

**Forecasting Volatility in GCC Emerging Markets: The
Predictive Power of Alternative Models***

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Abstracts: In this paper forecast of conditional volatility in Saudi, Kuwait, and Abu-Dhabi markets is performed. To capture skewness and excess kurtosis that characterize asset returns in GCC markets, conditional volatility of asset returns estimated using skewed t-distribution, symmetric student t-distribution, and the Normal distribution specifications. Prediction performance results indicate the Normal and symmetric t-distribution models outperform the skewed t-distribution model.

Keywords: GARCH, Volatility, Asymmetry, skewness, Forecast
JEL: C10, C50, G10

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1-Introduction:

Forecasting stock markets volatility help controlling stock markets irregularities and detecting the impact of economic policy decisions on stock markets volatility. The increasing inflow of foreign investments to Gulf Cooperation Council (GCC), countries motivated by increasing openness of those countries, enhanced cointegration of GCC stock markets and increased volatility spillover across GCC capital markets. The increasing interdependence of GCC capital markets highlights the importance of modeling distributional aspects of asset returns to capture volatility dynamics.

During the past few years more research work emphasized the importance of skewness and kurtosis in modeling volatility in emerging capital markets. Brooks and Persaud (2003), Vilasus (2002), Hansen and Launda (2003) modeled volatility in stock markets as skewed t-distribution model. Whereas Bollerslev (1987) suggest using Student t-distribution with degrees of freedom greater than two .While in recent years growing research work employed fat tailed and skewed distribution models to predict volatility dynamics in developed and emerging Asian stock markets, there is no similar work presented on GCC stock markets. The main purpose in this paper to explore the predictive power of three alternative specifications of volatility in three GCC stock markets. The three models include skewed t-distribution which takes into account skewness and leptokurtic (high peaks and fat tailedness) behavior of volatility of asset returns; symmetric student t- distribution; and the Normal distribution.

The benefits of estimating volatility dynamics using asymmetric leptokurtic distributions are more substantial for highly volatile series evidenced in a number of emerging stock markets which have a higher degree of non-normality.

Following Poon and Granger (2001), it is possible to divide the current literature on forecasting volatility in financial markets in two main approaches. The first one refers to models of time series analysis that uses recursive volatility behavior, whereas the second approach comprises those techniques that uses actual option prices using Black and Scholes model of option pricing. Since derivative markets in

GCC markets are non-existent so far, the analysis in this research belong to the former approach.

In the past decade several distributions that provide effective alternative means of modeling asymmetry and fat tailedness of financial data have been developed. These models include skewed t-distribution specification of Hansen (1994), non-central t-distribution , model of Harvey and Siddique (1999), and log generalized gamma distribution, model of Brannas and Nordman (2003).

More recently, investigation of skewness and kurtosis attracted the attention of academics in the Middle East countries. Maghyereh and Zoubi (2007) establish evidence of skewness and fat tailedness of stock prices in some GCC markets. Labidi and Ane (2007) also conclude similar findings for a number of Middle East and North Africa countries. In this paper asymmetric GARCH employed to investigate the predictive power of volatility using three alternative models: skewed t-distribution, symmetric student t-distribution, and Normal distribution.

Diebold and Mariano (1995) methodology is employed to test the statistical significance of the predictive power of the three competing models.

The remaining part of the paper is structured as follows. In section two several preliminary statistics on the data presented. Section three includes the methodology. Section four illustrates the empirical evidences. The final section concludes the study.

2- Data and preliminary statistics:

The data employed in this research includes daily price indexes for three stock markets in GCC countries, Saudi stock market, Kuwait, and Abu-Dhabi stock markets, for the period from April-11-2004 to September-2-2006 (852 observations).

The data has been transformed into daily stock returns using logarithmic transformation such as, $r_t = \log[(p_t)/(p_{t-1})]$, where p_t is the level of each series at time t. The mean and the standard deviation figures in table (1) rule out existence of significant profitable arbitrage opportunities in the three markets, and indicate inverse relationship between stock returns and risks, implying risk aversion behavior of investors. The skewness statistic show departure from symmetry as

Saudi market exhibit a negative skewness and the other two markets a positive skewness. kurtosis coefficients indicate the distributions of returns for the three markets characterized by peakness and fat tail relative to a normal distribution¹. The Jarque-Bera (JB) test for joint normal kurtosis and skewness reject the normality hypothesis for these markets². The augmented Dicky-Fuller (ADF) test results reject the null-hypothesis that stock returns follow random walk process with drift.

