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Modeling the Risk of Crude Oil Import Prices in Kenya

[1]Euchabeth Musenya Muvengei, [2]Proffesor Anthony Gichuhi Waititu, [3]Dr.Joseph Mungatu

[1]Department of Statistics and Acturial Science, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

[2]Department of Statistics and Acturial Science, Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

Abstract: **Crude oil being the main source of energy in Kenya, oil investors and policymakers would benefit greatly if they understand the behaviors of the oil imports and how it affects the Kenyan oil market. This is because oil import prices experience serious fluctuations, making the Kenyan oil market unstable and exposing it to great risks. The objective of this study is to model the risk of the daily crude oil import prices in Kenya from 2005 to 2018. To model the oil price volatility, several heteroscedastic models were fitted and their AICS compared. The EVT approach is also employed in determining the VaR and CTE. The results of this study reveal that the returns are stationary, non-normal and presence of ARCH effects which justified the application of the ARCH models. This paper adopted EGARCH(2,1) model as the best to model the volatility. EGARCH (2,1) results indicated the presence of asymmetric effects that can be attributed to leverage effects. Secondly, there was a clear indication of volatility persistence. Point estimates of extreme tail risk measure were estimated at sufficiently high probability levels 99.9%, 99.5% and 99%. The Value-at-Risk gave quantitative information for the extent of potential extreme risks in oil market and the CTE gave a measure of the extra capital an investor should have incase this VaR is exceeded.**

Keywords: **EGARCH, Volatility persistence, Asymmetric effects, Value-at-Risk, Conditional Tail Expectation.**

1. INTRODUCTION

The energy sector which is mainly composed of electricity and petroleum products is one of the key sectors that drive the Kenyan economy. In Kenya, just like many other countries globally, energy is mainly used by the transport and industrial sectors. Over the years, these sectors have been growing very fast and as a result, their demand for energy which is primarily met by petroleum has been rising.

The crude oil import prices are highly volatile hence leading to unstable petroleum pump prices in the Kenya. This has resulted to the major risks faced in the oil markets in the country. Volatility refers to the conditional variance of an underlying asset return. Simply stated, volatility is the degree of variation of a time series around its conditional mean. It's widely believed by financial analysts that oil price volatility have considerable consequences on businesses, governments and the global economic activity.

(Robert, 1999)argues that changes in oil prices have an impact on economic activity. He asserts that the economies that depend on oil for industrial purposes experience significant uncertainty during periods of high volatility resulting in high volatility of exports and consequently government revenues.

This has made financial analysts to investigate this phenomenon in the oil market.(Sadosky & Syed, 2006), examined the relationship between oil price volatility and the macro economy, (Chen & Chen, 2007) also examined the relationship between oil price volatility and stock prices. (Robert, 1999)Comparatively examined volatility of crude oil, refined petroleum and natural gas prices.(Regnier, 2006) And (Robert, 1999)also examined the asymmetry of the impact of oil price shocks on economic activities. They discovered that the more volatile crude oil prices become the more uncertainty it creates, leading to economic instability for both oil exporting and importing countries.

The goal of this study is to model crude oil import price risk using recent daily data for the period 2005 to 2018. To model the volatility, an appropriate asymmetric heteroscedastic model is to be identified. EGARCH(2,1)model was adopted the model in this paper as the best model to fit the data compared to TGARCH and PGARCH. In using the EGARCH model, important features of crude oil import price volatility, namely asymmetry; volatility clustering and persistence of shocks could be captured. Evidence that shocks are persistent and asymmetric effects on volatility is discovered. The fact that oil price volatility has asymmetric effects suggests that negative and positive shocks have different effects on oil price volatility. The market risk measures i.e. VaR and CTE have also been determined using the EVT approach.

2. RELATED WORKS

Crude oil is a very precious commodity that is of great importance to all countries in the world. It can be refined to produce various products such as gasoline, diesel and different forms of petrochemicals. Its components are used to manufacture almost all chemical products, such as plastics, detergents, paints, and even medicines.

It is widely accepted that there is a strong relationship between crude oil prices and global economic activity (Sadorsky P. , 1999). Studies on the volatility and risk of international oil prices, exchange rates, prices of agricultural products and many other financial time series data have been conducted in the past. The GARCH models have successfully met this objective. Also commodity price risks have also been modeled using the EVT approach.

In order to model the volatility of the financial time series data, a new class of stochastic processes called Autoregressive conditional heteroscedastic (ARCH) processes were introduced by(Engle R. F., 1982). The basic idea of ARCH models is that the shock of an asset return is serially uncorrelated, but dependent. They have a mean of zero and with non-constant variances that are conditional on the past. Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset return. Thus (Bollerslev, 1986)proposed the Generalized ARCH (GARCH) model which is an extension of the ARCH model. The virtue of this approach is that a GARCH model with a small number of terms appears to perform as well as or better than an ARCH model with many terms. In a GARCH model, returns are assumed to be generated by a stochastic process with time-varying volatility. This implies that the conditional distributions change over time in an auto-correlated way and the conditional variance is an autoregressive process. GARCH models provide an accurate assessment of variances and covariances through their ability to model time-varying conditional variances as they assume that the conditional variance is a deterministic linear function of past squared innovations and past conditional variances.

