Estimating Stock Returns Volatility of Khartoum Stock Exchange through GARCH Models

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Abstract: This study modeled and estimated stock returns volatility of Khartoum Stock Exchange (KSE) Index using symmetric and asymmetric GARCH family models, namely: GARCH(1,1), GARCH-M(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models. The study was carried out based on daily closing prices over the period from 2nd January 2006 to 31 August 2010.The empirical results reveals that a high volatility process is present in KSE Index returns series. The results also provide evidence on the existence of risk premium and indicates the presence of the leverage effect in the KSE index returns series. Our findings indicate that Student-t is the most favored distribution for all models estimated.

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1. Introduction

Financial time series analysis is directed to the understanding of the mechanism that drives a given time series of data, or, in other words: financial time series analysis focuses on "the truth behind the data" so that one can find physical models that explain the empirically observed features of real life data. With such models one can make distributional forecasts for future values in time series Karlsson (2002).

Volatility permeates finance and it is a key variable used in many financial applications such as investment, portfolio construction, option pricing and hedging as well as market risk management. Good forecasts of volatility, therefore, become extremely important in making financial decisions. First, knowledge of volatility could guide traders on the risk of holding an asset or the value of an option, and also provides reasonable forecasting confidence interval. Secondly, a reliable volatility model sheds further light on the data -generating process of the returns. Thirdly, estimates of financial markets volatility may be the telescope of envisaging how robustness of the economy is and the direction of monetary and fiscal policies. These might be the reasons why volatility modeling has gained considerable popularity in literatures of financial engineering.(Bassey and Issac, 2011).

It is well known that financial time series data, including stock market returns, often exhibit the phenomenon of volatility clustering, meaning that a period of high volatility tends to be followed by periods of high volatility, and periods of low volatility tend to be followed by periods of low volatility. Stock returns also exhibit leptokurtosis, meaning that the distribution of the financial data has heavy tailed, non-normal distributions. In addition, data on stock market returns is expected to show a so called "leverage effect" or asymmetric volatility. This means that the effect of bad news on stock market volatility is greater than the effect induced by good news Onour (2007).

The main objective of this paper is to model and estimate stock returns volatility of Khartoum Stock Exchange (KSE) index, symmetric GARCH models will be employed to capture the nature of volatility and risk premium, while asymmetric GARCH models to capture leverage effects. This paper is organized as follows: follows section 1 review the introduction, section 2 presents a brief review of Khartoum Stock Exchange models. Section 3 presents a brief review of relevant literature. Section 4 expounds data and methodology. Section 5 provides discussion of results and section 6 is a conclusion.

2- Khartoum Stock Exchange:

Located in Khartoum, the Khartoum Stock Exchange (usually abbreviated to KSE) is the primary stock exchange of Sudan. The Khartoum Index is the main stock of KSE. The origins of KSE go back to 1962 when the Ministry of Finance, Bank of Sudan and International Financial Corporation conceived the idea. This was followed by establishment within The bank of Sudan in 1964 of a department for government bonds. In fact, the first government bonds were issued in 1966 with a bar value of 15 million Sudanese pounds and life cycle of 10 years. However, a subsequent 1982 ACT to establish KSE was a failure. More serious effort in 1992 culminated in setting up KSE board. The KSE itself was recognized in 1994 as a legal entity in the wake of endorsement of the KSE ACT. The primary market activities were initiated in 1994 and were shortly followed by the secondary market early in 1995.the classification of listed companies was initiated in 1994, and in 2001 the Shahama certificates were issued. The Khartoum Index officially come into being in 2003. A further step was joining the African Market Union in 2007. As a matter of fact the KSE has been growing steadily over the past few years and now has 53 listed companies worth 5 billion dollars. However, the stock exchange is open for only one hour per day from Sunday through Thursday.

Despite its rapid growth in terms of market capitalization KSE is characterized as highly concentrated market as only top three companies constitute around 90% of the total market capitalization. It is also, considered an illiquid market as the shares of only three companies are tradable.

Like all financial institutions in Sudan, KSE is regulated by laws inspired from Islamic Shariaa. One of the most popular financial instruments introduced by Islamic Shariaa practices in the KSE activities is the existence of Government Musharakah Certificates (GMCs), which represents an Islamic equivalent of the conventional bonds (also known as Shahama bonds). Through Shahama bonds the state borrows money in the domestic market instead of printing more banknotes. After one year, holders of GMCs can either cash or extend them. These bonds are backed by the stocks and shares portfolio of various companies owned by the Ministry of Finance and therefore are asset-backed. The profitability of GMCs can reach 33 per cent per annum and depends on the financial results of the companies involved. Hence, the profit of a GMC is variable rather than fixed. The government issues these bonds on a quarterly basis and their placement is done very quickly- in just six days. KSE is relatively small market as compared to the stock markets of the developed countries or even to some countries in the Arab region; the number of listed companies is few and most stocks are infrequently traded, market capitalization and traded value are very low(Elsheihk,2011).