Table (1): Log-differenced statistics

	Ab.Dhabi	Saudi	Kuwait
Mean (%)	0.07	0.08	0.07
St.deviation:	0.01	0.02	0.01
Skewness	1.45	-0.35	0.90
Kurtosis	5.36	4.0	4.5
JB	115.5	49.7	71.9
p-value	(0.000)	(0.000)	(0.000)
ADF	120*	143*	131*
LM test	88.4*	113.4*	66.3*

*significant at 5% significance level

To test for the presence of GARCH-type effects in the data we employ Engle's (1982) Lagrange multiplier (LM) test which specify significant evidence of conditional heteroskedasticity for the three markets.

To test for normality of stock price returns more formally, we conducted a non-parametric runs test. The runs test determines if the total number of runs in the sample consistent with the hypothesis that the change in prices is consistent with the normal distribution pattern, which imply randomness and independence of the data series³. The standard normal z-test used in the runs test is:

$$z = -\frac{R - E(R) - 0.5}{\sigma_R}$$

where R is the observed number of runs, and $E(R) = \frac{2n_1n_2}{n_1 + n_2}$

where n_1 and n_2 are the number of observations below and above the mean, and

$\sigma^2_R = \frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)}$. The hypothesis of randomness is then rejected at

α – significance level if $2p\{z > |z|\} < \alpha$, where $z \sim \text{NID}(0,1)$.

The non-parametric test result in Table (2) show evidence of non-normality of the three stock returns, and this mainly due to the presence of skewness and excess kurtosis.

Table (2): Nonparametric test for randomness.

Runs test	Saudi	Kuwait	Abu-Dhabi
Observations	844	844	844
Cutoff	0	0	0
Bellow cutoff	470	507	478
Above cutoff	374	337	366
Number of runs	424	424	432
E[R]	416	404	414
Std.dev.	14.3	13.9	14.2
Z-value	0.48	1.30	1.18

To ensure the non-normality evidence indicated by the non-parametric test we also employed Kocenda and Briatka (2005) known as (K2K) test to test for strict white noise process that reflect sequence of independent and identically distributed (iid) random variables, and detect non-linear dependence in the return series⁴. Result in Table (3), confirm the significance of non-linear dependence in the return series and reject the assumption of iid in the data.

Table (3): Non-Linear dependence test (K2K):

Dimension	Saudi	Ab.Dhabi	Kuwait
2	0.64	0.77	0.83
3	0.89	1.02	1.19
4	1.10	1.23	1.52
5	1.31	1.38	1.79
6	1.49	1.49	2.01
7	1.67	1.57	2.21
8	1.81	1.62	2.37
9	1.92	1.65	2.51
10	2.20	1.69	2.68

Note: Critical values from Kocenda and Briatka (2005).

All values of K2k reject the null-hypothesis at 1% significance level.

3-Methodology

3.1: GJR-GARCH

Although the simple GARCH specification is widely used in the empirical research of finance, there are substantial evidences that volatility of asset returns characterized by time varying asymmetry (Glosten, Jagannathan and Runkle (1993)). As a result, to avoid misspecification of the conditional variance equation, a leverage term in the GARCH specification is included. The GARCH-type specification introduced by Glosten, et al, (1993) allows a quadratic response of volatility to news with different coefficients for good and bad news, but maintains the assertion that the minimum volatility will result when there is no news⁵.

Given that stocks return defined as:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) = \mu + \varepsilon_t$$

where

$$\varepsilon_t | \Psi_{t-1} = \sigma_t z_t$$

For p=q=1, GJR-GARCH model specify volatility as:

$$\sigma_t^2 = w + (\alpha + \delta I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (1)$$

where I_t indicator function equal to 1 when $\varepsilon_{t-1} < 0$, and zero otherwise. In this model good news (or positive shocks, $\varepsilon_{t-1} > 0$) have an impact of $\alpha\varepsilon_{t-1}^2 \geq 0$ on volatility, while bad news or negative shocks, ($\varepsilon_{t-1} < 0$) have an impact of $(\alpha + \delta)\varepsilon_{t-1}^2 \geq 0$. Therefore if $\delta \neq 0$, we can say that there exist asymmetric effects on conditional volatility.

In the coming sections we estimate conditional volatility of stock returns based on the specifications in equation (1) and assuming the distribution of the standardized error term, z_t , is Normal (GJR-N); Skewed t-distribution (GJR-skt); and Student t-distribution (GJR-t).

3.2: Skewed and Fat-tailed distributions:

It is well documented that even asymmetric GARCH models fail to fully account for skewness and leptokurtosis of high frequency financial time series when they are assumed to follow normal or symmetric student's t-distributions. This has led to the use of asymmetric non-normal distributions to better specify conditional higher moments. An important candidate in this respect is Hansen's (1994) distribution.

