International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 4 Issue 02, February-2015

Estimating and Forecasting Stock Market Volatility using GARCH Models: Empirical Evidence from Saudi Arabia

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Abstract: **In this paper we used symmetric and asymmetric GARCH models such as GARCH(1,1) ,EGARCH(1,1) and GRJ-GARCH(1,1) models to estimate and forecast volatility of Saudi stock market under various assumptions namely: Normal,Student- t and GED distributions .The study carried out using daily closing prices index over the period of 1st January 2005 to 31st December 2012. The common measures of forecast evaluation of the models such as Root Mean Square Errors(RMSE), Mean Absolute Errors (MAE), Mean Absolute Percentage Errors(MAPE) and Theil Inequality Coefficient(TIC) were computed .The empirical results showed that the asymmetric GARCH models with a heavy-tailed error distribution better than the symmetric GARCH model in the estimation the conditional variance equations. Moreover ,we found that the GRJ- GARCH(1,1) model provide the best out – of – sample forecast for Saudi stock market . Finally, the empirical results reveal that conditional variance process is highly persistent and confirm the presence of leverage effect in returns of Saudi stock market.**

1. INTRODUCTION

Over the last few decades volatility forecasting has been an important area of research in financial markets for academics, policy makers and market participants. Since 1982 when Engle proposed the Autoregressive Conditionally Heteroscedastic (ARCH) model, a lot of effort has been expended in improving volatility models since better forecasts translate into better pricing of options and better risk management [1]. Therefore, in this section we overview a number of papers that have investigated the performance of GARCH models with regard to non-normal error distribution in mature stock .

There is a large number of research studies that examine stock market volatility carried out in the context of both developed and developing countries. However, such a study does not exist for Saudi Arabia [2] . We try to fit an adequate model to estimate and forecast stock volatility of Saudi Arabia

REVIEW OF SAUDI STOCK MARKET

The Saudi stock Market, the Tadawul, is the largest in the Gulf region, it was established in 1984. It lists 156 publicly traded companies (as of September 2, 2012) , divided into nine sectors, according to Bloomberg's classification, each of which has its own sub-index. In order of size, they are: Financials, Basic Materials (Petrochemicals), Industrials ,Telecoms, Consumer Goods, Consumer Services, Oil and Gas, Utilities, Healthcare . The Saudi Arabia Monetary Agency (SAMA) was responsible for supervising the market from 1984 until 2003. In July 2003, authority was handed over to the newly-formed Capital Market Authority (CMA). The CMA is now the sole regulator and supervisor of Saudi Arabia's capital markets, and issues the necessary rules and regulations to protect investors and ensure fairness and efficiency in the market. The main index, the Tadawul All Share Index (TASI) reached its highest point at 20,634.86 on 25 February 2006 and a record low of 1140.57 Index points in May of 1995. During 2004-2007 period, interesting events emerge[3] . First, the index price started at 4,432 point during year 2004 and increased sharply to 20,600 point in 2006, which represent highest level during the last 18 years and only lasted for one day (25th February 2006) before the index decline. This sharp increase in the index price could be due to the good news effects, such as the European Union WTO and the sharp increase in the oil price ($70) in 2005. Secondly, the market index lost more than 10,554 points during a short period of time (from26th January 2006 to 1st May 2006), despite the continuous increase in oil price, which reached to $90 in 2008. By the end of 2008-2009, the stock market lost about 5,343 points where the price declined to the same level as in 2004.

LITERATURE REVIEW

There has been a large amount of literature on modeling and forecasting stock market volatility in both developed and developing countries around the world. Many econometric models have been used to investigate volatility characteristics. However, no single model is superior. K.Lakshmi estimated the conditional volatility of Saudi stock market by applying AR(1)- GARCH(1,1) models to the daily stock returns data spending from August 1,2004 to October 31,2013. The results show that a linear GARCH(1,1) is adequate to estimate the volatility stock market of the country and Saudi stock market returns are characterized by volatility clustering and followed a non normal distribution .Moreover, the study showed that past returns play an important role in determining the current period return [2].

