

Modeling and Forecasting Volatility of the Malaysian Stock Markets

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Abstract: Problem statement: One of the main purposes of modeling variance is forecasting, which is crucial in many areas of finance. Despite the burgeoning interest in and evaluation of volatility forecasts, a clear consensus on which volatility model/or distribution specification to use has not yet been reached. Therefore, the out-of-sample forecasting ability should be a natural model selection criterion for volatility models. **Approach:** In this study, we used high-frequency data to facilitate meaningful comparison of volatility forecast models. We compared the performance of symmetric GARCH, asymmetric EGARCH and non-levered asymmetric NAGARCH models with six error distributions (normal, skew normal, student-t, skew student-t, generalized error distribution and normal inverse Gaussian). **Results:** The results suggested that allowing for a heavy-tailed error distribution leads to significant improvements in variance forecasts compared to using normal distribution. It was also found that allowing for skewness in the higher moments of the distribution did not further improve forecasts. **Conclusion:** Successful volatility model forecast depended much more heavily on the choice of error distribution than the choice of GARCH models.

Key words: GARCH-models, asymmetry, stock market indices and volatility modeling

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. During the last few decades we have seen a multitude of different suggestions for how to model the second moment, often referred to as volatility, of financial returns. Indeed, it is now widely accepted that high frequency financial returns are heteroskedastic. Among the models that have proven the most successful are the Auto-Regressive Conditional Heteroskedasticity (ARCH) family of models introduced by Engle^[4] and the models of Stochastic Variance (SV) pioneered by Taylor^[14]. One of the main purposes of modeling variance is forecasting, which is crucial in many areas of finance such as option pricing, value at risk applications and portfolio selection. Therefore, the out-of-sample forecasting ability should be a natural model selection criterion for volatility models. The vast

majority of variance forecasting articles have used squared daily returns as the proxy for ex post variance. This is, as shown by Andersen and Bollerslev^[2], an unbiased but exceedingly noisy estimator.

While the literature that examines competing variance models is abundant, very little work has been done comparing different distribution assumptions, with the noticeable exceptions of Anders^[1] and Shamiri^[10,11]. However, none of these papers has explicitly focused on evaluating asymmetric GARCH models forecast using different error distributions. The previous studies paid more attention on the symmetric GARCH model, while in this study we focus on both symmetric and asymmetric volatility models as well as symmetric and asymmetric distributions. Unfortunately, ARCH models often do not fully capture the thick tails property of high frequency financial time series. However, another striking characteristic of high-frequency financial returns is that they are often characterized by fat-tailed distribution. In fact, the kurtosis of most asset returns is higher than three, which means that extreme values are observed more frequently than for the normal distribution. While the high kurtosis of the returns is a well-established fact, the situation is much more obscure with regard to the symmetry of the distribution.

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Many authors do not observe anything special on this point, but other researchers, such as Simkowitz and Beedles^[13] and Kon^[7] have drawn the attention to the heavy tail of the distribution. Shamiri^[10,12] have shown that a fat-tailed distribution is required for modeling daily returns of East Asian equity markets.

This study adds to the literature in several important directions. Firstly, in this study we demonstrate that this gap can be filled by a rigorous density forecast models comparison methodology. Secondly, we compare the performance of the GARCH, EGARCH and NAGARCH models and also introduce different densities (Normal, Skew normal, Student-t, Skew student-t, Generalized Error Distribution GED and Normal Inverse Gaussian (NIG)). Thirdly, using high-frequency data from Kuala Lumpur Composite Index (KLCI) of Malaysian's stock market to facilitate meaningful comparison of the forecast results. In the model estimation, it is shown that allowing for a leptokurtic return distribution significantly improves the fit of the model. In terms of out-of-sample forecasting performance, allowing for excess kurtosis leads to significant improvements over the normal distribution, whereas allowing for non-centrality does not further enhance forecasts.

