A Comparative Study of ARIMA and GARCH Models in Forecasting Agricultural Commodity Prices in Sudan from (1/1/ 1997 to 30 /8/ 2010)

Abdelaziz Gibreel Mohammed Musa
PhD, School of statistics and actuarial science, Alneelain University
E-mail:azizgibreel@yahoo.com
Mobile: 00249912825318
Khartoum –Sudan
Abstract:

The paper attempts to modeling and forecasting agricultural commodity prices data in the Sudan. Tow financial time series approaches namely; Box-Jenkins (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were applied to four agricultural commodity prices series cover the period 1\textsuperscript{st} January 1997 – 30\textsuperscript{th} September 2010; these commodities are surgham, seasme, millet and wheat. Based on Box-Jenkins approach, through the model identification, estimation and diagnostic checking, the most appropriate models for forecasting agricultural commodity prices are ARIMA (1,1,1) for surgham commodity, ARIMA (0,1,0) for seasme commodity, ARIMA (1,1,2) for millet commodity and ARIMA (1,1,1) for wheat commodity respectively.In addition, this paper also develops an empirical analysis of various types of Generalized Autoregressive Conditional Heteroskedasticity models for instance; GARCH (1,1), EGARCH(1,1), TGARCH(1,1) and APARCH(1,1) to test the hypothesis of persistence, asymmetry and volatility of the prices of agricultural commodities. The Empirical analysis concluded that, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models provided appropriate models to forecast agricultural commodity prices volatility, because of their smallest values of AIC and SIC of the comparison criteria. Hence, for data of this type, a forecast based on GARCH approach is strongly recommended.
الدراسة: 
تهدف هذه الورقة لمقارنة أداء طريقتي بوكس-جنكنز و نماذج الانحدار الذاتي لاختلاف التباين الشرطي في نمزجة و التنبؤات اسعار السلع الزراعية الزراعية في السودان باستخدام بيانات اسعار سلع الذرة، السمسم، الدخن و القمح للفترة من 1/1/1997 إلى 30/8/2010.

بالاستخدام منهجية بوكس-جنكنز للتنبؤ، أُسفرت نتائج التحليل، إلى أن بالنسبة لهذه البيانات، فإن نماذج ARIMA (1,1,1) و ARIMA (1,1,0), ARIMA (1,1,2) و ARIMA (1,1,1) تعد الأفضل للتنبؤ بتقلبات اسعار سلع الذرة، السمسم، الدخن و القمح على التوالي. بالإضافة إلى منهجية بوكس-جنكنز، استخدمت في هذا الورقة نماذج GARCH (1,1)، EGARCH (1,1) و TGARCH (1,1) و GARCH (1,1) للاستقرار الشرطي لاختلاف التباين الشرطي، لنموذج التنبؤ بوجود، إنتظام و التغيرات التي تحدث في اسعار سلع الذرة، السمسم، الدخن و القمح الزراعية في السودان لنفس الفترة. وقد أوضحت نتائج الدراسة أنة بالنسبة لهذا النوع من البيانات، فإن نماذج الانحدار الذاتي لاختلاف التباين الشرطي تعد الأفضل لنمزجة و التنبؤ بوجود، إنتظام و تقلبات اسعار السمع الزراعية الزراعية في السودان.

Introduction

Agriculture is the dominant sector of the Sudanese economy. The background information given should clearly show that the social and economic growth of Sudan depends to a great extent on the performance of the agricultural sector. In addition to generating directly about two-fifths of GDP, agriculture also drives activity in the industry and service sectors such as transportation, agro-industries, and commerce, which account for a large part of the rest of the economy. Even more importantly, 80 percent of the labor force is employed in agricultural and related activities, and the performance of agriculture is the main determinant of year-to-year changes in poverty levels and the food security of the population. Finally, agriculture is the source of virtually all of the Sudan’s exports (before oil extraction in 1999) and therefore, it is a key determinant of balance of payments developments.
Volatility of Primary Agricultural Commodity Prices