However, the ARCH and GARCH models have two common disadvantages; first, the models assume that both positive and negative shocks have the same effect on volatility, which is not always the case. Second, for the volatility to be positive, the two models artificially impose non negativity constraints on the model parameters. In order to overcome these weaknesses, more extensions of the GARCH model that have an extra parameter that can capture the asymmetric effects have been developed. Such models include Exponential GARCH (EGARCH) model of (Nelson, 1991), GJR GARCH model of (Glosten, lawrence, & Runkle, 1992), Threshold GARCH model (Ding, 1993), and Asymmetric Power GARCH (PGARCH) model of (Crouhy, 1997)among others.

The forecasting accuracy of the asymmetric conditional volatility models was compared by (Dumitru & Cristiana, 2010) i.e. the TGARCH, PGARGH and EGARCH. Of the three asymmetric conditional models, The EGARCH model was found to dominate the other two models as it generally exhibited lower forecast errors. Another research conducted by (Chen P. Y., 2012)applied the GARCH model in modeling the Effects of Oil Prices on Global Fertilizer Prices and Volatility. In order to capture the asymmetric effects, they used the GJR model of (Glosten, lawrence, & Runkle, 1992)and the EGARCH model of(Nelson, 1991). The EGARCH model was found to dominate the other two models as they generally exhibited lower forecast errors.

(Bernard & Florentina, 2014)Forecasted the crude oil market volatility in the context of economic slowdown in emerging markets. In their analysis, they focused on the estimation of crude oil future price volatility using daily closing data for Brent Blend, Dubai Fateh, and WTI (West Texas Intermediate) crude oil. The classical GARCH, EGARCH and PARCH with three different distributional assumptions i.e. the normal distribution, student t distribution and generalized error distributions were used and their forecasting accuracy was assessed. The use of these models allowed them to understand specific features of crude oil market and further to compare the models and selects the best one in order to forecast volatility of this market. Their paper presented a very detailed analysis only for Brent crude oil market volatility and displayed only the best selected model. Similar results were also obtained for Dubai and WTI market volatility. To summarize, the empirical results suggested that EGARCH(1,1) model with normal distribution was the best fit for Brent crude oil volatility modeling.

In order to establish whether the EGARCH model can capture the asymmetric effects in time series data, (Achal, 2015)applied the ARIMA, GARCH and the EGARCH model in modeling and forecasting of Price volatility of three agricultural products. The EGARCH model was employed in addition to the ARIMA and the GARCH models in order to capture asymmetry pattern of the data which could not be captured using the other two models. The empirical results obtained supported the theory that EGARCH model can capture asymmetric volatility.

(Albert, 2015)used the monthly Ghana exchange rate data set to examine the volatility for the period lagging from 1990 to November 2013. Both the symmetric and asymmetric models that captured volatility persistence and leverage effects were applied. EGARCH (2, 2) was identified as the overall best fit model. The results revealed that there was volatility persistence and an adverse asymmetric reaction with good news increasing the volatility more than bad news.

(Epaphra, 2017)Applied the ARCH, GARCH and EGARCH models in modeling the volatility of the Exchange rates in Tanzania.To capture the symmetry effect in exchange rate data, this paper applied both ARCH and GARCH models. The exponential GARCH (EGARCH) model was employed to capture the asymmetry in volatility clustering and the leverage effect in exchange rate. The paper revealed that exchange rate series exhibits the empirical regularities such as clustering volatility, non-stationarity, non-normality and serial correlation that justify the application of the ARCH methodology. The results also suggested that exchange rate behavior is generally influenced by previous information about exchange rate. This also implies that previous day's volatility in exchange rate can affect current volatility of exchange rate. In addition, the estimate for asymmetric volatility suggests that positive shocks imply a higher next period conditional variance than negative shocks of the same sign. The main policy implication of these results was that since exchange rate volatility (exchange-rate risk) may increase transaction costs and reduce the gains to international trade, knowledge of exchange rate volatility estimation and forecasting is important for asset pricing and risk management.

(Kandei, 2018)compared the symmetric effect and the asymmetric effects of GARCH family models using volatility of exchange rates for the period of January 2010 to August 2018. Currencies of Chinese Yuan, Sterling Pound, Japan Yen, Euro and U.S.dollar were selected for the investigation against Sri Lankan Rupees. By using daily exchange rate return series symmetric effect evaluated with ARCH(1) and GARCH(1,1) models, Asymmetric effect were evaluated with TGARCH, EGARCH and PGARCH models. The Normal (Gaussian) distribution was taken as the only method to be incorporated. This study provided some insight to the policy makers of the Sri Lankan government as the final model indicated the ability of identify the future forecast using the positive and negative shocks of multiple exchange rates return series at once with the world market values. In his findings, the EGARCH model gave forecasts with the minimum errors.

In determining the risk measures, the EVT approach has been applied since it has emerged as one of the most important statistical disciplines for the applied sciences, and for other fields in the recent years (e.g., finance). The distinguishing feature of EVT is to quantify the stochastic behavior of a process at unusually large or small levels. Specifically, EVT usually requires estimation of the probability of events that are more extreme than any other that has been previously observed. A study by (Koima, 2013) applied the EVT approach in the estimation of VaR in the Kenyan Market. They pointed out that quantification of VaR using EVT has the ability to estimate observations at the extreme quantiles. The study used Barclays Bank data from the Nairobi Securities Exchange and observed that POT model of EVT and the GPD captured the rare events hence, making it a robust method of estimating the VaR. Similar works by(Kellezi & Gilli, 2000) gave results on tail distribution modeling that showed that tail-related risk measures such as the VaR and the expected shortfall can be modeled using EVT.