Hassan B. Ghassan and Hassan R. Alhajhoj tested the effect of capital market liberalization on volatility of TASI. The results of return equation exhibit the existence of a positive relationship between return and risk, which indicates the high risk and explains the dynamics of shareholders behavior, especially on Saturday and Tuesday, where utmost important information is excreted[4].

Ajab Al Freedi, Ahmed Shamiri and Zaidi Isa in their study examined several stylized facts (heavy-taileness, leverage effect and persistence) in volatility of stock price returns exploiting symmetric and asymmetric GARCH family models for Saudi Arabia. Their study was carried out using closing stock market prices over 15 years covering the period 1st January 1994 to 31th March 2009.The sample period was divided into three sub-periods according to the local crisis in 2006. Their findings revealed that asymmetric models with heavy tailed densities improve overall estimation of the conditional variance equation. Moreover, they found that AR (1)- GJR GARCH model with Student-t outperform the other models during and before the local crisis in 2006,while AR (1)- GARCH model with GED exhibits a better performance after the crisis. Furthermore, their results revealed that the existence of leverage effect at 1 percent significance leve[3].

Elsheikh and Suliman use the Generalized Autoregressive Conditional Heteroscedastic models to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan namely, Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. The models include both symmetric and asymmetric models that capture the most common stylized facts about index returns such as volatility clustering and leverage effect. The empirical results show that the conditional variance process is highly persistent (explosive process), and provide evidence on the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns[5].

A paper by D.N. Vee and P.Gonpot aimed at evaluating volatility forecasts for the US Dollar/Mauritian Rupee exchange rate obtained via a GARCH (1,1) model under two distributional assumptions: the generalized Error Distribution (GED) and the Student's-t distribution. They make use of daily data to evaluate the parameters of each model and produce volatility estimates. The forecasting ability was subsequently assessed using the symmetric loss functions which are the Mean Absolute Error(MAE) and Root Mean Square Error (RMSE). They latter show that both distributions may forecast quite well with a slight advantage to the GARCH(1,1)- GED for out-of-sample forecasts[6].

A paper by Dumitru and Cristiana compares several statistical models for daily stock return volatility in terms of sample fit and out-of-sample forecast ability. The focus is on U.S. and Romanian daily stock return data corresponding to the 2002-2010 time interval .They investigate the presence of leverage effects in empirical time series and estimate different asymmetric GARCH-family models (EGACH, PGARCH and TGARCH) specifying successively a Normal, Student's t and GED error distribution. They find that GARCH family models with normal errors are not capable to capture fully the leptokurtosis in empirical time series, while GED and Student's t errors provide a better description for the conditional volatility. presence in empirical time series. Finally, they report that volatility estimates given by the EGARCH model exhibit generally lower forecast errors and are therefore more accurate than the estimates given by the other asymmetric GARCH models[7].

Ahmed Shamiri and Zaidi Isa investigated the relative efficiency of several different types of GARCH models in terms of their volatility forecasting performance. They compared the performance of symmetric GARCH, asymmetric EGARCH and non-linear asymmetric NAGARCH models with six error distributions (normal, skew normal, student-t, skew student-t, generalized error distribution and normal inverse Gaussian. Their results suggested that allowing for a heavy-tailed error distribution leads to significant improvements in variance forecasts compared to using normal distribution[8].

In an investigation by C. Kosapattarapim, Yan-Xia and M. Michael employed six simulated studies in GARCH (p,q) with six different error distributions are carried out. The analysis was then carried out using the daily closing price data from Thailand (SET), Malaysia (KLCI) and Singapore (STI) stock exchanges. Their Results show that although the best fitting model does not always provide the best future volatility estimates the differences are so insignificant that the estimates of the best fitting model can be used with confidence. The empirical application to stock markets also indicated that a non normal error distribution tends to improve the volatility forecast of returns. They conclude that volatility forecast estimates of the best fitted model can be reliably used for volatility forecasting[9].

G.R.Pasha,Tahira Qasim and Muhammad Aslam in their paper compare the performance of different GARCH models such as GARCH, EGARCH,GJR and APARCH models, to characterize and forecast financial time series volatility in Pakistan. The empirical results demonstrate that the use of asymmetry in the GARCH models and the assumption of fat-tail distributions for the innovations improve the volatility forecasts. Overall, EGARCH fits the best while the GJR model, with both normal and non-normal innovations, seems to provide superior forecasting ability over short and long horizons[10].