3.Literature Review

The autoregressive conditional heteroscedasticity (ARCH) model was first elaborated in a seminal paper by Engle(1982). Since then, the topic of modeling volatility in financial time series has been the focus of numerous researchers. 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 markets. For instance, a paper by Arabi (2012) has estimated the volatility of exchange rate that was caused by inconsistent economic policies adopted by successive governments which failed to realize realistic exchange rate of the Sudanese pound. The consequences of high inflation rate, deterioration of the productive sectors, continuous internal and external deficits and depreciation of the exchange rate. To estimate the volatility of the exchange rate, EGARCH (1,1) was used. The results show that leverage effect term is negative and statistically different from zero, indicating the existence of the leverage effect (negative correlation between *past returns and future volatility.*

Xin Zheng (2012) tested whether stock return distribution's assumptions influence the performance of volatility forecasting. The methodologies include empirical analysis using GARCH-Normal, GARCH-Student-t and GARCH-Skewed Generalized Error Distributions. Not only daily returns, realized weekly and monthly volatilities of S&P/ASX 200 Index and ASX All Ordinaries Index are calculated over 10 years, but also the out-of sample-volatilities are compared. Their output indicates that GARCH-Student-t is superior to others over short-run forecast horizon while GARCH-SGED performs better than others over long-run forecast horizon.

Freedi etal(2012) 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 1 January 1994 to 31 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 level. They conclude that volatility persistence in the samples during and after crises decreases in all models under various distribution assumptions.

A paper by Vee and Gonpot (2011) 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). The latter show that both distributions may forecast quite well with a slight advantage to the GARCH(1,1)- GED for out-of-sample forecasts.

Prashant(2010) has stated that volatility in the Indian and Chinese stock markets exhibits the persistence of volatility, mean reverting behavior and volatility clustering. His study based on more than three years of recent daily data on Nifty and SSE to illustrate these stylized facts, and the ability of GARCH(1,1) to capture these characteristics. Daily returns in the stock markets exhibit nonlinearity and volatility clustering which are satisfactorily captured by the GARCH models. In both markets, volatility tends to die out slowly. In their findings revealed that the volatility is more persistent in the Chinese stock market than the Indian stock market.

A project by Ladokhin (2009) focused on the problem of volatility modeling in financial markets. It began with a general description of volatility and its properties, and discussed its usage in financial risk management. The research was divided into two parts: estimation of conditional volatility and modeling of volatility skews. The first one was focused on comparing different models for conditional volatility estimation. They examined the accuracy of several of the most popular methods: historical volatility models (e.g., Exponential Weighted Moving Average), the implied volatility, and autoregressive conditional heteroskedasticy models (e.g., the GARCH family of models). The second part of the project was dedicated to modeling the implied volatility skews and surfaces.

Shamiri and Isa (2009) 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.

In an investigation by Kosapattarapim et al (2008), employed six simulated studies in GARCH (p,q) with six different error distributions are carried out. In each case, they determine the best fitting GARCH model based on the AIC criterion and then evaluate its out of-sample volatility forecasting performance against that of other models. 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. Moreover, their empirical studies demonstrated that a skewed error distribution outperforms other error distributions in terms of out-of-sample volatility forecasting.

According to Engle etal(2007) 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. Moving from single assets to portfolios made of multiple assets, they found that not only idiosyncratic volatilities but also correlations and covariance's between assets are time varying and predictable. Multivariate ARCH/GARCH models and dynamic factor models, eventually in a Bayesian framework, were the basic tools used to forecast.

According to Karmakar(2005) one of the objectives of the various GARCH models is to provide good forecasts of volatility which can then be used for a variety of purposes including portfolio allocation, performance measurement, option valuation, etc. Investors seeking to avoid risk, for example, may choose to adjust their portfolios by reducing their commitments to assets whose volatilities are predicted to increase or by using more sophisticated dynamic diversification approaches to hedge predicted volatility increase

A study by Alshogea(1988) was devoted to examining whether the volatility of the macroeconomic variables have any influence on Saudi stock market volatility. They present descriptive statistics for Saudi stock market returns. Then, they estimates Bollerslev's GARCH(p,q)-model with no exogenous variables and checks weather it provides an adequate model for the volatility of Saudi stock returns. Finally, they explore the impact of macroeconomic variables on the volatility of the Saudi stock market return by examining three different sets of the GARCH models namely AR(1)-GARCH-X(1,1), the AR(1)-GARCH-S(1,1, and the AR(1)-GARCH-G(1,1) model.