MATERIALS AND METHODS

Data source: 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 of KLCI, which is measured in local currency. The sample consists of 2869 daily observations on stock returns of the KLCI index. The index spans a period of approximately 11 years from 1/1/1998 to 31/12/2008. In the database, the daily return R_t consisted of daily closing price P_t , which is measured in local currency and computed as:

$$R_t = \ln[P_t / P_{t-1}]$$

GARCH: Bollerslev^[3], introduced GARCH model known as the Generalized auto-regressive conditional heteroskedasticity model which suggest 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:

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

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

EGARCH: Nelson^[8] introduced the first asymmetric GARCH model known as exponential GARCH model (EGARCH). This model 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:

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

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:

$$g(z_t) = \underbrace{\theta_1 z_t}_{\text{sign effect}} + \underbrace{\theta_2 [|z_t| - E|z_t|]}_{\text{magnitude effect}} \tag{3}$$

Notice moreover that $E|z_t|$ depends on the assumption made on the unconditional density. The EGARCH model differs from the standard GARCH model in two main aspects. First, it allows positive and negative shocks to have a different impact on volatility. Second, the EGARCH model allows large shocks to have a greater impact on volatility than the standard GARCH model.

NAGARCH: Engle^[5] proposed the Asymmetric Non-Linear GARCH Model (NAGARCH), given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i (\varepsilon_{t-i} + \lambda \sigma_{t-i}^2)^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \tag{4}$$

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. Since it may be expected that excess kurtosis and skewness displayed by the residuals of conditional heteroskedasticity models will be reduced when a more appropriate distribution is used, we consider six distributions in this study: the normal, skew-normal, student-t, skew-student-t, GED and NIG. In the following, $f(z)$ is the standardized density function of the standardized residuals $\{z_t\}$.

Normal distribution:

$$f(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right), E|z| = \sqrt{2/\pi}, \gamma_2 = 0 \tag{5}$$

Skew-normal distribution:

$$f(z) = \frac{1}{\sigma\pi} e^{-\frac{(z-\zeta)^2}{2\sigma^2}} \int_{-\infty}^{\alpha\left(\frac{z-\zeta}{\sigma}\right)} e^{-\frac{t^2}{2}} dt$$

$$E|z| = \zeta + \sigma\delta\sqrt{\frac{2}{\pi}}$$

$$\gamma_1 = \frac{4-\pi}{2} \frac{(\delta\sqrt{2/\pi})^3}{(1-2\delta^2/\pi)^{3/2}}$$

$$\gamma_2 = 2(\pi-3) \frac{(\delta\sqrt{2/\pi})^4}{(1-2\delta^2/\pi)^2}$$
(6)

ζ and α are the location scale and shape respectively, where, $\delta = \frac{\alpha}{\sqrt{1+\alpha^2}}$.

Student-t distribution:

$$f(z;v) = \frac{\Gamma(v+1/2)}{\Gamma(v/2)} \frac{1}{\sqrt{\pi(v-2)}} \left(1 + \frac{z^2}{v-2}\right)^{-(v+1/2)}, v > 2$$

$$E|z| = \frac{4\Gamma(1+v/2)\sqrt{v-2}}{1+\sqrt{\pi}\Gamma(v/2)(v-1)}$$

$$\gamma_2 = \frac{6}{v-4}, v > 4$$
(7)

Skewed-t distribution:

$$f(z) = \begin{cases} \frac{(2s/\zeta + \zeta^{-1})[\Gamma(v+1/2)/\Gamma(v/2)](1/\sqrt{\pi(v-2)})}{[1 + \zeta^2(sz+m)^2/v-2]^{-(v+1/2)}} & \text{if } z \leq -m/s \\ \frac{(2s/\zeta + \zeta^{-1})[\Gamma(v+1/2)/\Gamma(v/2)](1/\sqrt{\pi(v-2)})}{[1 + \zeta^{-2}(sz+m)^2/v-2]^{-(v+1/2)}} & \text{if } z > -m/s \end{cases}$$

$$E|z| = \frac{4\zeta^2\Gamma(1+v/2)\sqrt{v-2}}{\zeta + 1/\zeta\sqrt{\pi}\Gamma(v/2)(v-1)}$$