In agricultural commodities, volatility originates mainly from supply disturbances and can differ for different groups of products. This aspect gives support to the fact that the production decisions made by farmers are mostly based on current market prices, which affect prices farmers will receive for their products once these are supplied to the market. Another important characteristic of agricultural products is that prices can be highly volatile and yet show trend over long period of time; or show little volatility. These two aspects of agricultural products justify the need to study the nature of price fluctuation in order to inform policy-making process. In view of increasing fluctuations and volatility on agricultural commodity markets, forecasting agricultural commodity prices became more relevant for management decisions. Obtaining an effective and accurate price forecasting will support decision maker towards a variety of decisions, such as storage decisions, hold and sell decisions and hedging decisions. This paper compares the ability of ARIMA and GARCH Models in Forecasting Agricultural Commodity Prices in Sudan with the objective of deciding which of this methods provides accurate predictions.

Box-Jenkins (ARIMA) Models

Several models may be used to represent a time series depending on the underline process assumed to operate on the series. Below is a review of these models.

The Autoregressive Model:

In the autoregressive model the current value $X_t$ in the time series is expressed as a linear combination of the previous values, and an unexplained portion $e_t$. A typical autoregressive model of order $p$ takes the form:

$$\left(1-\phi_1B - \phi_2B^2 - \ldots - \phi_pB^p\right)X_t = e_t$$

where the term $m$ is a constant which representing the mean of the process, $\phi_j$ $(j=1,2,\ldots,p)$ is the jth autoregressive parameter and $e_t$ are the error term at time t.
The \( e, s \) are assumed to be independent normally distributed random variable with mean zero and variance \( \sigma^2_{e_t} \).

**The Moving Average Model:**

In the moving average model of order \( q \) denoted by \( MA(q) \) the current observation \( X_t \) is expressed as a linear combination of the random disturbances going back \( q \) periods, it is equation is written as:

\[
\dot{X}_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}
\]

**The Mixed Autoregressive – Moving Average Models:**

For stationary time series \( X_t, X_{t-1}, X_{t-2}, \ldots \) the mixed ARMA model is expressed as follows:

\[
\phi(B) \dot{X}_t = \theta(B)e_t
\]

where \( \delta \) is the constant mean of the series.

\( \phi_j \) are the autoregressive part parameters.

\( \theta_j \) are the moving average part parameters. \( e_t \) is the error term at time \( t \).

**The ARIMA models:**

ARIMA model takes the form:

\[
\phi(B)(1-B)^d X_t = \theta(B)e_t
\]

where \( (1-B)^d \) is the \( d \)th order difference.

This is the model that calls for the \( d \)th order difference of the time series in order to make it stationary. In practice \( d \) is 0,1, or at most 2.

**The seasonal model:**

Seasonal ARIMA model of order \( (p,d,q) \times (P,D,Q)^s \) can be written as:
\( \phi(B)D(B^s)\nabla^s X_t = \theta(B)\Theta(B^s)\epsilon_t. \)

where

\((p,d,q)\) = nonseasonal part of the model.

\((P,D,Q)\) = seasonal part of the model.

\(S\) is the number of periods.

**ARCH / GARCH models**

In 1982, Robert Engle proposed a volatility process with time varying conditional variance, which is Autoregressive Conditional Heteroskedasticity (ARCH) process. Bollerslev 1986, proposed the Generalized ARCH (GARCH) models as a natural solution to the problem with the high ARCH orders. In ARCH / GARCH models the conditional variance is expressed as a linear function of past squared innovations and earlier calculated conditional variances. To generate the autoregressive conditional heteroskedasticity process the conditional variance of the error term is expressed as a function of its past values squared as follows:

\[
p_t = E (x_t | \Omega_{t-1}) + \epsilon_t,
\]

\[
\epsilon_t | \Omega_{t-1} \sim N(0, h_t), \quad \epsilon_t = \eta_t \sqrt{h_t},
\]

\[
h_t^2 = \delta + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2
\]

Where \(\epsilon_t\) is the unconditional shock, \(\eta_t\) is an independently identically distribution random variable (conditional) shock with mean zero and variance 1, \(h_t^2\) denotes the conditional variance of the information set \(\Omega_{t-1}\), and \(\delta > 0, \alpha_i \geq 0\) for all \(i = 2,3,\ldots,p\), \(\alpha_1 + \alpha_2 + \ldots + \alpha_p < 1\) are necessary to make \(\epsilon_t^2\) positive and covariance stationary.