An extensive research carried out by(Mwelu & Waititu, 2015) modeled the oil price risk. They argued that the presence of high volatility within oil markets leads to the requirement of implementation of effective risk models. The peaks over threshold method were adopted as it tends to utilize data more efficiently and mean excess function was applied to select appropriate thresholds for the respective tails. They discovered that the EVT-based Value-at-Risk approach adopted provided quantitative information for analyzing the extent of potential extreme risks in oil markets, particularly based on two crude oil markets. Generally, the WTI benchmark yields higher risk measures than the Brent. This lead to the conclusion that the WTI faces an increased exposure to price risk as compared to the Brent.

(Motonu, 2016)modeled the public debt where GPD was used and conditional and unconditional VaRs were determined. The efficiency of the two VaRs was determined using the Lopez's Loss Function. The conditional VaR which uses other explanatory variables on top of the historical data was found to be the most efficient one in measuring the risk associated with modeling the public debt in Kenya. The unconditional approach uses historical data only and it wasconcluded to be appropriate when there are no explanatory variables.

3. RESEARCH METHODOLOGY

The crude oil prices were converted to the corresponding crude oil log returns since returns are complete and scale-free summary of the investment opportunity and that return series are easier to handle than price series because the former have more attractive statistical properties.

Equation 1

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

Where p_t is the crude oil price at time t and r_t is the log return of the oil prices.

3.1 Modeling the volatility crude oil import prices

Volatility is defined as the degree of variation of an underlying asset return around its conditional mean. Although volatility is not directly measurable, it has some common properties that are common in asset returns: There are volatility clusters, volatility evolves over time in a continuous manner, volatility doesn't diverge to infinity and it seems to react differently to a big positive return and a big negative return. Returns properties such as stationarity, non-normality and ARCH effects tests were carried out.

3.1.1 Augmented Dickey-Fuller test for stationarity

A time series is stationary if it doesn't exhibit secular trend and seasonal effects. Statistical modeling requires the time series to be consistent over time. The ADF test also called the unit root test is widely used test for stationarity. It tests the null hypothesis that the return series is non-stationary against the alternative hypothesis that the return series is stationary. It is applied to the model;

Equation 2

$$\Delta \boldsymbol{r}_{\{t\}} = \boldsymbol{\alpha} + \boldsymbol{\beta t} + \boldsymbol{\gamma r}_{\boldsymbol{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{p}} \boldsymbol{\delta}_{\boldsymbol{i}} \, \Delta \, \boldsymbol{r}_{\boldsymbol{t-1}} + \cdots$$

Where α is a constant, β is the coefficient on the trend p is the lag order of the autoregressive process. The ADF test statistic is defined as follows;

Equation 3

$$\boldsymbol{DF} = \frac{\widehat{\boldsymbol{\Upsilon}}}{\boldsymbol{SE}(\widehat{\boldsymbol{\gamma}})}$$

This computed value is compared to the critical value of the DF test. The null hypothesis is rejected if the ADF statistic is less than the critical value.

3.1.2Jarcque-Bera normality test

The JB test of(Bera & Jarque, 1981) is a goodness-of-fit test of whether the crude oil prices have the skewness and kurtosis matching the normal distribution. The JB test uses the test statistic defined below;

Equation 4

$$\boldsymbol{JB} = \frac{(\boldsymbol{\tau})^2}{\boldsymbol{6/T}} + \frac{(\boldsymbol{K}-\boldsymbol{3})^2}{\boldsymbol{24/T}}$$

The JB test is asymptotically distributed as a chi-squared distribution with two degrees of freedom, to test for the normality ofr_t. The null hypothesis states that the return series is not different from the normal distribution while the alternative hypothesis states that the return series is not normally distributed. The null hypothesis is rejected if the p-value of the JB statistic is less than the significance level α.

Mean equation

Let $\mu_t = r_t - a_t$ where μ_t is the mean equation. The mean equation was modeled as an Autoregressive Integrated Moving Average process, which is a mixture of Autoregressive/moving average process expressed as follows;

Equation 5

$$\boldsymbol{r_t = \emptyset_1 r_{t-1} + \emptyset_2 r_{t-2} + \cdots + \emptyset_p r_{t-p} + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \cdots + \theta_q a_{t-q}}$$

Where $a_t \sim N(0, \sigma^2)$. The squared residuals $(a_t)^2$ of the mean equation would be used in testing for the presence of ARCH effects.

3.1.3 ARCH effects test by Ljung-Box test

ARCH effects are evident if the series doesn't have serial correlations and that the squared series shows some serial dependencies. Evidence of ARCH effects in the return series of the crude oil prices were investigated using the Ljung-Box test since ignoring the ARCH effects would lead to over parameterization of the model (Weiss, 1984). The squared residuals $(a_t)^2$ are used in testing for the presence of ARCH effects.The Ljung-Box statistic is given as follows;

Equation 6

$$Q(m) = n(n+2) \sum \frac{(\rho_j)^2}{n-j}$$

Where m is the maximum number of lags included in the ARCH effects test, $(\rho_j)^2$ is the sample autocorrelation at lag j for both the squared time series and n is the number of non-missing values in the data sample.The null hypothesis stated that there are no ARCH effects while the alternative hypothesis stated that ARCH effects are present in the squared residuals. The Ljung-Box test has an asymptotic chi-square distribution with m degrees of freedom. The decision rule is to reject the null hypothesis if the p-value of F is less than α.