4.Data and Methodology

4.1 Data

The data used in this study is the daily closing price index of the Khartoum Stock Exchange (KSE) over the period from 2 January 2006 to 31 the August 2010 consisting of 1217 observations. The daily closing prices were converted to returns series as follows:

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

Where r_t is the continuously compounded daily returns of KSE index at time t, p_t and p_{t-1} are the closing price index of KSE at time t and t-1 respectively. It is very important to note that since October 18, 2009, the index on the Khartoum stock market has been on decline. In a mere 16 days of trading (October 18,2009 to November 10,2009),the stock market index fell from 3077.12 to 2363.3. Since that time,the KSE index was reporting to fluctuate around an average value 0f 2363.3 (Zakria and Winker, 2012). In the light of this knowledge, we divided the daily closing prices index into two sub periods, the first sub- period covering the period from jan.2,2006 to October.18,2009 with 1042 observations;the second sub –period which is from Nov.10.2009 to Aug.31,2010 with 209 observations.

4.1.1 Descriptive Statistics

Descriptive statistics of daily returns series are presented in table 1 to reach an understanding of the nature and distribution characteristics of the KSE index returns series. From table 1, we observe that the average daily returns is positive and close to zero for all periods, with the values of standard deviation reflecting a high level of dispersion from the average returns in the market. The high kurtosis values reveal that the daily returns series of KSE index are clearly leptokurtic. The skewness values are positive skewed for all periods implying that the distribution has a long right tail and departure from normality. The departure from normal distribution in the KSE daily returns series was confirmed with Jarque-Bera test as it is associated significant level less than 1% confidence level.

Engle (1982) ARCH LM test statists indicate the presence of ARCH process in the conditional variance for all the periods. This provide an evidence of the validity of using GARCH family models. The Ljung Box Q statistics order16 in returns and its corresponding squared reflects a high serial correlation.

Table 1. Descriptive Statistics of the KES returns series

statistics	First sub-period	Second sub-period	Whole sample
Minimum	-0.111724	-0.009719	-0.115865
Maximum	0.211215	0.013787	0.211437
Mean	0.0000134	0.000004	0.000004
Median	0.0000	0.000000	0.000209
Standard deviation	0.014709	0.001351	0.014332
Skewness	2.570619	3.203592	1.692250
Kurtosis	65.306	66.91315	67.74630
Jarque- bera	2.570619	35930.08	212979.3
Prob. of Jarque- bera	0.0000	0.0000	0.0000
Q 16	87.414	29.975	82.782
Prob.Q16	0.0000	0.019	0.0000
$Q^2 16$	71.401	32.663	199.49
Prob.of $Q^2 16$	0.0000	0.008	0.0000
ARCH(2)	22.53764	30.56323	34.95850
Prob.of ARCH(2)	0.0000	0.0000	0.0000

Figure 1 shows the daily returns series of the KSE index for the first and second sub – periods and for the whole sample period. We can see from this figure small returns tend to be followed by smaller returns and large returns tend to be followed by larger returns. This behavior of stock returns series indicates that there is a clear evidence of volatility clustering in KSE index returns.