According to R. Engle, D. Lilien and R.Robins Volatility is a key parameter used in many financial applications, from derivatives valuation to asset management and risk management. Volatility measures the size of the errors made in modeling returns and other financial variables. It was discovered that, for vast classes of models, the average size of volatility was not constant but changes with time and is predictable. Autoregressive conditional Heteroscedasticity (ARCH)/generalized autoregressive conditional Heteroscedasticity (GARCH) models and stochastic volatility models are the main tools used to model and forecast volatility[1]

A paper by J. Frimpong and F. Oteng aimed to make models and forecasts volatility (conditional variance) on the Ghana Stock Exchange using a random walk (RW), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) models. The unique 'three days a week' Databank Stock Index (DSI) is used to study the dynamics of the Ghana stock market volatility over a 10-year period. The competing volatility models were estimated and their specification and forecast performance compared with each other, using AIC and LL information criteria and BDS nonlinearity diagnostic checks. The DSI exhibits the stylized characteristics such as volatility clustering, leptokurtosis and asymmetry effects associated with stock market returns on more advanced stock markets. The random walk hypothesis is rejected for the DSI. Overall, the GARCH (1,1) model outperformed the other models under the assumption that the innovations follow a normal distribution[11].

MATERIALS AND METHODS

Methodology: Autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models represent the main methodologies that have been applied in modeling and forecasting stock market volatility [5] .In this project different symmetric and asymmetric GARCH models are use .In the volatility modeling process using GARCH models, the mean and variance of the series are estimated simultaneously. This section briefly reviews this methodology

Volatility Models: Volatility model should be able to forecast volatility. Virtually all the financial uses of volatility models entail forecasting aspects of future returns. Typically a volatility model is used to forecast the absolute magnitude of returns. Volatility models can be divided into symmetric and asymmetric models. In this paper we use one symmetric GARCH models which is GARCH(1,1) and two asymmetric GARCH models, namely EGARCH(1,1) and GJR-GARCH(1,1).

ARCH Model: ARCH models based on the variance of the error term at time t depends on the realized values of the squared error terms in previous time periods. The model is specified as:

$$y_t = \varepsilon_t \qquad (1)$$

$$\varepsilon_t \sim N(0, h_t) \qquad (2)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_j \varepsilon^2{}_{t-1} \qquad (3)$$

This model is referred to as ARCH(q), where q refers to the order of the lagged squared returns included in the model. If we use ARCH(1) model it becomes:

$$h_t = \alpha_0 + \alpha_1 u^2{}_{t-1} \qquad (4)$$

Where y_t is observed time series. ε_t is residual. α_0 is constant. α_j represents ARCH effect. q is length of ARCH lags. Since h_t is a conditional variance, its value must always be strictly positive; a negative variance at any point in time would be meaningless. To have positive conditional variance estimates, all of the coefficients in the conditional variance are usually required to be non-negative. Thus coefficients must be satisfy $\alpha_1 \geq 0$.

GARCH Model: The model allows the conditional variance of variable to be dependent upon previous lags; first lag of the squared residual from the mean equation and present news about the volatility from the previous period which is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon^2{}_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (5)$$

Under the hypothesis of covariance stationary, the unconditional variance h_t can be found by taking the unconditional expectation of equation 5 . We find that

$$h_t = \alpha_0 + \alpha_1 h + \beta_1 h \qquad (6)$$

Where α_1 and β_1 are the ARCH effect and GARCH effect

Solving the equation 6 we have

$$h = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} \qquad (7)$$

For this unconditional variance to exist, it must be the case that $\alpha_1 + \beta_1 < 1$ and for it to be positive, we require that $\alpha_0 > 0$.

GJR- GARCH Model: The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries [12] .Glosten, Jaganathan and Runkle (1993) develop the GARCH model which allows the conditional variance has a different response to past negative and positive innovations [13].