Volatility models

These are the models used to model the volatility of asset returns The simplest model is the ARCH model of (Engle R. F., 1982).

ARCH model

In order to model the volatility, (Engle R. F., 1982)suggested the ARCH model as an alternative to the standard timeseries treatments that cannot adequately explain the property of heteroscedasticity. The AR comes from the fact that these models are autoregressive models in squared returns. The conditional comes from the fact that in these models, next period's volatility is conditional on the current periods information. However, when modeling using ARCH model, there might be a need for a large values of the lag p, hence a large number of parameters. This may result in a model with a large number of parameters, violating the principle of parsimony and this can present difficulties when using the model to adequately describe the data. Also, the more parameters there are in the conditional variance equation, the more likely it is that one or more of them will have negative estimated value, violating the non-negativity constraints. Hence to counter this challenge, (Bollerslev, 1986)extended the ARCH model of Engle (1982) to the GARCH model.

GARCH model

The Generalized ARCH (GARCH) of (Bollerslev, 1986)is an extension of the ARCH model. It may contain fewer parameters as compared to an ARCH model, and thus making it more preferred to an ARCH model. The virtue of this approach is that a GARCH model with a small number of terms appears to perform as well as or better than an ARCH model with many terms. In a GARCH model, returns are assumed to be generated by a stochastic process with time-varying volatility. This implies that the conditional distributions change over time in an auto-correlated way and the conditional variance is an autoregressive process. GARCH models provide an accurate assessment of variances and covariances through their ability to model time-varying conditional variances as they assume that the conditional variance is a deterministic linear function of past squared innovations and past conditional variances. A GARCH(p,q) model takes the form;

Equation 7

$$r_t = \mu_t + \varepsilon_t$$

$$a_t = \sigma_t \varepsilon_t$$

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

where $r_t$is the return series of the oil prices,μ_t is the mean equation and $\varepsilon_t$is a sequence of identically and independent distributed random variable with mean zero and variance equals to one defined by the volatility model and can take any of the following distributions; standard normal distribution, the student t-distribution with 3-6 df or the Generalized Error distribution. The mean value$\omega, \alpha_i, \beta_j > 0$ for i=1,2,...p andj=1,2,3,...,q so that$\sigma_t^2 > 0$. In order to ensure for the stationarity of the volatility process, then; $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$. It has the following properties; They exhibit the well-known behavior of volatility clustering in financial time series i.e. the phenomenon by which large a_{t-1}^2orσ_{t-1}^2 tends to be followed by another large a_t^2 or σ_t^2, the tail distribution of a GARCH process is heavier than that of a normal distribution i.e. they have a positive excess kurtosis, the model provides a simple parametric function that can be used to describe the volatility evolution and they do not reflect the asymmetric behavior of volatility to positive and negative shocks. Since most of the financial time series are known to be asymmetric in nature, asymmetric models were developed.

Asymmetric GARCH models

The GARCH model is symmetric in nature, hence the EGARCH model proposed by(Nelson, 1991), PGARCH model of (Ding, 1993), GJR GARCH of (Glosten, lawrence, & Runkle, 1992), and the TGARCH model of (Crouhy, 1997)were developed as improvements of the GARCH model. They have an extra parameter γ that enables the models to respond asymmetrically to positive and negative shocks, hence overcoming the major weakness of the GARCH model. Several APGARCH, EGARCH and TGARCH models were fitted. This study identified the EGARCHmodel as the best to model the volatility of the import prices for crude oil in Kenya by AIC technique. Specifically, the EGARCH model differs with the GARCH model in the following ways. First, it uses logged conditional variance to relax the positivity constraint of model coefficients. Secondly, the use of γ enables the model to respond asymmetrically to positive and negative shock. The general EGARCH (p, q) model has the following form;

Equation 8

$$r_t = \mu_t + \varepsilon_t$$

$$a_t = \sigma_t \varepsilon_t$$

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \frac{|a_{t-i|}| + \gamma_i a_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2$$

3.3 Extreme Value Theory

EVT deals with the extreme deviations from the mean of a probability distribution. The foundations of the EVT were set by (Fisher & Tippet, 1928). They identified all extreme value distributions which means that all possible degenerate limit laws for properly centered and scaled maxima$m_n = max(x_1, x_2, \dots, x_n)$where$X_n$is a sequence of iid random variable. According to(Embrechts, Kluppelberg, & Mikosch, 1990), the Fisher-Tippet theorem specifies the form and the limit distribution for the centered normalized maxima and minima. The theory postulates that for a sequenceX_n, there exists a norming constant$c_n > 0$and $d_n \in R$ and some nondegenerate density function H called the Generalized Extreme value distribution defined as follows;

Equation 9

$$f(x,\mu,\sigma,\xi)=\exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\beta}\right)\right]^{-1/\xi}\right\} \text{For } 1+\xi\left(\frac{x-\mu}{\beta}\right)>0,$$

where μ is the location parameter, β is the scale parameter and ξ is the shape parameter that governs the tail behaviour of the limiting distribution;then $c_n^{-1}\left(m_n-d_n\right)\xrightarrow{d}H$ the distribution belongs to only one of the following three types of distributions;