Given the standardized errors $\frac{\varepsilon_t}{\sqrt{\sigma_t^2}} = z_t$, then Hansen's (1994) autoregressive conditional density model with skewed error terms specified as:

$$skt(z \setminus \phi, \theta) = \begin{cases} bc \left(1 + \frac{1}{\theta - 2} \left(\frac{bz + a}{1 - \phi} \right)^2 \right)^{-(\theta+1)/2} & \text{if } z < -a/b \\ bc \left(1 + \frac{1}{\theta - 2} \left(\frac{bz + a}{1 + \phi} \right)^2 \right)^{-(\theta+1)/2} & \text{if } z \geq -a/b \end{cases} \quad (2)$$

where

$$a = 4\phi c \frac{\theta - 2}{\theta - 1}, \quad b = 1 + 3\phi^2 - a^2, \quad c = \frac{\Gamma(\theta + 1)/2}{\sqrt{\pi(\theta - 2)}\Gamma(\theta/2)} \quad (3)$$

Specification of conditional distribution of the standardized residuals, Z_t , in equation (2) is determined by two parameters, Kurtosis (θ) and the skewness parameter (ϕ). The two parameters are restricted to $\theta > 2$, and $-1 < \phi < 1$. When $\phi = 0$, the skewed t-distribution tend to symmetric t-distribution, and when $\theta \rightarrow \infty$, tend to standardized normal distribution.

Hansen's skewed t-distribution is fat tailed, and skewed to the left (right) when ϕ is less (greater) than zero. The log-likelihood function of the GJR-skt is defined as:

$$L(\Omega; \Psi_{t-1}) = \sum_{t=2}^T \ln[SKt(z \setminus \theta, \phi; \Psi_{t-1})]$$

The maximum likelihood estimator for Φ is the solution of maximizing the log likelihood function stated above. Alternatively, when the standardized residuals distributed symmetric t-distribution the density function specified as:

$$f(z \setminus \theta) = \frac{\Gamma(\theta + 1)/2}{\sqrt{\theta\pi}\Gamma(\theta/2)} \left(\frac{\theta}{\theta + z^2} \right)^{(\theta+1)/2} \quad \text{for } -\infty < z < \infty \quad (4)$$

where $\Gamma(\cdot)$, denotes gamma function.

Bollerslev et al.(2003) indicate ARCH models with conditional normal errors, result in a leptokurtic unconditional distribution. However, the degree of leptokurtosis induced by the time-varying conditional variance often does not capture all of the leptokurtosis present in high frequency speculative prices. To circumvent this problem Bollerslev (1987) suggest using Student t-distribution with degrees of freedom greater than two.

Given there is no common single conventional model selection criteria, to assess the goodness-of-fit for the three models we employed, the log-likelihood function and three information criteria, including Akaike information criteria (AIC), Schwarz criteria (SC), and Hannan-Quinn (HQ), as indicated below:

$$AIC = -2(l/T) + 2(k/T)$$

$$SC = -2(l/T) + k \log(T)/T$$

$$HQ = -2(l/T) + 2k \log(\log(T))/T$$

where k and (T) are respectively the number of parameters and the sample size, and l is the lag length. The model that minimizes the above information criteria considered the best fit, given that the model also yield highest log likelihood value.

4. Empirical Results

4.1: Estimation of Parameters:

To estimate parameters in equations (1) - (4), maximum likelihood estimation method employed. Table (4) presents estimation results. The significance of the asymmetry coefficient (δ) for all three markets indicate negative shocks (or bad news) have more significant effect on volatility than good news. Result in table (4) also indicate significance of the Kurtosis

coefficient (θ) for the three markets, which suggest fat-tailed student t-density is needed to fully model the distribution of return. Despite Saudi market exhibit significant skewness and fat-tailedness, the log-likelihood value and information criteria support the symmetric t-distribution in model fitting.

The log-likelihood values and the three information criteria strongly suggest that GJR-t model outperform the other two models for Saudi and Kuwait markets, whereas for Abu-Dhabi market GJR-N model outperform the other modeling specifications. For all three markets, superiority of GJR-t and GJR-N models over GJR-skt model is astounding, as both models not only have the highest likelihood values, but also the smallest values of information criteria which imply that GJR-N and GJR-t models not only the best but also parsimonious as they include fewer parameters for estimation, compared to skewed t distribution model.