Bollerslev (1986) proposed a useful extension known as Generalized ARCH (GARCH) process. In GARCH model the conditional variance of return series is expressed as a function of constant, past news about volatility \((\epsilon_{t-i}^2)\) terms and past
forecast variance \((h_{t-i}^2)\) terms. In the GARCH \((p,q)\) the conditional variance is expressed as follows:

\[
\varepsilon_t = \eta_t \sqrt{h_t}
\]

\[
h_t^2 = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2
\]

Where \(\eta_t\) is independently identically distributed random variable with mean zero and variance 1, \(\omega > 0, \alpha_i \geq 0, \beta_j \geq 0\) and \(\sum_{i=1}^{\max\{p,q\}} (\alpha_i + \beta_j) < 1\)

Another volatility model with common use to handle leverage effects is the Threshold GARCH (TGARCH) model. In the (TGARCH) model the conditional variance of the model can be expressed as:

\[
h_t = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i d_{t-i} \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i h_{t-j}
\]

Where \(d_i = 1\) if \(\varepsilon_t < 0\) and \(d_i = 0\) otherwise.

Adverse market conditions and bad news \((\varepsilon_{t-1}^2 < 0)\) such as frost, drought, or political instability has an impact of \((\alpha + \gamma)\). Good news about the demand and supply conditions in the commodity market \((\varepsilon_{t-1}^2 > 0)\) has an impact of \(\alpha\).

In the EGARCH models, the effect of recent residuals is exponential rather than quadratic. The variance equation of this model can be expressed as follows:

\[
\log (h_t^2) = \delta + \pi_1 \left| \frac{\varepsilon_t}{\sqrt{h_{t-i}^2}} \right| + \pi_2 \frac{\varepsilon_{t-1}}{h_{t-1}^2} + \beta \log (h_{t-1}^2)
\]

Asymmetry is a chivied when\(\pi_2 \neq 0\). The impact of good news such as new market infrastructure is captured by \(\left(\frac{\pi_1 + \pi_2}{\sqrt{h_{t-1}^2}}\right)\) while the impact of bad news such as political stabilities or unfavorable weather is expressed by \(\left(\frac{\pi_1 - \pi_2}{\sqrt{h_{t-1}^2}}\right)\). A negative and
significant $\pi_2$ is an evidence of a symmetry and greater impact of negative shocks on price volatility.

The Asymmetric Power Autoregressive Conditional Heteroskedasticity (APARCH) model proposed by Ding, Granger and Engle (1993) is a model that nests several other popular univariate parameterizations and therefore allows the data to determine the true form of asymmetry (Harris and Sollis, 2003). It extends TARCH and GJR-GARCH models in the sense that non-linearity in the conditional variance is directly parameterized through a parameter $\delta$. It thus gives a greater flexibility when modeling the memory of volatility, the variance equation of this model is given by:

$$h_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i (|\epsilon_{t-1}| - \gamma_i \epsilon_{t-1})^\delta + \sum_{j=1}^{q} \beta_j h_{t-j}^\delta$$

where $\omega > 0$, $\delta \geq 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, $-1 < \gamma_i < 1$, $i=1,2,...,p$, $j=1,2,...,q$.

The model is couples the flexibility of varying exponent with the asymmetry coefficient, moreover The APARCH includes other ARCH extensions as special cases.

**Database:**

Monthly readings of sorghum, sesame, millet and wheat of agricultural commodity prices series, with length of fourteen years covered the period from 01/01/1997 to 30/08/2010 are obtained from different fundamental sources; these are central bureau of statistics, Ministry of Agriculture & Forests and Gadaref crops market. The logarithm of relative prices is used to calculate monthly stock returns.