- Gumbel distribution

Equation 10

$$F(x)=\exp\left(-\exp\left(-x\right)\right), x\in\Re, \xi=0$$

- Frechetdistribution

Equation 11

$$F(x)=\begin{cases}\exp\left\{-x^{-\xi}\right\}, x,\xi>0\\ 0 elsewhere\end{cases}$$

- Weibulldistribution

Equation 12

$$F(x)=\begin{cases}\exp\left\{-\left(-x^{\xi}\right)\right\}, \xi\le 0\\ 1, \xi>0\end{cases}$$

Extremes happen "near" the upper end (or lower end) of the support of the distribution, hence, the asymptotic behavior of the maxima, M_n(or minima, m_1) must be related to the density function, say, F; in its tail near the end point.

The EVT has two substantial ways of obtaining results or the principle models; i.e. the Block maxima model and the peak over threshold. Through the block maxima method, the asymptotic distribution of a series of maxima (minima) is modeled and the distribution of the standardized maximum is shown to follow extreme distributios of Gumbel, Fretchet and Weibbul distributions. The GEV is a standard form of these three distributions, and hence the series is shown to converge to GEV. To analyse the extreme markets, we are not always interested in maxima or minima of observations, but also in in the behavior of a large exceedance over a given threshold. The POT method models a distribution of excess over a given threshold. EVT shows that the limiting distribution of the ofexceedances is a GPD. The main focus in this research would be confined to the POT approach since it is considered to be more efficient in modeling as it fits the exceedances over a given threshold in a data set.

3.3.2 Peaks Over Threshold

The Peaks over Threshold method models the exceedances above some high threshold u so sufficiently. The main interest here is estimating the distribution function $f_u$of the excess values of r_t over a high threshold u. The mean excess function is defined as follows;

Equation 13

$$F_u(x)=p_r\left(x-u\le x\,|\,x>u\right)=\frac{F\left(x-u\right)-F\left(u\right)}{1-F\left(u\right)}$$

In modeling these excesses distribution over high threshold, the Generalized Pareto Distribution is used. The conditional distribution function of the excesses over the threshold u can be defined as follows;

Equation 14

$$f(x)=\begin{cases}\left(1-\xi\left(\dfrac{x-\mu}{\beta}\right)\right)^{-\frac{1}{\xi}} & ,\xi\neq 0\\ 1-\exp\left(-\left(\dfrac{x-\mu}{\beta}\right)\right),\xi=0\end{cases}$$

However, the choice of a threshold is crucial. There isa challenge between setting a high threshold value that reduces the sample size to an insufficient level to meet the asymptotic properties and setting a low threshold level that ends up with a sizeable sample size but with more of the non-extreme values in the estimation. Variousmethodscan be considered when selecting an appropriate threshold. One of the methods is thegraphical representation. The empirical mean excessfunctionwhich refers to the sum of excesses over threshold u divided by the number of datapoints exceeding the threshold isdefined as:

Equation 15

$$e(u)=E\left(X-u\mid X>u\right)$$

$$e_n(u)=\frac{\sum_{i=1}^{n}\left(X_i-u\right)I_{(X_i>u)}}{\sum_{i=1}^{n}I_{(X_i>u)}(X_i)}$$

A plot of the mean excess function is used where anappropriate threshold is selected at the point the plot tends to be linear and positively sloped.Upon selection of an appropriate threshold the returns arethen modeled using the GPD. .

3.3.3 Value-at-Risk and Conditional Tail Expectation

Value-at-Risk is a single estimate of risk of the potential loss for investments i.e. the worst case scenario. It estimates how much a set of investments might lose with a given probability, given normal market conditions in a set time periods. Suppose that at the time index t we are interested in the risk of a financial position for the next l periods. Let $\Delta V(l)$ be the change in the value of the assets in the financial position from time t to t+l. If we denote the cumulative distribution function (CDF) of $\Delta V(l)$ by F_{l}(x) , then the VaR of a long position over the time horizon l with probability p is defined as;

Equation 16

$$VaR=\begin{cases}\mu+\dfrac{\beta}{\xi}\left\{1-\left[-D\ln\left(1-p\right)\right]^{\xi}\right\} if\,\xi\neq 0\\ \mu+\beta\ln\left[1-D\ln\left(1-p\right)\right] if\,\xi=0\end{cases}$$

Where D is the baseline time interval used in the estimation. Mostly D=252, which is approximately the number of trading days in a year. The parameters μ, β and ξ are the location, scale and the shape parameters respectively. The parameters are estimated using the maximum likelihood estimation method.

The Conditional Tail Expectation is a risk measure which gives the expected loss given that the VaR is exceeded. It provides a measure of the extra capital needed due to exposure to the loss. It is also referred to as Tail VaR or the Expected Shortfall. Specifically, for a given probability p, the CTE is defined by;

Equation 17

$$CTE_p=E\left[r\mid r\geq VaR_p\right]=VaR+E\left[r-VaR_p\mid r\geq VaR_p\right]$$

$$=\frac{VaR_p}{1+\xi}+\frac{\beta+\xi\eta}{1+\xi}$$

where VaR_p is the Value-at-Risk for a given probability p , β and ξ are the estimated shape and the scale parameters of the GPD and η is the threshold and r is the loss series.