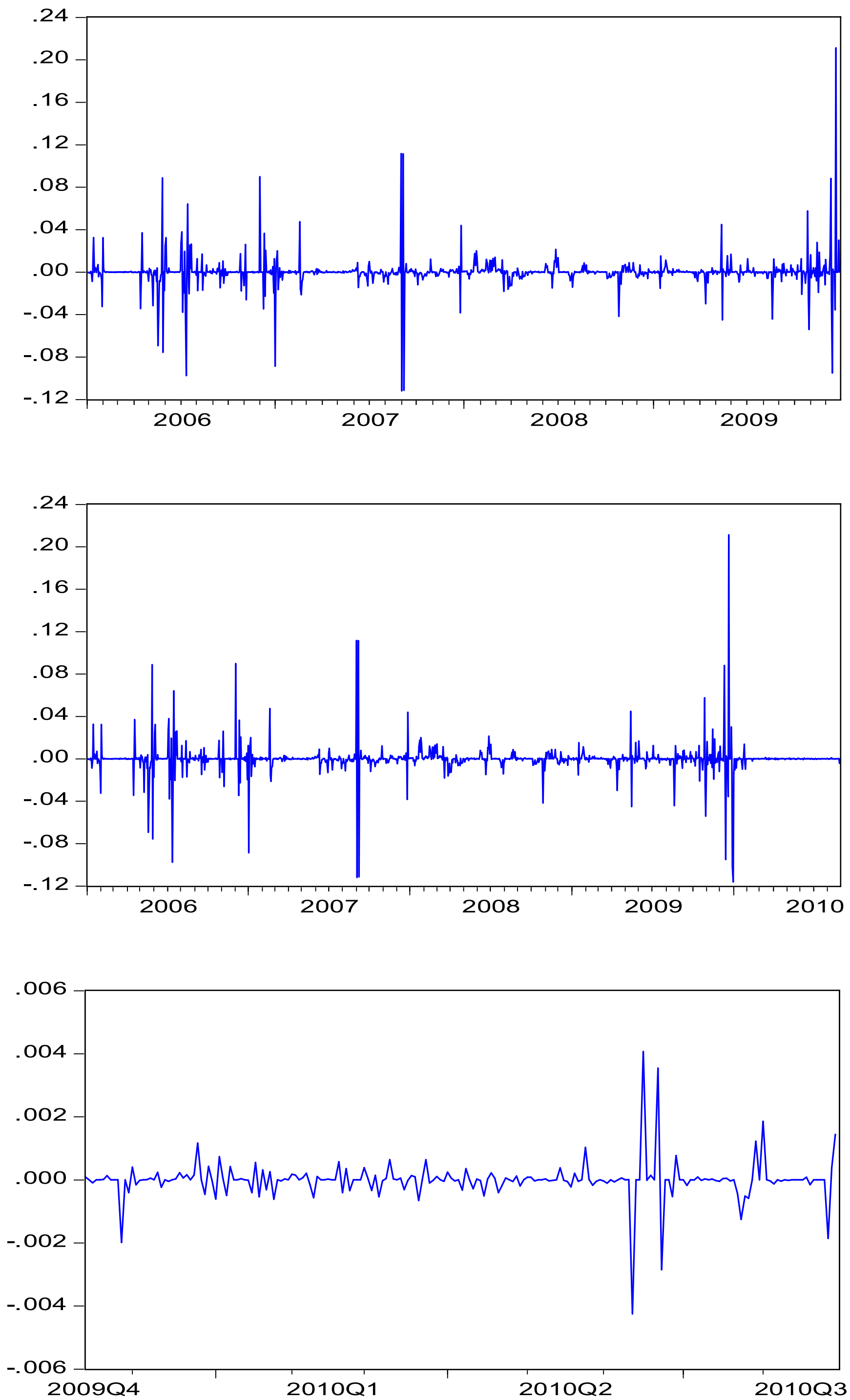

Figure 1: Daily returns of KSE for first and second sub- periods, and for the whole sample (respectively)

4-1-2 Unit Root Test for the KSE daily Index

Table 1 presents results of the unit root test for both daily closing prices index and its returns series using Augmented Dickey Fuller (ADF) Test statistic. The (ADF) test for KSE price index in level form reveal that it is of stationary type for first and second sub period, but it is non- stationary series for the whole sample. However when applying the same test for the returns series, we can reject the null hypothesis of a unit root for all periods.

Table 2: Stationary Test for daily closing prices and returns series

		KSE closing prices series				KSE returns series		
period	ADF statistic	Critical values			ADF statistic	Critical values		
		1%	5%	10%		1%	5%	10%
First sub-period	-2.70	-3.43	-2.86	-2.57	-29.42	-3.44	-2.86	-2.57
second sub-period	-4.94	-3.46	-2.88	-2.57	-15.52	-3.46	-2.87	-2.57
Whole sample	-2.38	-3.43	-2.86	-2.56	-17.81	-3.44	-2.86	-2.57

4-2 Methodology

To capture nature of volatility, risk premium, and leverage effects on KSE returns series, different symmetric and asymmetric GARCH models were used.In the volatility modeling process using GARCH models, the mean and variance of the series are estimated simultaneously.

4-2-1 Exchange Rate Volatility

Exchange rate volatility is a measure of the fluctuations in an exchange rate. It is also known as a measure of risk, whether in asset pricing, portfolio optimization, option pricing, or risk management, and presents a careful example of risk measurement, which could be the input to a variety of economic decisions. It can be measured on an hourly, daily, weekly, monthly or annual basis. Based on the assumption that changes in an exchange rate follow a normal distribution, volatility provides an idea of how much the exchange rate can change within a given period. Volatility of an exchange rate, just like that of other financial assets, is usually calculated from the standard deviation of movements of exchange.

4.2.2 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 used two symmetric GARCH models which are GARCH(1,1) and GARCH –M(1,1), and two asymmetric GARCH models, namely EGARCH(1,1) and GJR-GARCH(1,1).