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 d_{t-1} + \sum_{i=1}^{p} \beta_j h_{t-j} \qquad (8)$$

Where d_{t-1} is a dummy variable that is:

$$d_{t-1} = \begin{cases} 1 \text{ if } \varepsilon_{t-1} < 0, & \text{bad news} \\ 0 \text{ if } \varepsilon_{t-1} \geq 0, & \text{good news} \end{cases}$$

The coefficient γ is known as leverage term . In the model, effect of good news shows their impact by α_i , while bad news shows their impact by $\alpha+\gamma$. In addition if $\gamma \neq 0$ news impact is asymmetric and $\gamma > 0$ leverage effect exists. To satisfy non-negativity condition coefficients would be $\alpha_0 > 0$, $\alpha_i > 0$, $\beta \geq 0$ and $\alpha_i + \gamma_i \geq 0$. That is the model is still acceptable, even if $\gamma_i < 0$, provided that $\alpha_i + \gamma_i \geq 0$. [12]

EGARCH Model: Nelson (1991) proposed a GARCH-class model named Exponential GARCH that allows for asymmetric effects and therefore solves one of the important shortcomings of the symmetric models. While the GARCH model imposes the nonnegative constraints on the parameters, EGARCH models the log of the conditional variance so that there are no restrictions on these parameters [14] .

$$\log(h^2{}_t)) = w + \beta \log(h^2{}_{t-1}) + \alpha\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{h_{t-1}} \qquad (9)$$

Where α and β are the ARCH and GARCH parameters . γ is leverage parameter and w is constant

Note that the left-hand side is the logarithm of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. If $\gamma \neq 0$, then the impact is asymmetric E-GARCH basically models the log of the variance (or standard deviation) as a function of the lagged logarithm of the variance/std dev and the lagged absolute error from the regression model. It also allows the response to the lagged error to be asymmetric, so that positive regression residuals can have a different effect on variance than an equivalent negative residua.

DATA FOR ANALYSIS

The data used in this paper consist of daily closing price of Saudi Arabia stock market index namely ,Tadawul All-Share Index(TASI) over the period of 1st January 2005 to 31st December 2012. This yields of 2317 observations. The estimation process is run using data from 1st January 2005 to 30th June 2012, while the remaining data (1st July2012 to 31th December 2012) are used for the evaluation of the out sample forecast performance .The data series of stock market have been taken from the Saudi Stock Market Website (http://www.tadawul.com.sa) . Daily returns r_t were calculated as a logarithm of TASI indices such as :

$$r_t = \log(\frac{p_t}{p_{t-1}}) \qquad (10)$$

Where r_t is daily return of the index at time t, p_t and p_{t-1} are the closing market index at the current t and previous day(t-1) respectively .

DESCRIPTIVE STATISTICS

Table 1 presents descriptive statistics on TASI returns over the sample period. As expected for time series of returns, the mean is close to zero , while the daily volatility is represented by standard deviation is 0.01845, which is high value indicating high fluctuations of the TASI daily returns. The skweness coefficient is negative , reveal that the TASI returns has a heavy left tail ,while kurtosis is very high (39.70), suggesting that the distribution is highly leptokurtic confirming previous finding that stock returns are not normally distributed. The high value of Jarque- Bbera corroborate that normality is rejected at a p-value of almost 1 % . Moreover, Engle (1982) LM test statistics indicates the existence of ARCH effects in the residual series and therefore the variance of returns series is non- constant for period under review . The Ljung Box Q statistics of order 20 on both returns and squared returns reflects a high serial correlation.

Table 1. Descriptive Statistics of TASI returns series

Minimum	-0.137730
Maximum	0.040780
Mean	-0.0000391
Median	0.000545
Standard deviation	0.008450
Skewness	-2.709126
Kurtosis	39.70133
$Q\,20$	60.83
Prob. of $Q\,20$	0.0000
$Q^2\,20$	1623
Prob. of $Q^2\,20$	0.0000
Jarque- Bera	125706.2
Prob. of Jarque- Bera	0.0000
ARCH(2)	55.43
Prob. Of ARCH(2	0.0000

Fig 1 presents the patterns of daily logarithm returns of the TASI for the period under review . We observe that small returns changes tend to be followed by small changes and large returns changes tend to be followed by other large returns changes of same signs. This behavior of stock returns series indicates that there is a clear evidence of volatility clustering in TASI returns .The implication of volatility clustering is that volatility shocks to day will influence the expectation of volatility in the immediate future periods .Fig 2 shows the distribution of TASI log returns, which clearly indicate the departure from normality with a high peaked distribution.