4. RESULTS AND DISCUSSION

4.1 Data exploration

The analysis in this paper was based on the daily import prices of crude oil in Kenya for the period lagging 2005 to 2018.

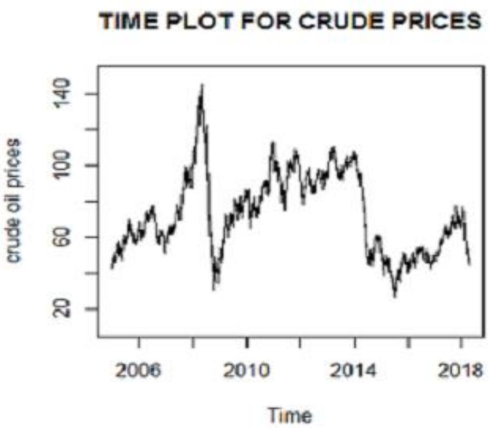

Figure 1: Plot for the daily crude oil prices

Figure 1: Plot for the daily crude oil pricesShows the general trend in oil prices. For the period between 2005 and 2008, the oil prices were on a consistent upward trend, where the prices rise upto a peak of US$145.16per barrel, the highest level ever recorded. This price increase would be attributed to tension experienced during that period in the Middle East (the major exporter of oil to Kenya). However, between August 2008 and early 2010, a major shock is observed where the prices are consistently on a downward trend. The prices then rebound to an upward trend with significant volatility being experienced. Towards the end of 2014 into 2016, there is a decline in the oil prices. This can be attributed to increased production of American shale oil that created a surplus in the market resulting to decline in prices. Between 2017 until 2018, a gradual upward trend is observed in the prices with some volatility being experienced.

The crude oil import prices were converted into log returns$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$since the returns have more attractive statistical properties and they give complete and scale-free summary of the investment opportunity. Also, unlike the raw price data, the log returns tend to evolve a stationary process.

Return series for the data set is as shown in Figure 2 below. The returns plot indicates that the returns are stationary.

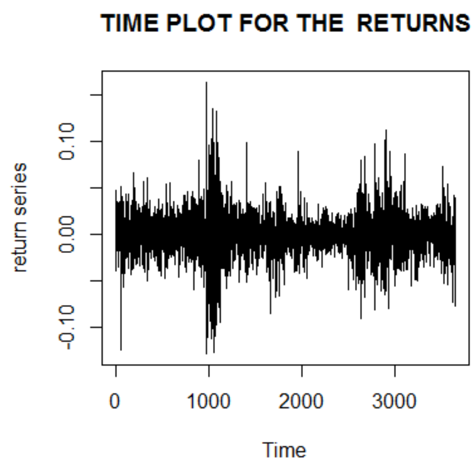

Figure 2: Return series plot

In Figure 2, volatility clustering is observed. It describes the tendency of large changes in asset returns (of either sign) to follow large changes and small changes (of either sign) to follow small changes. In other words, the current level of volatility tends to be positively correlated with its level during the immediately preceding periods.

4.1.1 Stationarity test by ADF test

A stationarity test using the Augmented Dickey-Fuller test was carried out to ascertain if the returns are stationary. This is because Statistical modeling requires the time series to be consistent over time. The null hypothesis states that the returns are not stationary.

Table 0.1: ADF test Results

ADF	DF	Pvallue
-14.59	15	0.01

At 5% significance level, the test rejected the null hypothesis leading to a conclusion that the return series is stationary.

4.1.2 Normality Test on the returns

Essentially, return series is characterized by heavy tails, skewness and excess kurtosis. It is therefore important to do a normality test on the returns to establish if they are normally distributed or not. A QQ plot and Jarcque-Bera test were applied in this study.The null hypothesis stated that the returns are normaly distributed.

Quantile-Quantile plot for Normality

On the QQ plot in Figure 1 below, a 45 degree reference line is plotted. Essentially, when all the points lie along the reference line, then the returns are said to be perfectly normally distributed. A departure of some of the points from this reference line, as seen in the plot, is evidence that the returns do not follow the normal distribution.

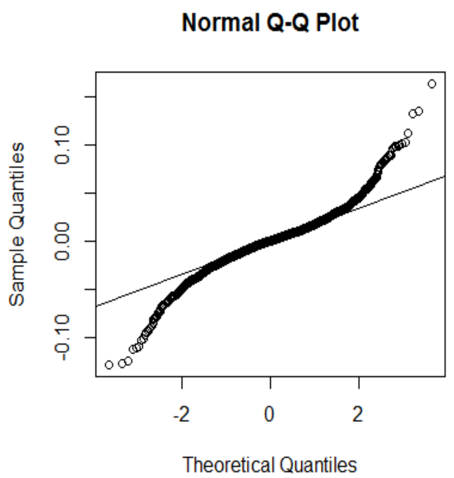

Figure 3: QQ-plot for normality

On the QQ plot, a 45 degree reference line is plotted. Essentially, when all the points lie along the 45 degree reference line, then the returns are said to be perfectly normally distributed. A departure of some of the points from this reference line, as seen in the plot, is evidence that the returns do not follow the normal distribution.

Jarcque-Bera Test for normality

Table 0.2: JarcqueBera test Results

Xsquared	DF	Pvalue
-14.59	2	2.2×10^{-16}

The JB results in Table 0.2 are statistically significant at 5%. This leads to the conclusion that the oil returns are not normally distributed.