4-2-2-1 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:

$$y_t = u_t \qquad (2)$$

$$u_t \sim N(0, h_t) \qquad (3)$$

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2 \qquad (4)$$

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

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2$$

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 $\alpha_0 > 0$ and $\alpha_1 \geq 0$.

4-2-2-2 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:

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

In the literature most used and simple model is the GARCH(1,1) process, for which the conditional variance can be written as follows:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \qquad (6)$$

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

$$h = \alpha_0 + \alpha_1 h + \beta_1 h \qquad (7)$$

Solving the equation 5 we have

$$h = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} \qquad (8)$$

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 $\alpha_0 > 0$.

Advantages of GARCH models compared to ARCH models

The main problem with an ARCH model is that it requires a large number of lags to catch the nature of the volatility, this can be problematic as it is difficult to decide how many lags to include and produces a non-parsimonious model where the non-negativity constraint could be failed. The GARCH model is usually much more parsimonious and often a GARCH(1,1) model is sufficient, this is because the GARCH model incorporates much of the information that a much larger ARCH model with large numbers of lags would contain.

4-2-2-3 GARCH-M Model

The importance of the relationships between market risk and expected returns is crucial infinance theory. The idea from Engle et al.(1987) was consequently used to estimate the conditional variances in GARCH and then the estimations will be used in the conditional expectations' estimation. This is the so called *GARCH in Mean* (GARCH-M) modelas:

$$r_t = \mu + \lambda h_t + u_t \qquad (9)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u^2{}_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (10)$$

Where:

λ is the volatility coefficient (risk premium) for the mean.

P is the order of the ARCH component model

q is the order of the GARCH component model

A positive risk-premium (i.e. λ) indicates that data series is positively related to its volatility. Furthermore, the GARCH-M model implies that there are serial correlations in the data series itself which were introduced by those in the volatility h_t process. The mere existence of risk-premium is, therefore, another reason that some historical stocks returns exhibit serial correlations.

4-2-2-4 GJR GARCH Model

The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries (Brooks, 2008:405).Glosten, Jagananthan and Runkle (1993) develop the GARCH model which allows the conditional variance has a different response to past negative and positive innovations.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} + \sum_{i=1}^{p} \beta_j h_{t-j} \qquad (11)$$

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

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

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 $\alpha_i + \gamma_i \geq 0$ (Brooks, 2008:406).

4-2-2-5 Exponential GARCH Model

Exponential GARCH (EGARCH) proposed by Nelson (1991) which has form of leverage effects in its equation. In the EGARCH model the specification for the conditional covariance is given by the following form:

$$\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}} \qquad (12)$$

Two advantages stated in Brooks (2008) for the pure GARCH specification; by using $\log(h_t)$ even if the parameters are negative, will be positive and asymmetries are allowed for under the EGARCH formulation.

In the equation γ_k represent leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the restrictions the EGARCH model allows unrestricted estimation of the variance (Thomas and Mitchell2005:16).

If $\gamma_k < 0$ it indicates leverage effect exist and if $\gamma_k \neq 0$ impact is asymmetric. The meaning of leverage effect bad news increase volatility.

5- Empirical Results

In this section we estimate and discuss different GARCH models for the first and second sub- period of KSE returns series. The models are estimated using maximum likelihood method under three errors distributions namely normal, Student- t and generalized error distribution (GED). The likelihood function is maximized using Marquardt iterative algorithm to search for optimal parameters. Tables 3,5,7,and 9 presents parameters estimates of GARCH(1,1), GARCH-M(1,1), EGARCH(1,1) and GJR- GARCH(1,1) models respectively.

In the variance equation from table 3, all coefficients α_0 (Constant), ARCH term (α_1)and GARCH term(β_1) are highly significant at conventional levels and with expected sign for the two periods. The significance of α_1 indicates the information about volatility from the previous day and it explanatory power on current volatility. In the same way, statistical significance of the GARCH parameter (β_1) not only indicates explanatory power on current volatility but also suggests volatility clustering in the daily returns of KSE volatility. Furthermore, the sum of parameters α_1 and β_1 of second sub- period is less than one and close to unity,indicating that volatility persistence is present in KSE index returns series. In contrast, the sum of these parameters for the second sub -period is larger than one,indicating that the conditional variance process is explosive.