Table (4): Estimation of Parameters

	Saudi			Kuwait			A.Dhabi		
	GJR-t skewed	GJR-t student	GJR- Normal	GJR-t skewed	GJR-t student	GJR- Normal	GJR-t skewed	GJR-t student	GJR- Normal
ω	0.00 (0.00)	0.01 (0.00)	0.00 (0.05)	3433 (0.00)	0.01 (0.00)	4013 (0.00)	0.01 (0.00)	-0.02 (0.00)	0.00 (0.00)
β	0.18 (0.00)	-0.05 (0.00)	0.96 (0.00)	0.087 (0.01)	-0.04 (0.02)	0.10 (0.00)	0.38 (0.00)	0.02 (0.15)	0.27 (0.00)
α	0.00 (0.98)	0.05 (0.00)	0.03 (0.00)	0.00 (0.98)	0.02 (0.00)	-0.001 (0.95)	0.00 (0.98)	0.04 (0.00)	0.08 (0.00)
δ	0.05 (0.51)	-0.06 (0.00)	-0.001 (0.79)	0.92 (0.001)	-0.02 (0.00)	0.004 (0.00)	0.95 (0.001)	-0.05 (0.00)	0.31 (0.00)
ϕ	0.60 (0.00)	--	--	0.46 (0.16)	--	--	-0.46 (0.84)	--	--
θ	3.0 (0.00)	2.94 (0.00)	--	2.96 (0.00)	2.99 (0.00)	--	2.97 (0.00)	2.74 (0.00)	--
LnL	505	5382	4635	1592	6749	2866	1637	5655	8366
AIC	0.017	0.1E-6	0.8E-6	0.001	0.6E-8	0.6E-3	0.001	0.8E-7	0.11E-9
SC	0.02	0.1E-6	0.9E-6	0.001	0.6E-8	0.6E-3	0.001	0.8E-7	0.12E-9
HQ	0.02	0.1E-6	0.8E-6	0.001	0.6E-8	0.6E-3	0.001	0.9E-7	0.11E-9

Note: Estimated values of parameters rounded into two decimals.
Terms in parenthesis are P-values.

4.1: Predictive Power of Models:

To forecast s-step ahead forecast for the conditional variance in equations

(1) - (4), we need first to simplify equation (1) by assuming:

$$E(I(\varepsilon_t > 0) = p(\varepsilon_t > 0) = 0.5$$

$$E(I(\varepsilon_t \leq 0) = p(\varepsilon_t \leq 0) = 0.5$$

and

$$E(\varepsilon^2 \setminus \Omega_t) = \sigma_t^2,$$

Since ε_t^2 and the indicator function $I_t(\varepsilon_t)$ are uncorrelated, then s-step ahead forecast can be stated as:

$$\hat{\sigma}_{t+s|t}^2 = w + [(\alpha + \delta) + \beta]\sigma_{t+s-1|t}^2 \quad (6)$$

The parameters of the models estimated using the sample data up to three days before the end of the sample data (Aug/30/2006). And then a forecast of one day ahead (Aug-31) is computed from the estimated model. Using the estimated parameters and the one day-ahead forecast value of volatility a new forecast for volatility of Sept/1, is computed from equation (6) to obtain two days ahead forecast value. This procedure is repeated until we exhaust the actual realized values.

To test the predictive power of the three competing models (GJR-N, GJR-*skt*, and GJR-t) the Root Mean Squared Error (RMSE) employed, which is computed by comparing the forecast values F_{t+j} with the actually realized

values, A_{t+j} , or
$$RMSE(k) = \sqrt{\frac{\sum_{j=0}^{N_k-1} [F_{t+j+k} - A_{t+j+k}]^2}{N_k}}$$

Where $k=1,2,3$ denotes the forecast step, N_k , is total number of k -steps ahead forecasts.

Diebold and Mariano (1995) (DM) test has been employed to compare the accuracy of forecasts. When comparing forecasts from two competing models; model A, and model B, an important question need to be answered, whether the prediction of model A is significantly more accurate, in terms of a loss function, $DM(d)$, than the prediction of model B. The Diebold and Mariano test aims to test the null hypothesis of equality of forecast accuracy against the alternative of different forecasts across models. The null hypothesis of the test can be written as:

$$d_t = E(h(e_t^A) - h(e_t^B)) = 0 \quad (14)$$

where e_t^i refers to the forecast error of model $i = A, B$, when performing k -steps ahead forecast. The Diebold and Mariano test uses the autocorrelation-corrected sample mean of d_t in order to test significance of equation (14). If N observations available, the test statistic is:

$$DM = [\hat{w}(\bar{d})]^{-1/2} \bar{d}$$

where $\hat{w}(\bar{d}) = \frac{1}{N} \{ \hat{\rho}_0 + 2 \sum_{h=1}^{K-1} \hat{\rho}_h \}$

and

$$\hat{\rho}_h = \frac{1}{N} \sum_{t=h+1}^N (d_t - \bar{d})(d_{t-h} - \bar{d})$$

Under the null hypothesis of equal forecast accuracy, DM is asymptotically normally distributed.