$$\gamma_1 = \frac{(v-2)^{3/2}(\zeta^2-1)(\zeta^4+1)\Gamma[(v-3)/2]}{\sqrt{\pi}\zeta^3s^3\Gamma(v/2)} - \frac{m(m^2+3s)}{s^3}$$

$$\gamma_2 = \frac{3(\zeta^5 + \zeta^{-5})(v-2)}{(\zeta + \zeta^{-1})(v-4)s^4} - \frac{3m^2(m^2+2s)}{s^4}$$

$$- \frac{4m(v-2)^{3/2}(\zeta^2-1)(\zeta^4+1)\Gamma[(v-3)/2]}{\sqrt{\pi}\zeta^3s^4\Gamma(v/2)}$$
(8)

where, $\zeta > 0, v > 2, m = \Gamma[(v-1)/2]\sqrt{(v-2)/\pi}(\zeta-1/\zeta)/\Gamma(v/2), s = \sqrt{(\zeta^2+1/\zeta^2-1)-m^2}$ γ_1 exists if $v > 3$ and γ_2 exists if $v > 4$.

GED:

$$f(z;v) = \frac{v \exp(-0.5|z/\lambda|^v)}{\lambda 2^{(1+1/v)}\Gamma(1/v)}$$

$$v > 0, \lambda = \sqrt{2^{(-2/v)}\Gamma(1/v)/\Gamma(3/v)}$$

$$\gamma_2 = \frac{\Gamma(1/v)\Gamma(5/v)}{[\Gamma(3/v)]^2}$$
(9)

NIG:

$$f(z) = \left(\frac{\tau}{\pi}\right)\phi(z)^{-1/2} K_1(\tau\delta\sqrt{\phi(z)})$$

$$\exp\left(\delta\sqrt{\tau^2-\beta^2} + \beta(z-\mu)\right)$$

$$E|z| = \mu + \frac{\delta\beta}{\omega}$$

$$\gamma_1 = \frac{3\beta}{\tau(\delta\omega)^{1/2}}$$

$$\gamma_2 = 3 + \frac{3(1+4\beta^2/\tau^2)}{\delta\omega}$$
(10)

where, $\tau = \sqrt{\omega^2 + \beta^2}, \phi(z) = 1 + ((z-\mu)/\delta)^2,$
 $K(u) = \frac{1}{2} \int_0^{\infty} y^{\lambda-1} \exp\left\{-\frac{u}{2}\left(y + \frac{1}{y}\right)\right\} dy, u > 0$ denotes the modified Bessel function of the third kind of order λ evaluated at u and $w = \sqrt{\tau^2 - \beta^2}$ let $E_{i,T}(h_{T+h})$ denote the h -step ahead forecast of h_{T+h} at time T from GARCH model i using rolling methods. Define the corresponding forecast error as $\varepsilon_{i,T+h} = E_{i,T}(h_{T+h}) - h_{T+h}$ Common evaluation statistics based on Mean Squared Error (MSE), Mean Absolute Error (MAE), Median Squared Error (MDSE) and Root Mean Squared Error (RMSE).

RESULTS

Descriptive statistics: Table 1 shows the descriptive statistics of KLCI series for the sample under consideration. The mean return is positive 0.014%, however, accompanied by high volatility 1.51%. It is clear that the Malaysian market offer high average returns but these high returns are also characterized by high volatility, which is common for emerging markets and is consistent with previous studies^[9,10]. Moreover, we check the statistical features of the data reported in Table 1, the skewness, kurtosis and their tests.