Table 3: parameter estimation of GARCH(1,1) model

Period		Normal	Student-t	GED
		Mean Equation		
First sub-period	α_0 (Constant)	0.000189 (0.4341)	0.0001023 (0.5016)	0.0000121 (0.944)
		Variance Equation		
	α_0 (Constant)	0.000035 (0.0000)	0.000000363 (0.0000)	0.0000158 (0.0000)
	α_1 ($ARCH$ effect)	0.739475 (0.0000)	0.906947 (0.0000)	0.710333 (0.0000)
	β_1 ($GARCH$ effect)	0.407046 (0.0000)	0.262485 (0.0000)	0.349251 (0.0000)
Second sub-period	Mean Equation			
	α_0 (Constant)	-0.0000094 (0.8664)	0.00000508 (0.8356)	0.000000316 (0.9928)
		Variance Equation		
	Constant)(α_0	0.0000000616 (0.0000)	0.0000000224 (0.0000)	0.0000000426 (0.0000)
	α_1 ($ARCH$ effect)	0.113809 (0.0000)	0.150947 (0.00000)	0.149968 (0.0000)
	β_1 ($GARCH$ effect)	0.669848 (0.0000)	0.598786 (0.0000)	0.600016 (0.0000)

Table 4: Model diagnostics of GARCH(1,1) mod

Period		Normal	Student-t	GED
First sub-period				
	$Q(20)$	17.79 (0.601)	3.9008 (1.0000)	13.682 (0.846)
	$Q^2(20)$	2.3089 (1.0000)	0.3827 (1.0000)	1.3274 (1.0000)
	$LM(10)$	1.64 (0.9984)	0.210237 (1.0000)	0.814397 (0.9999)
	AIC	-6.33938	-8.404881	-7.061110
	SC	-6.32037	-8.381116	-7.042098
	Log-L	3030.649	4379.741	3679.308
Second sub-period				
	$Q(20)$	20.029 (0.456)	15.321 (0.758)	17.936 (0.592)
	$Q^2(20)$	7.9301 (0.992)	1.574 (1.0000)	3.5407 (1.0000)
	$LM(10)$	7.3081 (0.6961)	0.8276 (0.9999)	2.6115 (0.9891)
	AIC	-11.9462	-12.5091	-12.4933
	SC	-11.8823	-12.4292	-12.4292
	Log-L	1252.379	1312.203	1309.539

Figures in the parentheses are p-values. $Q(20)$ and $Q^2(20)$ are respectively the Box-Pierce statistics at lag 20 of standardized and squares standardized residuals. AIC, SC, Log-L are the Akaike Information Criterion, Schhwarz Criterion and Log likelihood value respectively.

Table 5: parameter estimation of GARCH-M(1,1) model

Period		Normal	Student-t	GED
Mean Equation				
First sub-period	α_0 (Constant) λ($risk$ premium)	-0.002411 (0.0000) 0.282338 (0.0000)	-0.000228 (0.1140) 0.069422 (0.0055)	-0.000903 (0.0159) 0.139179 (0.0005)
Variance Equation				
	α_0 (Constant)	0.0000370 (0.0000)	0.000000363 (0.0000)	0.0000227 (0.0000)
	α_1 ($ARCH$ effct)	0.714855 (0.0000)	1.055555 (0.0000)	0.709943 (0.0000)
	β_1 ($GARCH$ effect)	0.377484 (0.0000)	0.281332 (0.0000)	0.364385 (0.0000)
Second sub-period	Mean Equation			
	α_0 (Constant) λ($risk$ premium)	-0.0000428 (0.7945) 0.046927 (0.8603)	0.0000256 (0.5966) 0.092723 (0.6142)	-0.0000105 (0.9463) 0.0011763 (0.9949)
Variance Equation				
	(α_0) Constant)	0.0000000801 (0.0000)	0.000000015 (0.0000)	0.0000000703 (0.0000)
	α_1 ($ARCH$ effct)	0.335840 (0.0000)	0.494815 (0.00000)	0.354217 (0.0000)
	β_1 ($GARCH$ effect)	0.603810 (0.0000)	0.493785 (0.0000)	0.592805 (0.0000)

Table 6: Model diagnostics of GARCH -M(1,1) model for KSE

Period		Normal	Student-t	GED
First sub-period				
	$Q(20)$	15.833 (0.727)	9.3681 0.978)(	14.692 (0.794)
	$Q^2(20)$	1.6128 (1.0000)	0.7294 (1.0000)	1.3945 (1.0000)
	$LM(10)$	0.9806 (0.9998)	0.3938 (1.0000)	0.8416 (0.9999)
	AIC	-6.347832	-7.075862	-6.753552
	SC	-6.34067	-7.052096	-6.729787
	Log-L	3309.047	3687.896	3520.224
Second sub-period				
	$Q(20)$	16.940 (0.657)	12.124 (0.912)	16.541 (0.863)
	$Q^2(20)$	2.9124 (1.0000)	0.6420 (1.0000)	2.3963 (1.0000)
	$LM(20)$	1.9461 (0.9967)	0.1692 (1.0000)	1.4653 (0.9990)
	AIC	-11.88792	-12.6671	-12.01381
	SC	-11.82395	-12.6031	-11.94984
	Log-L	1246.288	1327.288	1259.44