4.1.3ARCH effects test

Consider μ_t=r_t− $a_t$where μ_t,$r_t$and $a_t$are the mean equation, return series and the innovationsrespectively. The mean equation was modeled as an ARIMA (p,d,q) model since they are best in capturing the deterministic component of the series but they cannot capture the conditional variance and other facts of the return series.ARIMA(2,2) best fitted the data with the lowest AIC. The squared residuals a_t of the mean equation were applied in the Ljung-box method to test the null hypothesis that there are no ARCH effects.

Table 0.3: Ljung-Box test results

Xsquared	DF	Pvalue
222.92	1	2.2×10^{-16}

The results Table 0.3 are significant at 5% level of significance.The null hypothesis is thus rejected leading to the conclusion that ARCH effects are present in the squared residuals. This justifies the use of heteroscedastic models to fit the series.

4.2 Volatility modeling

In order to model the volatility of the oil prices, various ARIMA(2,2)/GARCH family of asymmetric models were fitted and their AICs and log likelihoods compared. The model that had the highest LLH and smallest AIC was considered the best model to fit the data.

Table 0.4: Model selection by AIC

Model	AIC	log likelihood
TGARCH(1,1)	-4.9987	9135.689
EGARCH (1,1)	-5.0096	9156.54
PGARCH(1,1)	-5.0122	9162.242
TGARCH(1,2)	-5.0003	9139.624
EGARCH (1,2)	-5.0112	9160.462
PGARCH(1,2)	-5.0140	9166.564
TGARCH(2,1)	-4.9984	9136.081
EGARCH (2,1)	**–5.0166**	**9171.255**
PGARCH(2,1)	-5.0153	9169.866
TGARCH(2,2)	-5.0032	9145.769
EGARCH (2,2)	-5.0131	9165.898
PGARCH(2,2)	-5.0129	9166.476

From Table 0.4, ARIMA(2,2)/EGARCH(2,1) proved to have the lowest AIC and highest Log likelihood values. Thus, the study concluded that it was the best model to fit the data.

The estimated EGARCH(2,1) model parameters are presented in Table 0.5 below;

Table 0.5: EGARCH model parameters

Parameter	Estimate	p-value
μ	0.000032	0.908409
φ_1	0.611960	0.000000
φ_2	-0.994938	0.000000
θ_1	-0.615654	0.000000
θ_2	0.994622	0.000000
ω	-0.064011	0.000000
α_1	-0.084817	0.000000
α_2	0.033797	0.000000
β_1	0.991456	0.000000
γ_1	-0.235609	0.000000
γ_2	-0.137962	0.000001

All the parameter estimates from Table 0.5 are statistically significant at the 5% level of significance exceptμ. The non significant parameter was dropped from the model. The Garch term βwas found to be less than 1 and relatively large i.e.$\beta \to 0.991456$. These results indicate that the process was stationary and that shocks to the variance are persistent i.e.large positive or a large negative return will lead future forecasts of the volatility to be high for a protracted period.

Regarding the indicator for leverage and asymmetric effects, the estimates show that the coefficients lagged γ are negative and significant, suggesting that bad news imply a higher next period conditional variance than good news of the same sign at lag 1 and lag 2. These asymmetric effects would be attributed to the leverage effects.The leverage effect is the phenomenon of a correlation of past returns with future volatility. Volatility tends to increase when stock pricesdrop. When volatility rises, expected returns tend to increase, leading to a dropin the stock price. As a result, volatility and stock returns are negatively correlated.Leverage effects enable the conditional variance σ_t^2 to respond asymmetrically to positive and negative shock.

Diagnostic checking of EGARCH (2,1) model

In the ACF plots

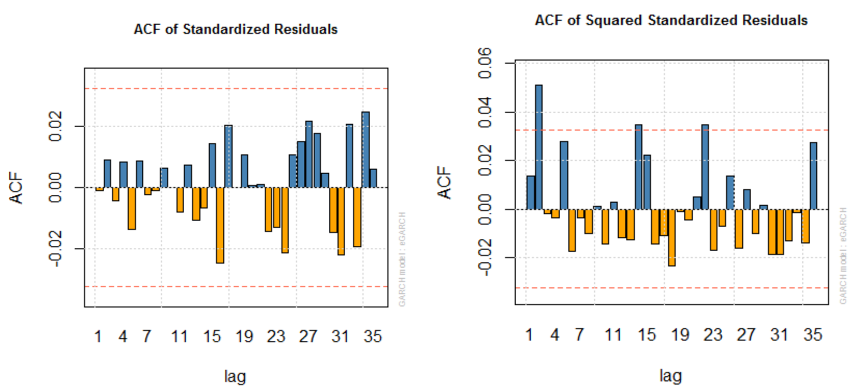

Figure 4: ACF for both the standardized residuals and the squared standardized residuals

From Figure 4, there areno noteworthy spikes protruding from the confidence bands both the ACF graphs. Therefore, this implies that there is no significant serial correlation. The presence of serial correlation would render inaccurate forecasts. The above plots indicate that the conditional variance model is adequate i.e. it fits the data so well, and it can be used for forecasting.

4.4 Volatility Forecasting

Forecasting provides a strong basis for economic and business planning, inventory and production control and optimization of industrial process. EGARCH(2,1) model was the best to model these returns. The predictive ability of EGARCH (2,1) above was evaluated using MSE and MAE.

