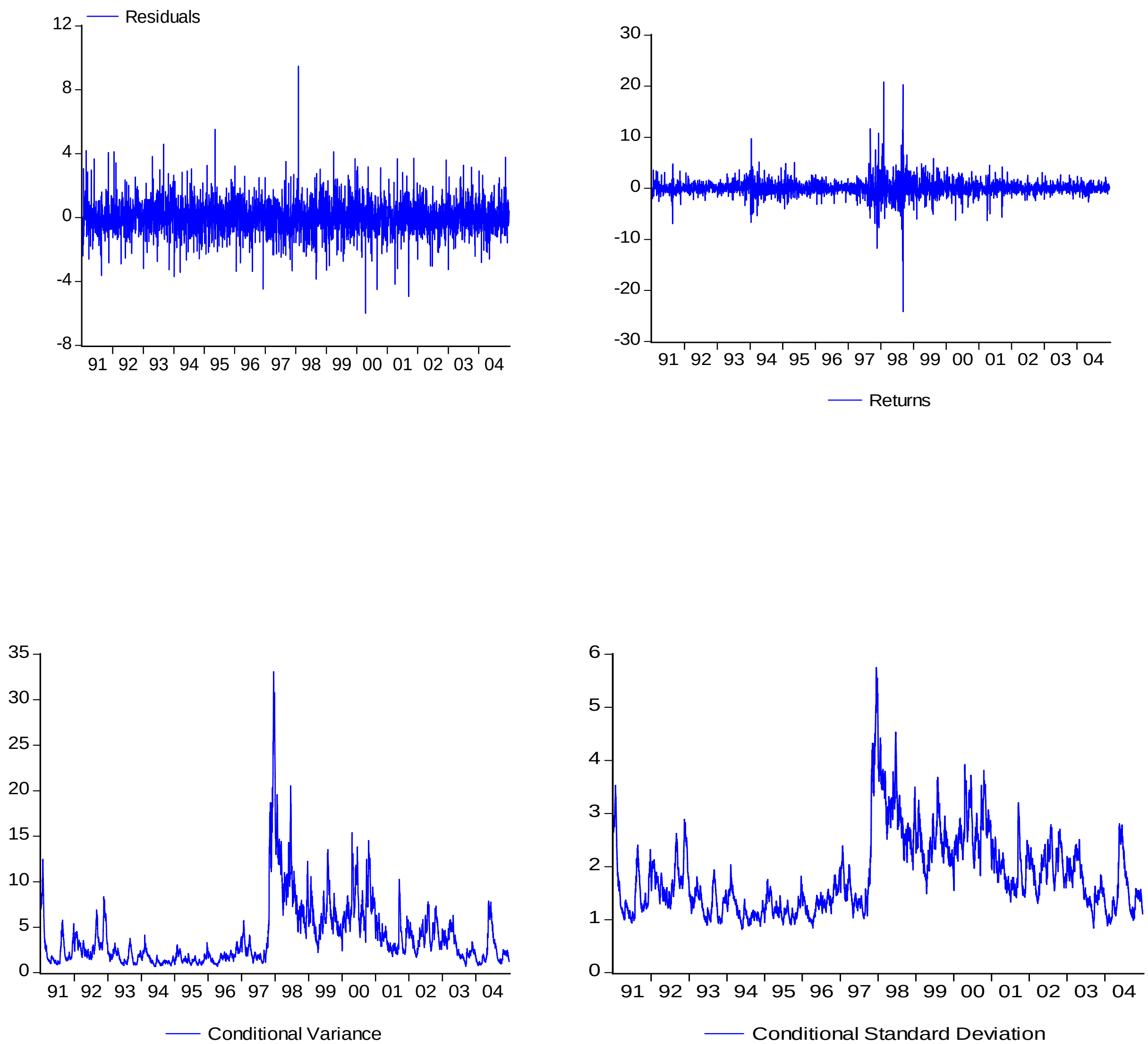

Fig (5): EGARCH, the fitted and forecasted variance, estimated through 2005 for STI

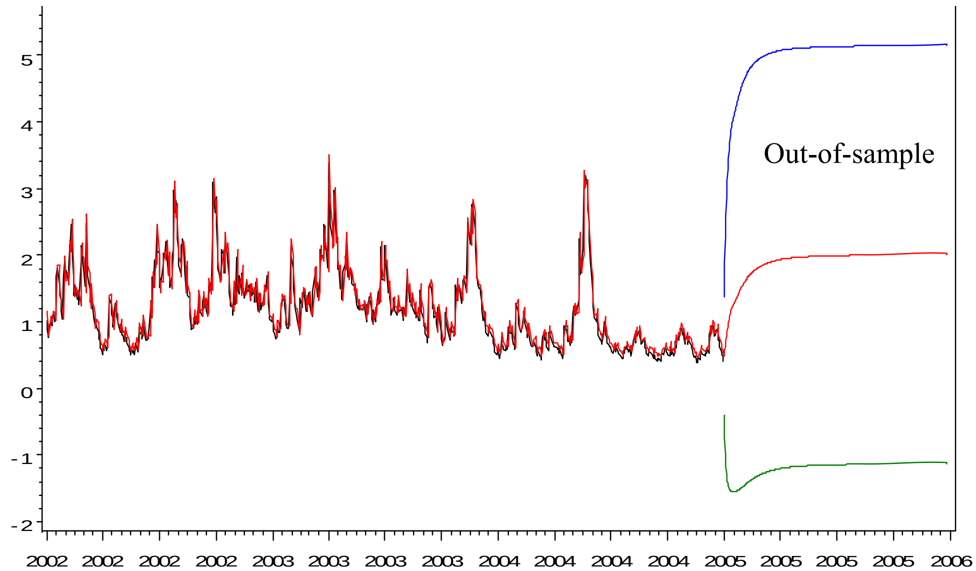

Fig (6): GJR, the fitted and forecasted variance, estimated through 2005 for KLCI