From estimation results in table 5,the estimated coefficient (risk premium) of conditional variance in the mean equation of the GARCH- M(1,1) model for the first sub –period is positive and significant, indicating that KSE return it is risky "accept". In other words, when risk goes up volatility also goes up, so the more the volatility the more the risky "accept" it is. These results underscore that high and low of KSE index are associated with the rise and fall of the returns volatility, that is, an increase in the risk leads to an increase in the amount of the risk premium demanded by investors to compensate for the additional amount of risk to which they are exposed. For the second sub- period, the estimated of risk premium is positive, but insignificant. The results of the variance equation for the GARCH-M(1,1) model shows that all coefficients are highly significant at traditional levels.

The estimated results of EGARCH(1,1) and GJR -GARCH(1,1) models in table 7 and 8 reveal that all estimated coefficient in the variance equations are Statistically significant at conventional levels. Moreover, the estimates of the leverage effect term(γ) in each of asymmetric models(EGARCH and GJR -GARCH) are significant accept but is insignificant in GJR -GARCH under normal distribution for the second period. The sign of γ is negative in EGARCH model and positive in GJR-GARCH model, which is consistent with the normal conditions. These results signify that bad news or shocks market or disturbing information has more effect on conditional variance than good news, indicating that the existence of leverage effect is observed in returns of the KSE index.

Tables 4,6,8 and 10 present the diagnostics tests for different GARCH models (GARCH, GARCH-M, EGARCH and GJR -GARCH). From the results of these tables the Ljung Box Q statistics of order 20 on both standardized residuals and squared standardized residuals are all non –significant at 5% levels, indicating that no serial correlation exist in the standardized residuals of the models. The LM test for presence of ARCH effects at lag 10 for all GARCH models did not exhibit additional ARCH effects. The conclusion drawn from these results is that the GARCH models considered in similar investigations are all adequate for describing the volatility of Khartoum Stock Exchange(under similar conditions).

Table 7: parameter estimation of EGARCH(1,1) model

Period		Normal	Student-t	GED
		Mean Equation		
First sub-period	α_0 (Constant)	0.000571 (0.0000)	0.0000305 (0.7760)	0.0000557 (0.6676)
		Variance Equation		
	α_0 (Constant)	-3.9523439 (0.0000)	-3.414329 (0.0000)	-3.903888 (0.0000)
	α_1 (*ARCH* effct)	0.862875 (0.0000)	0.507665 (0.0000)	0.712322 (0.0000)
	β_1 (*GARCH* effect)	0.605768 (0.0000)	0.729441 (0.0000)	0.640076 (0.0000)
	γ (*Leverage* effect)	-0.127479 (0.0000)	-0.059544 (0.0000)	-0.109134 (0.0000)
Second sub-period		Mean Equation		
	α_0 (Constant)	-0.0000765 (0.1837)	-0.0000112 (0.6204)	0.00000440 (0.9013)
		Variance Equation		
	α_0 (Constant)	-1.679786 (0.0000)	-1.386165 (0.0000)	-1.684524 (0.0000)
	α_1 (*ARCH* effct)	0.211943 (0.0000)	0.188216 (0.00000)	0.175846 (0.0000)
	β_1 (*GARCH* effect)	0.893776 (0.0000)	0.922142 (0.0000)	0.897791 0.0000)(
	γ (*Leverage* effect)	-0.069697 (0.0182)	-0.086664 (0.0042)	-0.07213 (0.0123)

Table 8: parameter estimation of GJR -GARCH(1,1) model

Period		**Normal**	**Student-t**	**GED**
		Mean Equation		
First sub-period	α_0 **(Constant)**	**0.0000772 (0.8029)**	**0.0000412 (0.5428))**	**0.00000564 (0.9785)**
		Variance Equation		
	α_0 **(Constant)**	**0.0000355 (0.0000)**	**0.00000142 (0.0000)**	**0.0000157 (0.0000)**
	$\alpha_1(ARCH \text{ effct})$	**0.487518 (0.0000)**	**1.008363 (0.0000)**	**0.518998 (0.0000)**
	$\beta_1(GARCH \text{ effect})$	**0.399902 (0.0000)**	**0.220067 (0.0000)**	**0.349663 (0.0000)**
	$\gamma\,(Leverage \text{ effect})$	**0.399902 (0.0000)**	**0.540603 (0.0000)**	**0.402596 (0.0001)**
Second sub-period	**Mean Equation**			
	α_0 **(Constant)**	**-0.0000136 (0.8072)**	**0.000000850 (0.9696)**	**0.000224- (0.0347)**
		Variance Equation		
	Constant)(α_0	**0.000000064 (0.0000)**	**0.000000173 (0.0000)**	**0.000000153 (0.0000)**
	$\alpha_1(ARCH \text{ effct})$	**0.096319 (0.0022)**	**0.105759 (0.00006)**	**0.091579 (0.0254)**
	$\beta_1(GARCH \text{ effect})$	**0.674706 (0.0000)**	**0.612551 (0.0000)**	**0.728680 0.0000)(**
	$\gamma\,(Leverage \text{ effect})$	**0.030477 (0.4311)**	**0.080220 (0.01530)**	**0.137244 (0.0312)**