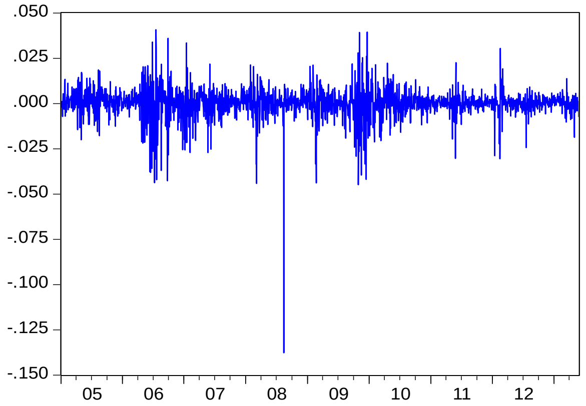

Fig 1 : Daily Returns series

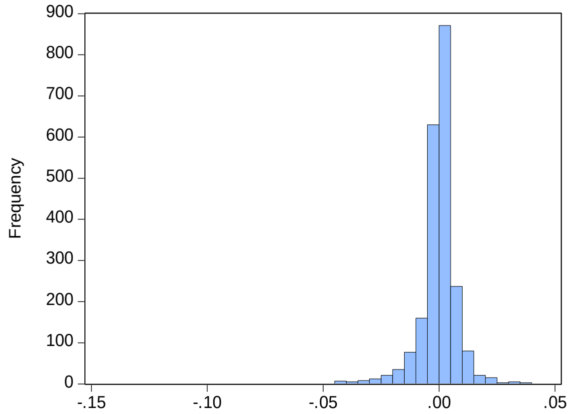

Fig 2 : Daily Returns Distribution

Generally , the TASI returns series do not confirm that there is normal distribution, but display negative skewness and leptokurtic distribution. This predicated that a fatter – tailed distribution such as as Student-t or GED distribution should generate better results than normal distribution

UNIT ROOT TEST FOR THE TASI DAILY RETURNS

To verify whether the daily returns are stationary series, the Augmented Dickey fuller (ADF) test was used. The results of test are present in table 2.The results reject the null hypothesis of a unit root test. Consequently, we Deduce that returns are stationary in level for the period under review.

Table 2: Stationary Test for daily returns series

	TASI returns series		
ADF statistic	Critical values		
	1%	5%	10%
-43.17877	-3.43313	-2.86265	-2.56741

EMPIRICAL RESULTS AND DISCUSSION

In this section, we present the estimates of different GARCH models for TASI returns series . The basic estimation models consist of two equations; one for the mean, which is a simple autoregressive model and the other for the variance represented in the GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models . A maximum likelihood approach is used to estimate the models, with three underlying error distributions namely: normal, Student-t and Generalize Error Distribution (GED). Table3, 4 and 5 present the estimation results for the parameters of GARCH, EGARCH and GJR-GARCH models while tables 6 - 8 report diagnostic tests.

In the variance equation from table 3 , the first three coefficients α_0 (constant) , α_1 (ARCH term) and β_1 (GARCH term) are highly significant , at standard level . Moreover, the tail coefficients δ are significant justifying the use of non- normal densities, the sum of α_1 and β_1 is close to unity , suggesting that shocks to the conditional variance are highly persistence, indicating that large changes in returns tend to followed by large changes and small changes tend to be followed by small changes , this mean that volatility clustering is observed in TASI index returns series.

The results presented in table 4and 5 show that all asymmetric coefficients are statistically significant at 1% significance level, implies that the use of asymmetric GARCH models seem to be justify .The leverage effect term γ in the asymmetric models EGARCH(1,1) and GJR-GARCH(1,1)are statistically significant with negative sign , denoting that negative shocks tend to produce a higher volatility in the immediate future than positive shocks of same sign ,indicating that the existence of leverage effect is observed in returns of TASI market index.