**Empirical Results:**

This section discusses empirical results from the unit root and correlogram tests of the series level and first difference of the agricultural commodity prices under consideration to the construction of ARIMA and GARCH-types models used to forecast agricultural commodity prices data.
The first step to perform the analysis is to find unit roots and correlogram tests in the agricultural commodity prices series. Augmented Dickey Fuller (ADF) and correlogram tests are more appropriate tools used. All agricultural commodities series level shows a unit roots (i.e. the commodity series level are non stationary), however the first difference of these commodities series reject the null hypothesis that there is unit root (i.e. the commodity series are stationary). Also both ADF and correlogram tests conclude that all agricultural commodities prices return series are stationary.

Several ARIMA (p,d,q) models have been suggested with the objective of deciding which of these models is adequate to fit agricultural commodity prices data. For the selected ARIMA models and their corresponding AIC, SBC criteria, both ADF and Correlogram of diagnostic checking tests conclude that ARIMA (1,1,1) model is adequate in forecasting surgham commodity prices series, ARIMA (0,1,1) model is adequate, in forecasting seaseme commodity prices, ARIMA (1,1,2) model is adequate to represent millet commodity prices series and ARIMA (1,1,1) model is adequate in forecasting wheat commodity prices data, therefore, the above models are appropriate in forecasting agricultural commodity prices data.

The univariate GARCH (1,1), EGARCH(1,1), TGARCH (1;1), and APARCH (1,1) models for both the mean and the variance equation for all agricultural commodities under examination are estimated using the maximum likelihood estimation method. Bellow is the reports parameter estimates of each model.

Table (1) contains the results of the Augmented Dickey Fuller and correlogram tests on the series levels and first differences of surgham, seaseme, millet and wheat commodities. These results show that both ADF and correlogram tests are strongly rejected i.e (the commodity prices series levels are non stationary) however; both tests confirm that the first difference of these commodities are stationary.
Table (1) Summary of ADF and correlogram tests results on commodity prices

<table>
<thead>
<tr>
<th>Test</th>
<th>Augmented Dickey Fuller test</th>
<th>Correlogram test</th>
</tr>
</thead>
<tbody>
<tr>
<td>commodity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>surgham</td>
<td>Accept H₀</td>
<td>Reject H₀</td>
</tr>
<tr>
<td>seaseme</td>
<td>Accept H₀</td>
<td>Reject H₀</td>
</tr>
<tr>
<td>millet</td>
<td>Accept H₀</td>
<td>Reject H₀</td>
</tr>
<tr>
<td>wheat</td>
<td>Accept H₀</td>
<td>Reject H₀</td>
</tr>
</tbody>
</table>

Modeling Agricultural commodity prices using ARIMA models:

This section provides the construction of an Autoregressive Integrated Moving Average models through the model identification, estimation and diagnostic checking, the correlogram and Augmented- Dickey Fuller (ADF) test are used to perform ARIMA models as well as determining p, d and q values for non seasonal part of the model and P, D and Q values for seasonal part of the model if the series contains seasonality.

For surgham commodity Both ADF and the ACF test results confirm that the first difference of surgham series is stationary, in addition shows that the ACF decays exponentially to zero at increasing lags and the PACF cut off to zero after lag of 1. These findings indicates that an ARIMA (1,1,0) model might be appropriate in modeling and forecasting surgham commodity prices series.

The estimated equation for surgham commodity prices series is expressed as follows:

\[ (1 + .12B)(1 - B)x_t = e_t \]

The diagnostic checking of the above model conclude the there seems to be serial correlation on the residuals.
Numerous statistical criteria for assessing the goodness of fit to time series models have been introduced. Akaike’s (1987) information criteria and Schwartz’s (1978) Bayesian criteria are useful tools for comparing models with different parameters number, the model with smallest AIC or SBC is considered best. Several ARIMA (p,d,q) models have been suggested with the objective of identifying which of these models is adequate to fit surgham commodity prices data, the suggested ARIMA models and their corresponding AIC, SBC values are stated as follows:

Table (2) The suggested ARIMA models and their corresponding AIC, SBC values

<table>
<thead>
<tr>
<th>ARIMA (p,d,q) model</th>
<th>AIC</th>
<th>SBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (1,1,0)</td>
<td>6.542</td>
<td>6.580</td>
</tr>
<tr>
<td>ARIMA (0,1,1)</td>
<td>6.529</td>
<td>6.567</td>
</tr>
<tr>
<td>ARIMA (1,1,1)</td>
<td>6.526</td>
<td>6.538</td>
</tr>
<tr>
<td>ARIMA (1,1,2)</td>
<td>6.540</td>
<td>6.616</td>
</tr>
<tr>
<td>ARIMA (2,1,1)</td>
<td>6.544</td>
<td>6.621</td>
</tr>
<tr>
<td>ARIMA (2,1,2)</td>
<td>6.551</td>
<td>6.547</td>
</tr>
</tbody>
</table>

A closer look to table (2) it can be seen that ARIMA (1,1,1) model has smallest values of both AIC and BSC criteria. In this model it is assumed that surgham commodity prices data is subject to autoregressive of order 1, moving average of order 1 and difference of order 1. Below are estimates of an ARIMA (1,1,1) model parameters and other related statistics.

The selected estimated equation for surgham commodity prices series is expressed as follows:

\[(1 + 0.68B)(1 - B)x_t = (1 - 0.83B)e_t\]
Both autoregressive and moving average parameters are seems significantly different from zero. Hence this model is chosen as the one to be used for forecasting surgham commodity prices.

After the surgham commodity price selected model has been identified and its parameters estimated, diagnostic checking is then applied to the fitted model. The correlogram test is one of the most useful statistical tools used in testing whether the surgham commodity price model is adequate, it is found that ACF of residuals series for the fitted ARIMA (1,1,1) model are not significantly different from zero, this implies that the residual series is random. These results indicate that ARIMA (1,1,1) model is adequate, therefore it can be used for forecasting purposes.

For seaseme commodity price series both ADF test and correlogram test result indicate that the first difference of seaseme commodity price series is stationary, the ACF decays exponentially to zero and the PACF cut off to zero after lag of 1. These results confirms that an ARIMA (1,1,0) model might be appropriate in modeling seaseme commodity price data.

The estimated equation for seaseme commodity prices series is stated as follows:

\[(1 + 0.027B)(1 - B)x_t = e_t\]

The autoregressive parameter is seems not significantly different from zero. Furthermore the correlogram test indicates that there seems to be serial correlation on the residuals since the autocorrelations and partial autocorrelations at first few lags are significant.

Several ARIMA (p,d,q) models have been suggested to fit seaseme commodity prices data, the suggested ARIMA models and their corresponding AIC,SBC values are stated as follows:
Table (3) shows the suggested ARIMA models and their corresponding AIC and SBC values for seaseme commodity prices data. A closer look to table (3) it can be shown that ARIMA (0,1,1) model have smallest value of BSC criteria. In this model it is assumed that seaseme commodity prices data is subject to moving average of order 1 and difference of order 1. Bellow are estimates of an ARIMA (0,1,1) model parameters and other related statistics.

The selected estimated equation for seaseme commodity prices series is expressed as follows:

\[(1 - B)x_t = (1 + 0.029B)e_t\]

The moving average parameters are seems not significantly different from zero. Hence this model is chosen as the one to be used for forecasting seaseme commodity prices.

The residuals ACF of the fitted model revels that no residuals autocorrelations longer than two stander deviation (no significant values). In addition, the corresponding Q statistics significant values based on 34 lags are less than 0.05 significant level. These results indicate that ARIMA (0,1,1) model is adequate, therefore it can be used for forecasting purposes.
For millet commodity Both ADF and correlogram test results indicate that the first difference of millet commodity price series is stationary. Moreover the ACF decays exponentially to zero and the PACF cut off to zero after lag of 1. These results confirms that an ARIMA (1,1,0) model might be appropriate in modeling and forecasting millet commodity prices data.