The Ljung-Box Q-statistics $Q(10)$ and $Q^2(10)$ are reported under the null hypothesis of non-serial correlation tests in daily return and squared returns,

Table 1: Summary statistics for daily returns 1 January 1998-31 December 2008

	Sample	Mean	Std.	Skewness	Kurtosis	Rob.Sk	Rob.Kr	Q (10)	Q ² (10)	LM (5)
KLCI	2870	0.0135	1.506	0.569	60.239	-0.004	0.37	85.29**	1365**	787**

Rob.Sk and Rob.Kr are outlier-robust versions of skewness and kurtosis described as Sk_2 and Kr_2 in Kim and White^[6], LM test of Engle^[4] for presence of ARCH at lag 5, **, *: Significant at 1 and 5% respectively

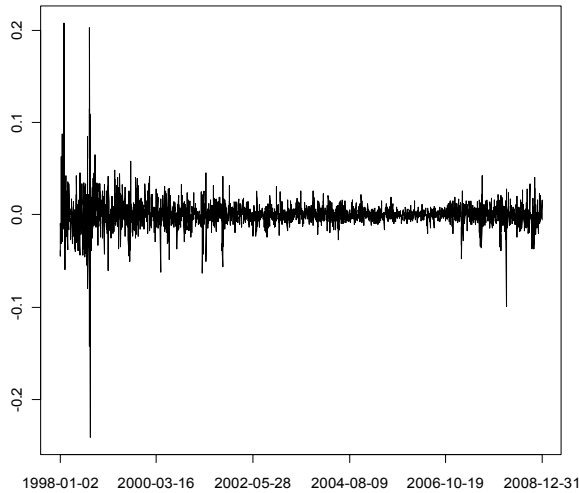


Fig. 1: KLCI daily returns

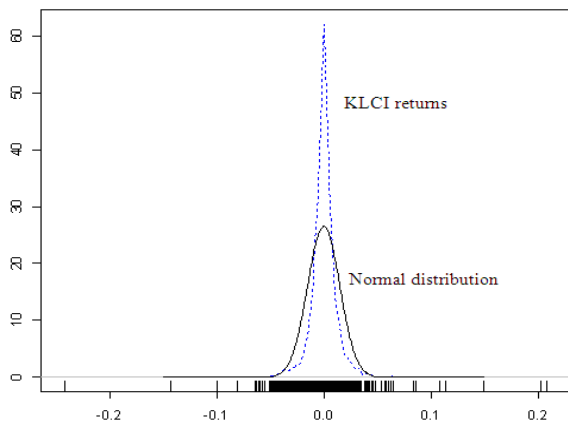


Fig. 2: KLCI daily return distribution

respectively. At significance levels of 5%, the null hypotheses (skewness = 0 or excess kurtosis = 0) and of non-serial correlation are rejected, respectively. This time series have the typical features of stock returns as fat tail, spiked peak and persistence in variance. In contrast, the robustified statistics, Rob.Sk and Rob.Kr, do not suggest non-normality. With evidence of ARCH effects, it is possible to proceed to the second step of the analysis focused on the GARCH modeling of market's volatility.

Figure 1 looks at the behavior of the KLCI returns, over the sample period. There is evidence of volatility clustering 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 figure indicates that the Malaysian equity market is not affected much by US recent financial crisis compared to the Asian crisis in 1997. Figure 2 shows the distribution of KLCI log returns, which clearly indicate the departure from normality with a high peaked distribution.

Estimation and diagnostic: A quasi maximum likelihood approach is used to estimate the Models GARCH, EGARCH and NAGARCH, with six underlying error distributions. Table 2, shows the estimation results for the parameters for the GARCH, EGARCH and NAGARCH models. 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 Bayesian information criterion values highlight the fact that EGARCH and NAGARCH models better estimate the series than the traditional GARCH. 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 standardized residuals with lag 15 which are all non-significant at 5% level. LM test for presence of ARCH effects at lag 5, indicate that the conditional hetskedasity that existed when the test was performed on the pure return series (Table 1) are removed. As, is typical of GARCH model estimates for financial asset returns data, the sum of the coefficients on the lagged squared error (α_i) and the lagged conditional variance (β_i) is close to unity 1.00 and 0.99 with the GED and NIG error term 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 KLCI financial returns series.