Table 3: parameter estimation of AR(1)-GARCH model

	Normal	Student-t	GED
Mean Equation			
ϕ_0	0.000232 (0.0345)	0.000532 (0.0000)	0.000569 (0.0000)
ϕ_1	0.248065 (0.0000)	0.066963 (0.0021)	0.030028 (0.0927)
Variance Equation			
α_0	0.00000188 (0.0000)	0.00000120 (0.0000)	0.00000131 (0.0000)
α_1	0.262093 (0.0000)	0.210373 (0.0000)	0.208464 (0.0000)
β_1	0.750247 (0.0000)	0.812193 (0.0000)	0.801742 (0.0000)
δ		3.56198 (0.0000)	0.946829 (0.0000)

Figures in parentheses are p-value

Table 4: parameter estimation of AR(1)- EGARCH model

	Normal	Student-t	GED
Mean Equation			
ϕ_0	0.000408 (0.0014)	0.000505 (0.0000)	0.000542 (0.0000)
ϕ_1	0.0.082199 (0.0002)	0.7427 (0.0013)	0.031784 (0.0693)
Variance Equation			
α_0	-0.986622 (0.0000)	-0.637683 (0.0000)	-0.729641 (0.0000)
α_1	0.357857 (0.0000)	0.272684 (0.0000)	0.273951 (0.0000)
β_1	0.925928 (0.0000)	0.955900 (0.0000)	0.947474 (0.0000)
γ	-0.230582 (0.0000)	-0.073230 (0.0000)	-0.096531 (0.0000)
δ		3.706843 (0.0000)	0.958149 (0.0000)

Figures in parentheses are p-value

Table 5: parameter estimation of AR(1)- GJR -GARCH model

	Normal	Student-t	GED
Mean Equation			
ϕ_0	0.000408 (0.0014)	0.000505 (0.0000)	0.000542 (0.0000)
ϕ_1	0.0.082199 (0.0002)	0.7427 (0.0013)	0.031784 (0.0693)
Variance Equation			
α_0	-0.986622 (0.0000)	-0.637683 (0.0000)	-0.729641 (0.0000)
α_1	0.357857 (0.0000)	0.272684 (0.0000)	0.273951 (0.0000)
β_1	0.925928 (0.0000)	0.955900 (0.0000)	0.947474 (0.0000)
γ	-0.230582 (0.0000)	-0.073230 (0.0000)	-0.096531 (0.0000)
δ		3.706843 (0.0000)	0.958149 (0.0000)

Figures in parentheses are p-value

Table 6 to 8 show models diagnostics of different GARCH models for the returns of TASI index. Ljung- Box-Pierce statistics $Q^2(20)$ on the squared standardized residuals is non-significant at 5% level, indicating that all models seem to be a adequately in describing the dynamics of the series. Moreover, LM test for presence of ARCH effect at lag 2 exhibit the absence of ARCH effect in standardize residual.

These results reveal that all variance equations are specified correctly. As expected asymmetric EGARCH and GJR-GARCH models have both smaller values of AIC and bigger log –likelihood function than the traditional GARCH model , therefore we conclude that the EGARCH and GJR-GARCH models better the estimation the TASI returns series than the traditional GARCH model. Overall, using AIC and log likelihood values as model selection criteria, for the GARCH models , the results show that GJR- GARCH model with all three distributions provide the best estimation for the TASI returns series. When we analyze the densities we find that ,the GED distribution clearly outperform the Student –t and Gaussian distributions for all models estimated in this study.