Table 9: Model diagnostics of EGARCH (1,1) model

Period		Normal	Student-t	GED
First sub-period				
	$Q(20)$	17.876 (0.596)	9.6229 0.975)(	13.425 (0.857)
	$Q^2(20)$	2.2517 (1.0000)	0.8430 (1.0000)	1.2709 (1.0000)
	$LM(10)$	1.6326 (0.9985)	0.4864 (1.0000)	0.7181 (1.0000)
	AIC	-6.3494	-7.588484	-7.060115
	SC	-6.3256	-7.564719	-7.036350
	Log-L	3309.868	3954.806	3679.790
Second sub-period				
	$Q(20)$	20.183 (0.447)	12.730 (0.889)	18.937 (0.524)
	$Q^2(20)$	6.8288 (0.9970)	0.7927 (1.0000)	3.5312 (1.0000)
	$LM(20)$	6.54208 (0.7679)	0.19094 (1.0000)	2.7940 (0.9859)
	AIC	-11.76931	-12.44424	-12.37291
	SC	-11.68935	-12.36427	-12.29295
	Log-L	1234.893	1305.423	1297.969

Tables 4,6,9 and 10 presents the diagnostics tests for different GARCH models (GARCH, GARCH-M, EGARCH and GJR- GARCH). From the results of these tables the Ljung Box Q statistics of order 20 on both standardized residuals and squared standardized residuals are all non –

significant at 5% levels, indicating that there is no serial correlation in the standardized residuals of the models. LM test for presence of ARCH effects at lag 10 for all GARCH models did not exhibit additional ARCH effects. The conclusion drawn from these results is that the all GARCH models considered in this study are all adequate for describing the volatility of Khartoum Stock Exchange

The results of three selection criteria(AIC, SC, Log-L) presented in tables 4,6,9 and 10 reveal that student-t is the most favored distribution for all models estimated in this study.

Table 10: Model diagnostics of GJR -GARCH (1,1) model

Period		Normal	Student-t	GED
First sub-period				
	$Q(20)$	16.85 (0.577)	6.8406 0.997)(	13.9 (0.836)
	$Q^2(20)$	1.8359 (1.0000)	0.6028 (1.0000)	1.0769 (1.0000)
	$LM(10)$	1.1841 (0.9996)	0.3311 (1.0000)	0.5934 (1.0000)
	AIC	-6.345448	-7.705328	-7.060414
	SC	-6.321682	-7.681563	-7.040376
	Log-L	3307.806	4015.623	3681.886
Second sub-period				
	$Q(20)$	19.821 (0.469)	14.265 (0.817)	19.512 (0.489)
	$Q^2(20)$	7.7083 (0.994)	1.2595 (1.0000)	6.6873 (0.998)
	$LM(20)$	7.04986 (0.7207)	0.563496 (1.0000)	2.7940 (0.9859)
	AIC	-11.93766	-12.6369	-12.09453
	SC	-11.85770	-12.55694	-12.01456
	Log-L	1252.486	1325.556	1268.878

6. Conclusions

In this paper we have modeled and estimated stock returns volatility of KSE using different GARCH models including symmetric and asymmetric models, GARCH(1,1), GARCH – M(1,1), EGARCH(1,1) and GJR –GARCH(1,1). Daily returns series of KSE index reveal some patterns such as positive skewness, leptokurtosis, significant departure from normality, volatility clustering and existence of Heteroscedasticity, all of which are commonly experienced in other stock markets. Empirical results is also show that explosive volatility process is present in KSE index returns over the sample period. The risk premium term for GARCH – M(1,1) is statistically significant with positive sign for the first sub-period,implying that an increase in volatility is associated with an increase in returns. Moreover, the results reveal the existence of leverage effect in EGARCH and TGARCH models. Our findings also show that Student- t is found to be the most favored distribution for all models estimated in our study.

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