Table 2: GARCH models estimation

	Normal	Skew normal	Student-t	Skew student	GED	NIG
Panel A: GARCH:						
α_0	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.00000)	0.0000** (0.00000)	0.0000** (0.0000)	0.0000** (0.0000)
α_1	0.1185** (0.0111)	0.1177** (0.0111)	0.14790** (0.02180)	0.14850** (0.02190)	0.1306** (0.0189)	0.1312** (0.0183)
β_1	0.8874** (0.0092)	0.8881** (0.0093)	0.86170** (0.01710)	0.86150** (0.01710)	0.8735** (0.0159)	0.8686** (0.0160)
γ_1		1.0122** (0.0197)		0.98630** (0.02250)		-0.0145 (0.0178)
γ_2		4.0477** (0.3345)	4.04160** (0.33420)	1.02360** (0.05580)	1.0000** (0.1463)	
Log like	-9113.6290	-9113.8230	-9287.87900	-9288.06000	-9301.719	-9290.2330
AIC	-6.3504	-6.3498	-6.47120	-6.47060	-6.4808	-6.47210
BIC	-6.3421	-6.3394	-6.46080	-6.45810	-6.4704	-6.45960
Q2(15)	8.4750	8.4800	7.64900	7.65500	7.786	7.72000
LM(5)	2.2450	2.2770	1.65710	1.65970	1.7187	1.66470
Panel B: EGARCH:						
α_0	-0.0682** (0.0195)	-0.0697** (0.0201)	-0.19600** (0.04680)	-0.19850** (0.04790)	-0.1451** (0.0372)	-0.1717** (0.0412)
α_1	0.2417 (0.4169)	0.4144 (0.5892)	0.78050 (0.95070)	0.48790 (0.43130)	0.4076 (0.5362)	0.37670 (0.49570)
β_1	0.9911** (0.0021)	0.9910** (0.0022)	0.97860** (0.00510)	0.97830** (0.00520)	0.9843** (0.0040)	0.981500** (0.00450)
ϕ_1	-0.0808* (0.0036)	-0.1290** (0.0027)	-0.08660** (0.00180)	-0.13830** (0.00130)	-0.1399** (0.0049)	-0.16660** (0.00540)
ϕ_2	0.3003* (0.0776)	0.4705** (0.0104)	0.32060** (0.09270)	0.52040** (0.01810)	0.5343** (0.0048)	0.61810** (0.01270)
γ_1		0.9766** (0.0192)		0.96360** (0.02310)		-0.05550 (0.04270)
γ_2			4.22540** (0.35380)	4.19210** (0.34980)	1.0786** (0.0376)	1.00000** (0.13650)
Log like	-9155.3020	-9156.0020	-9330.24800	-9330.62000	-9328.751	-9330.03200
AIC	-6.3773	-6.3771	-6.49790	-6.49820	-6.4976	-6.49780
BIC	-6.3628	-6.3605	-6.47920	-6.47950	-6.4809	-6.47910
Q2(15)	9.7570	9.4220	5.09100	4.06400	5.773	4.69100
LM(5)	5.6840	5.3950	0.88110	0.88780	2.166	1.33330
Panel C: NAGARCH:						
α_0	0.0000** (0.0000)	0.0000** (0.0000)	0.00000** (0.00000)	0.00000** (0.00000)	0.0000** (0.0000)	0.0000** (0.0000)
α_1	0.1124** (0.0106)	0.1132** (0.0108)	0.14520** (0.02150)	0.14600** (0.02140)	0.1287** (0.0183)	0.13070** (0.01810)
β_1	0.8770** (0.0099)	0.8757** (0.0103)	0.84770** (0.01870)	0.84580** (0.01870)	0.8588** (0.0173)	0.85200** (0.01780)
γ	0.3428** (0.0515)	0.3475** (0.0523)	0.31260** (0.06470)	0.32190** (0.06570)	0.3503** (0.0696)	0.346700** (0.06880)
γ_1		0.9873** (0.0195)		0.97150** (0.02260)		-0.04660 (0.03540)
γ_2			4.11600** (0.34350)	4.11280** (0.34420)	1.0341** (0.0407)	1.000000** (0.14470)
Log like	-9137.3100	-9137.5190	-9300.47800	-9301.25700	-9315.2340	-9304.15000
AIC	-6.3662	-6.3656	-6.47920	-6.47910	-6.4895	-6.48110
BIC	-6.3558	-6.3532	-6.46680	-6.46450	-6.4771	-6.46660
Q2(15)	8.8690	8.8380	8.51200	8.46600	8.5310	8.43100
LM(5)	2.6150	2.5790	2.22845	2.22186	2.1743	2.14490