Table 6 : Model diagnostics of AR(1) –GARCH Model

	Normal	Student-t	GED
$Q^2(20)$	0.972 (1.000)	0.6475 (1.000)	0.688 (1.000)
ARCH(2)	0.160 (0.923)	0.0596 (0.9706)	0.068239 (0.9665)
AIC	-7.115337	-7.459543	-7.446527
BIC	-7.102347	-7.443956	-7.430939
Log-Like	7799.852	8177.930	8163.670

Table 7 : Model diagnostics of AR(1) – EGARCH Model

	Normal	Student-t	GED
$Q^2(20)$	0.7627 (1.0000)	0.47200 (1.00)	0.5205 (1.000)
ARCH(2)	0.1511 (0.9227)	0.043468 (0.9785)	0.057271 (0.9718)
AIC	-7.105337	-7.451015	-7.441348
BIC	-7.102347	-7.432829	-7.423162
Log-Like	7843.501	8169.587	8158.997

Table 8: Model diagnostics of AR(1) – GJR-GARCH

	Normal	Student-t	GED
$Q^2(20)$	0.88 (1.00)	0.7102 (1.000)	0.7723 (1.000)
ARCH(2)	0.162 (0.922)	0.046820 (0.9542)	0.112581 (0.9453)
AIC	-7.183363	-7.465408	-7.45538(
BIC	-7.16775	-7.447223	-7.437194
Log-Like	7875.374	8185.355	8174.369

FORECAST PERFORMANCE

To evaluate and compare forecast performance of different GARCH models , several evaluation criteria were computed .In this study a variety of statistics have been used to evaluate and compare forecast performance. They include Root Mean Square Errors(RMSE), Mean Absolute Errors (MAE), Mean Absolute Percentage Errors(MAPE) and Theil Inequality Coefficient(TIC).The model exhibits the lowest value of the errors is considered to be the best one. In this paper the length of the out-sample period is chosen to be 124 days . The results reported in Tables 9,10and 11 show that the model exhibit the better forecasting performance is GJR –GARCH for all three distributions .From these results, we can conclude that volatility forecast of the TASI index may be improved by using asymmetric GARCH models with non- normal distributions.

Table 9: Forecast performance out of sample - Normal

	GARCH	EGARCH	GJR-GARCH
MSE	0.008509	0.008435	0.008435
MAE	0.005064	0.005054	0.5050
MAPE	161.8994	129.6981	121.4941
TIC	0.903665	0.912480	0.933341

Table 10: Forecast performance out of sample – Student- t

	GARCH	EGARCH	GJR-GARCH
MSE	0.008443	0.008442	0.008439
MAE	0.005050	0.005049	0.005051
MAPE	135.8133	133.9952	131.7062
TIC	0.915369	0.916719	0.91653

Table 11: Forecast performance out of sample - GED

	GARCH	EGARCH	GJR-GARCH
MSE	0.008475	0.008453	0.008451
MAE	0.005043	0.005043	0.005043
MAPE	133.4086	131.0476	130. 0740
TIC	0.931388	0.933566	0.934030

CONCLUSION

We find that most of the financial markets, characterized by feature of volatility, this property means a large and abnormal fluctuations. In, for instance, prices of shares and bonds .Naturally enough, these fluctuations are undesirable by investors and decisions-makers as they result in a state of uncertainty in financial transactions, and, thus, negatively affecting the economy. To deal with such problems, there is a need to use statistical models that take into account these fluctuations, one of these is the General Auto Regressive conditional heteroscedasticity models(GARCH models.

The main goal of this study is to compare the performance of different GARCH models including symmetric and asymmetric models in estimating and forecasting the volatility of Saudi stock market index . We found that the daily return of TASI exhibit the stylized fact such as volatility clustering, leptokurtosis , departure from normality and existence of heteroscdasticity in residuals series. The models were estimated assuming various assumptions namely: Normal, Student- t and GED distributions. The sum of the parameters estimates the GARCH (1,1) is close to unity , revealing that a high degree of persistent in the conditional volatility of stock returns on Saudi stock market. According to AIC and Log likelihood function among the competing models , asymmetric GARCH models(EGARCH and GRJ-GARCH) fit the conditional variance equations better than symmetric GARCH model. We have examined the empirical performance of the models for forecasting volatility in Saudi stock market and we found that the GRJ-GARCH(1,1) model outperformed the other models. We recommend that GRJ- GARCH can be use for estimating and forecasting the daily returns volatility of Saudi stock market.

ACKNOWLEDGMENT

The authors would like to express their sincere thanks to Taif university, Saudi Arabia for supported of this work

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