The estimated equation for millet commodity prices series is stated as follows:

\[(1 + 0.0858B)(1 - B)x_t = e_t\]

The autoregressive parameter is seems not significantly different from zero. In addition, the correlogram test indicates that there seems to be serial correlation on the residuals since the autocorrelations and partial autocorrelations at first few lags are significant. Several ARIMA (p,d,q) models have been suggested to fit millet commodity prices data, the suggested ARIMA models and their corresponding AIC,SBC values are illustrated as follows:

<table>
<thead>
<tr>
<th>ARIMA (p,d,q) model</th>
<th>AIC</th>
<th>SBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (1,1,0)</td>
<td>7.417</td>
<td>7.456</td>
</tr>
<tr>
<td>ARIMA (0,1,1)</td>
<td>7.411</td>
<td>7.449</td>
</tr>
<tr>
<td>ARIMA (1,1,1)</td>
<td>7.426</td>
<td>7.483</td>
</tr>
<tr>
<td>ARIMA (1,1,2)</td>
<td>7.393</td>
<td>7.470</td>
</tr>
<tr>
<td>ARIMA (2,1,1)</td>
<td>7.429</td>
<td>7.505</td>
</tr>
<tr>
<td>ARIMA (2,1,2)</td>
<td>7.415</td>
<td>7.510</td>
</tr>
</tbody>
</table>

Table (4) shows the suggested ARIMA models and their corresponding AIC and SBC values for millet commodity prices series data. A closer look to table (4) it can be seen that ARIMA (1,1,2) model has smallest AIC and BSC values. In this model it is assumed that millet commodity prices data is subject to autoregressive order 1,
moving average of order 2 and difference of order 1. Bellow the estimates of an ARIMA ((1,1,2)) model parameters and other related statistics.

The selected estimated equation for millet commodity prices series is expressed as follows:

\[(1 - 0.910B)(1 - B)x_t = (1 + 0.852B + 0.147B^2)e_t\]

The first order autoregressive and moving average parameters are seems not significantly different from zero. Hence this model is chosen as the one to be used for forecasting millet commodity prices.

The residuals autocorrelation function of an ARIMA (1,1,2) model for millet commodity prices data, it can be shown that the residuals ACF of the fitted model revels that no residuals autocorrelations longer than two stander deviation (no significant values). In addition, the corresponding Q statistics significant values based on 33 lags are less than 0.05 significance level, these results confirm that ARIMA (1,1,2) model is adequate to represent millet commodity prices data, therefore it can be used for forecasting purposes.

For wheat commodity Both the ADF of unit root and correlogram test results demonstrate that the first difference of wheat commodity price series is stationary. Furthermore, the ACF decays exponentially to zero and the PACF cut off to zero after lag of 1. These results confirms that an ARIMA (1,1,0) model is adequate to represents wheat commodity prices data.

The estimated equation for wheat commodity prices series is stated as follows:

\[(1 + 0.040B)(1 - B)x_t = e_t\]

The autoregressive parameter is seems not significantly different from zero. Moreover, the correlogram test indicates that there seems to be serial correlation on the residuals since the autocorrelations and partial autocorrelations at first few lags are significant. Several ARIMA (p,d,q) models have been suggested to model wheat commodity prices data, the suggested ARIMA models and their corresponding AIC,SBC values are stated as follows:
Table (5) offers the suggested ARIMA models and their corresponding AIC and SBC values for wheat commodity prices data. A closer look to table (5) it can be seen that ARIMA (1,1,1) model have smallest AIC and BSC values. In this model it is assumed that wheat commodity prices data is subject to autoregressive of order 1, moving average of order 1 and difference of order 1.

The selected estimated equation for wheat commodity prices series is expressed as follows:

\[(1 - 0.827B)(1 - B)x_t = (1 + 0.983B)e_t\]

The autoregressive and moving average parameters are seems not significantly different from zero. Hence this model is chosen as the one to be used for forecasting wheat commodity prices.

The residuals autocorrelation function of an ARIMA (1,1,1) model for wheat commodity price data, it can be shown that the residuals ACF of the fitted model revels that no residuals autocorrelations longer than two stander deviation (no significant values). In addition, the corresponding Q statistics significant values based on 34 lags are less than 0.05 significance level. These results indicate that
ARIMA (1,1,1) model is adequate, therefore it can be used for forecasting purposes.