Standard errors are given in parentheses. **, *: Significant at 1 and 5% respectively

DISCUSSION

Based on the findings, the symmetric distributions with fatter tails clearly outperform the Gaussian. According to AIC, GARCH and NAGARCH models

perform better with GED, while EGARCH model perform better with skew-student-t distribution. The leverage effect terms ϕ_1 and ϕ_2 in EGARCH model and asymmetric term λ in NAGARCH model are statistically significant, furthermore with ϕ_1 negative sign,

Table 3: Forecast performance out-of- sample

	Normal	Skew normal	Student-t	Skew student	GED	NIG
Panel A: GARCH:						
MSE	0.001098	0.001098	0.001294	0.001313	0.001099	0.001080
MDSE	0.000212	0.000212	0.000351	0.000362	0.000219	0.000159
RMSE	3.313204	3.313204	3.597198	3.623870	3.314653	3.286948
MAE	2.143484	2.143484	2.649073	2.683303	2.155249	2.008332
Panel B: EGARCH:						
MSE	0.001092	0.001072	0.001090	0.001090	0.001096	0.001100
MDSE	0.000339	0.000339	0.000118	0.000115	0.000107	0.000100
RMSE	3.304849	3.274849	3.300770	3.301175	3.309850	3.316831
MAE	2.244085	2.244085	1.851566	1.852097	1.838961	1.833950
Panel C: NAGARCH:						
MSE	0.002087	0.002087	0.013221	0.011741	0.003112	0.001978
MDSE	0.000908	0.000908	0.003131	0.002976	0.001271	0.000850
RMSE	4.568193	4.568193	11.498303	10.835615	5.578780	4.447064
MAE	3.645259	3.645259	8.491675	8.080493	4.479974	3.552767

MSE: Mean squared error; MDSE: The median squared error; RMSE: The root mean squared error; MAE: The mean absolute error

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 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 EGARCH model with skew-student-t provides the best in-sample estimation for KLCI compared to all other volatility models and distributions.

Now that we have estimated the series, the obvious question is how good are the forecasting models? Typically, there are several plausible models that we can select to use for our forecast. We should not be fooled into thinking that the one with the best fit is the one that will forecast the best.

The results of forecasting daily volatility with GARCH models together with various distributions and four evaluation criteria are given in Table 3. All results are presented for each distribution and for each model GARCH models, whose specification is always of order (1, 1). In this study the length of the out-of-sample period is chosen to be 100 days. From Table 3 some interesting comments emerge. A first major conclusion is that there is no single model that completely dominates the other models. Secondly, forecasting with normal distribution does not yield a significant reduction of the forecast error relative to heavy-tailed distributions. Thus, the failure of predictor h_{T+h} is justified due to that the GARCH model residuals follow a (possibly) heavy-tailed distribution. Third, it seems that asymmetric model (EGARCH) tend to perform better forecast with a fatter tailed distribution (student-t and Skew-student-t). It is apparent, that the simple predictor h_{T+h} seems to actually have some predictive ability, when a heavy-tailed is assumed for the GARCH

residuals (i.e., NIG distribution). A possible explanation is that modeling asymmetries contributes to the reduction of the magnitude of the bias.

CONCLUSION

This study 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 GARCH-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 NAGARCH) and the difference between normal tailed symmetric, heavy-tailed symmetric distributions and both heavy-tailed and asymmetric distributions for estimating the KLCI stock market index return volatility. As expected, the leverage KLCI market shown by EGARCH model is statistically significant at 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 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 EGARCH model provides the best out-sample estimation for KLCI clearly outperform the symmetric models. Our results show that, non-normal distributions provide better in-sample results than the normal 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 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 stock market index returns series.

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