Results in table (5) indicate that the GJR-t distribution model yield the lowest value of the loss function for Saudi and Kuwait markets, whereas for Abu-Dhabi market GJR-N specification yield lowest loss function.

DM test results confirm that the predictive power of the three models are significantly different for all three markets; implying that GJR- skt specification yield inferior forecast ability for the three markets.

Table (5): RMSE Loss functions and Diebold & Mariano test.

	<u>RMSE Loss Functions</u>			DM	DM
	GJR-N (1)	GJR-t (2)	GJR-sk(t) (3)	(1)&(2)	(1)&(3)
Saudi p-value	0.0006	0.0002	1.71	4.9 (0.00)	5.98 (0.00)
A.Dhabi p-value	0.00003	0.0001	1.50	3.9 (0.00)	7.32 (0.00)
Kuwait p-value	0.004	0.00003	1.50	3.27 (0.00)	7.22 (0.00)

*The loss functions are based on three days ahead forecast errors.

5-Concluding remarks:

Forecast of conditional volatility for Saudi, Kuwait, and Abu-Dhabi stock markets estimated under three alternative distributions for the error terms; skewed t-distribution, Normal distribution, and student t-distributions. Time varying volatility specification that allows a quadratic response of volatility to news with different coefficients for good and bad news, but maintains the assertion that the minimum volatility will result when there is no news, is adopted. Estimation results indicate negative shocks (or bad news) have more significant effect on volatility than positive shocks (good news).

Significance of Kurtosis coefficient for the three markets, suggest fat-tailed student t-density is needed to fully model the distribution of return.

For all three markets, superiority of student t-distribution and the Normal distribution models over skewed t-distribution model is astounding, as both models not only have the highest log likelihood values, but also smaller values of information criteria. This imply that Normal distribution and

Student-t models not only superior in capturing volatility dynamics, but also parsimonious as they include a smaller number of parameters for estimation, compared to skewed-t distribution model.

In comparing the forecast performance of the models, the model with the lowest value of the Root Mean Square Errors (RMSE) loss function is considered superior, since it minimizes forecast errors. The statistical significance of forecast performance between the three competing models investigated using Diebold and Mariano (1995) methodology. Our estimation results strongly suggest that the student t-distribution model yield the lowest value of the loss function for Saudi and Kuwait markets, whereas the Normal distribution yield lowest loss function for Abu-Dhabi market. DM test confirm that the predictive power of the three models (student t-distribution, the Normal distribution, and skewed t-distribution) are significantly different for the three markets.

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Notes:

* Gulf Cooperation Council (GCC) countries include Saudi Arabia, Kuwait, UAE, Oman, Bahrain, and Qatar.

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¹The skewness (sk) and excess kurtosis (k) statistics calculated using the formulas

$$sk = \frac{m_3}{(m_2)^{3/2}}, \text{ and } k = \frac{m_4}{(m_2)^2} - 3, \text{ where } m_j \text{ stand for the } j\text{th moment around the mean. Under}$$

the null-hypothesis of normality, the two statistics are normally distributed with standard errors,

$$\sigma_{sk} = \frac{\sqrt{6}}{N}, \text{ and } \sigma_k = \frac{\sqrt{24}}{N}, \text{ where } N \text{ is the sample size.}$$

² Some authors, (Green, W.; page 310) indicate that the Normality test based on JB statistic is essentially non-constructive, as a finding of Normality does not necessarily suggest what to do next, and failing to reject it does not confirm normality; it is only a test of symmetry and mesokurtosis

³ The randomness of stock returns is crucial for normal distribution of stock return series.

⁴ K2k test is more general form of BDS test introduced by Brock, Dechert, and Scheinkman (1996) used for testing the null-hypothesis that the data are independently and identically distributed, against unspecified alternative. Both tests aim to detect non-linear hidden patterns in time series data. Kocenda and Briatka, developed computer program for calculating K2K statistics and its critical values..

⁵ Any selection of an appropriate ARCH model requires having a good idea of what empirical regularities the model should capture. Among well documented regularities in the literature are thick tails that characterize asset returns, and volatility clustering, which refers to the phenomena that large changes in volatility tend to be followed by large changes of either sign, and small changes to be followed by small changes. Also another phenomena captured by ARCH specifications is the so-called leverage effect, which refers to the tendency for stock returns to be negatively correlated with changes in stock volatility.