Table (6) bellow reports parameter estimates, AIC and BIC criteria of conditional volatility GARCH (1,1) model for agricultural commodity prices under consideration. For the commodity prices returns series, the sum of ARCH and GARCH coefficients is not close to one in all commodities indicating that volatility shocks is not quite persistent, the coefficient of lagged squared returns is positive and statistically significant for all commodities, indicating that strong ARCH effects are apparent for all commodities. Also the coefficient of lagged conditional variance is significantly negative and less than one indicating that the impact of old news on volatility is not significant.

Table (6) Estimated GARCH (1,1) models for surgham, seaseme, millet and wheat commodity prices respectively

<table>
<thead>
<tr>
<th>commodity</th>
<th>$\mu$</th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\alpha + \beta$</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>surgham</td>
<td>0.0170</td>
<td>0.023</td>
<td>0.073</td>
<td>-0.725</td>
<td>0.77</td>
<td>-1.411694</td>
<td>-1.3357</td>
</tr>
<tr>
<td>seaseme</td>
<td>-0.010</td>
<td>0.016</td>
<td>0.517</td>
<td>-0.050</td>
<td>0.467</td>
<td>-0.952</td>
<td>-0.876</td>
</tr>
<tr>
<td>millet</td>
<td>0.020</td>
<td>0.017</td>
<td>0.332</td>
<td>-0.077</td>
<td>0.355</td>
<td>-1.009</td>
<td>-0.933</td>
</tr>
<tr>
<td>wheat</td>
<td>0.002</td>
<td>0.024</td>
<td>0.204</td>
<td>-0.103</td>
<td>0.101</td>
<td>-0.854</td>
<td>-0.778</td>
</tr>
</tbody>
</table>

Table (6) contains a summary of the empirical results for the agricultural commodity prices series and GARCH (1,1) specifications, in terms of the hypotheses under analysis (volatility, persistence in volatility, changes in volatility, and asymmetry in volatility) as well as other aspects that help to understand the structure of price volatility in the primary agricultural commodities studied.
Table (7) A summary of the empirical results of GARCH (1,1) model for the agricultural commodity prices returns series

<table>
<thead>
<tr>
<th>Item for analysis</th>
<th>Consequences</th>
<th>Products with the characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant of F- statistic</td>
<td>Result are significant</td>
<td>All commodities</td>
</tr>
<tr>
<td>Significant of coefficients</td>
<td>Result are consistent</td>
<td>Surgham, seaseme,</td>
</tr>
<tr>
<td>$\alpha + \beta$ close to one</td>
<td>Persistence of volatility</td>
<td>None of commodities</td>
</tr>
<tr>
<td>$\alpha + \beta = 1$</td>
<td>Persistence change in volatility ARCH and GARCH are present</td>
<td>None of commodities</td>
</tr>
<tr>
<td>$\alpha, \omega &gt; 0$</td>
<td>Well defined variance and covariance function</td>
<td>All commodities</td>
</tr>
<tr>
<td>$\beta &gt; 0$</td>
<td>Well defined variance and covariance function</td>
<td>None of commodities</td>
</tr>
<tr>
<td>$\alpha + \beta &lt; 1$</td>
<td>Well defined variance and covariance function</td>
<td>All commodities</td>
</tr>
</tbody>
</table>

A closer look to table (7) it can be observed, all GARCH (1,1) models of agricultural commodities have a significant F-statistics, although the significant of coefficients were found in surgham and seaseme commodity prices. For the agricultural commodities the hypothesis under testing is rejected for all commodities, which means that volatility, changes in volatility are not present in the commodity prices returns series used for this analysis (i.e. No volatility and changes in volatility in surgham, seaseme, millet and wheat of agricultural commodities).

The estimated parameters of GARCH (1,1) model for all commodities under the analysis are satisfy the autoregressive conditional heteroskedasticity characteristics, consequently it is well defined variance and covariance function. Thus the GARCH (1,1) model is appropriate in forecasting agricultural commodity prices data.