Performance Evaluation

To measure the forecasting ability of the EGARCH model, the study used one-step ahead rolling forecasts. 1000 observations were considered as out of sample and then used to compare with the in sample values. Table 0.6below shows the forecast evaluation measures;

Table 0.6: Forecast evaluation measures

Measure	Value
MSE	0.0005873
MAE	0.001668

From Table 0.6the MSE and MAE were small and not significantly different. If the data are not over-fitted, then error measures are expected to be somehow similar. Thus EGARCH model is well suited for forecasting the volatility of crude oil import prices.

4.5 Value-at-Risk and Conditional Tail Expectation

The EVT approach focuses on the exceedances of the returns over some high threshold and the times at which the exceedances occur. The GPD was fitted on the returns of the crude oil import prices and the optimum threshold determined by use of the mean excess plot.

Table 0.7: Threshold and GPD parameters

η	ξ	β
0.01466667	0.13154104	0.01326484

The estimates of the GPD model parameters the shape parameter, 0.1315 and the scale parameter, 0.01326. Since ξ>0, then the GPD model simplifies to Pareto type II distribution i.e. the Fretchet distribution. The scale and the shape parameters of the GPD are then used to determine the Value-at-Risk and the Conditional Tail Expectation.

Table 0.8: VaR and CTE estimation

Probability P	VaRp	CTEp
99.9%	0.116298	0.14697
99.5%	0.077665	0.10248
99%	0.063389	0.08604

From the result Table 0.8, the price corresponding to the return value, 0.116298 and 0.1469656 respectively,is given by $\ln_e\left(\frac{p_t}{P_{t-1}}\right) = 1.123$and 1.158, where $p_t$and $p_{t-1}$the oil prices in month t and t-1 respectively. This indicates that at a high confidence level of 99.9% , an investor holding a long position of $1million, the Value-at-Risk is $123000. If this VaR is exceeded, then the investors should have an extra capital of $158000 in order to remain in the market which is the CTE.

Similarly, with a confidence level of 99.50% the VaR value is 1.0808. With a financial position of $1 million, the value at risk is $80800. Given that this value is exceeded then, theconditional tail expectation value is 1.108. With the investor holding the same long financial position, then the Conditional Tail Expectation value is $108000. Similar inferences are drawn for the 99% confidence level.

5. CONCLUSIONS AND RECOMMENDATION

This paper has modeled the risk of the daily crude oil import prices in Kenya by applying theasymmetric heteroscedastic model to and the EVT approach respectively. The oil import prices were first explored to test the validity of key assumptions underlying the modeling environment. First, a time series plot exhibited a presence of trend and seasonality in the prices. The prices were then converted to their respective log returns, a time plot for the returns was fitted and volatility clustering was evident. ADF test for stationarity was carried out and the returns were found to be stationary. Secondly, the returns were tested for normality and the normality assumption was rejected in favour of heavy tailed distributions. Finally, the mean equation was modeled as ARIMA (2,2) and the squared residuals were applied in the test for the presence of ARCH effects. It was concluded that ARCH effects were evident in the residuals of the mean equation.

Considering the objectives of the study, the EGARCH(2,1) was identified as the best model by the AIC technique, for modeling the volatility. All the parameters of the model were explored. The results showed that the volatility was persistent. The study also revealed that the returns had asymmetric effects where negative events tend to affect the volatility more than positive events. Diagnostic tools proved that the model fitted the data adequately and it could be used for forecasting. The predictive ability of the model was evaluated using the MSE and MAE. It was inferred that it is the best model for forecasting the volatility of the crude import oil prices in Kenya.

The Value-at-Risk and the Conditional Tail Expectation were determined by the EVT approach. The threshold and the exceedances over the high threshold were determined by fitting the mean excess plot. The GPD was fitted and the location, scale and the shape parameters estimated by MLE technique. The shape parameter of the GPD distribution simplified to Pareto type II distribution i.e. the Fretchet distribution. The parameters were used in computing the risk measures at relatively very high probabilities. At the highest probability of 99.9%, an investor holding a long position of $1million, the VaR was to be $123000 and the CTE was found to be $158000. This means that the potential risk amount of that investment is 12.3% and for the investor to remain in the market when this VaR is exceeded should have an extra capital of 15.8% of the invested amount.

Since the energy sector is one of the key sectors that drive the Kenyan economy, further studies such as macroeconomic effect of crude oil import price volatility in Kenya may be considered. Further methods of threshold determination may also be considered.

ABBREVIATIONS

ARCH	Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive conditional Heteroscedasticity
EGARCH	Exponential Generalized Autoregressive conditional Heteroscedasticity
TGARCH	Threshold Generalized Autoregressive conditional Heteroscedasticity
POT	Peak Over Threshold
ERC	Energy Regulatory Commission
CDF	Cumulative density function
PDF	Probability density fuction
GPD	Generalized Pareto Distribution
DF	Degrees of freedom
EVT	Extreme Value Theorem
JB	JarcqueBera
CTE	Conditional Tail Expectation
LM	Langrage Multiplier
VaR	Value-at-Risk

NOC	National Oil Corporation
AIC	Akaike Information Criterion
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
MLE	Maximum Likelihood Estimation
ARIMA	Autoregressive Integrated Moving Average

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