Table (3) bellow reports parameter estimates, AIC and BIC criteria of conditional volatility EGARCH (1,1) model for agricultural commodity prices under the analysis. For the commodity prices returns series, EGARCH (1,1) shows that the parameter $\gamma$ is positive and statistically significant for seaseme and millet commodities, indicating that the series have asymmetry and greater impact of positive shocks on the price volatility, while for surgham commodity the parameter $\gamma$ is negative and statistically significant meaning that the series have asymmetry and greater impact of negative shocks on the price volatility. For wheat commodity the parameter $\gamma$ is positive and not statistically significant which indicating that wheat commodity prices series has not asymmetric effects on the price volatility.
Furthermore, EGARCH (1,1) model shows that the parameter $\beta$ is negative and statistically significant for all commodities, which is an indication of persistence of volatility on the conditional variance.

Table (8) Estimated EGARCH (1,1) models for surgham, seaseme, millet and wheat commodity prices respectively

<table>
<thead>
<tr>
<th>Commodity</th>
<th>$\mu$</th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\alpha + \beta$</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surgham</td>
<td>0.0149</td>
<td>-7.417</td>
<td>0.393</td>
<td>-0.639</td>
<td>0.166</td>
<td>-0.246</td>
<td>-1.443</td>
<td>-1.348</td>
</tr>
<tr>
<td>Seaseme</td>
<td>-0.009</td>
<td>-5.2415</td>
<td>0.899</td>
<td>-0.203</td>
<td>0.268</td>
<td>0.796</td>
<td>-0.983</td>
<td>-0.888</td>
</tr>
<tr>
<td>Millet</td>
<td>0.016</td>
<td>-7.715</td>
<td>0.372</td>
<td>-0.845</td>
<td>0.090</td>
<td>-0.473</td>
<td>-1.114</td>
<td>-1.019</td>
</tr>
<tr>
<td>Wheat</td>
<td>0.010</td>
<td>-5.887</td>
<td>0.339</td>
<td>-0.520</td>
<td>0.076</td>
<td>-0.181</td>
<td>-0.826</td>
<td>-0.731</td>
</tr>
</tbody>
</table>

Table (8) below shows a summary of the empirical results for the agricultural commodity prices series and EGARCH (1,1) specifications, in terms of the hypotheses under analysis (volatility, persistence, changes in volatility, and asymmetry in volatility) as well as other aspects that help to understand the structure of price volatility in the primary commodities studied.

Table (9) A summary of the empirical results of EGARCH (1,1) model for the agricultural commodity prices returns series

<table>
<thead>
<tr>
<th>Item for analysis</th>
<th>Consequences</th>
<th>Product with the characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant of F-statistic</td>
<td>Result are significant</td>
<td>All commodities</td>
</tr>
<tr>
<td>Significant of coefficients</td>
<td>Result are consistent</td>
<td>All commodities except wheat</td>
</tr>
<tr>
<td>A large and significant of $\beta$</td>
<td>Persistence of volatility</td>
<td>All commodities</td>
</tr>
<tr>
<td>Significant of $\gamma$</td>
<td>Support to the GARCH and TARCH specification</td>
<td>All commodities except wheat</td>
</tr>
<tr>
<td>Negative and significant of $\gamma$</td>
<td>A symmetry and greater impact of negates on price volatility</td>
<td>Surgham</td>
</tr>
<tr>
<td>$\gamma \neq 0$</td>
<td>A symmetry in volatility</td>
<td>Surgham, seaseme and millet</td>
</tr>
</tbody>
</table>

From Table (9) above, it can be shown that all EGARCH (1,1) models for agricultural commodities under the study have a significant F-statistics, also the significant of coefficients were found in all commodities except wheat.
For most of the commodities the hypothesis under testing (volatility, persistence, changes in volatility, and a symmetry) are present in some commodity. According to the significant of $\beta$ the persistence of volatility is present in all commodities. Asymmetry in volatility is achieved in all commodities except for wheat (i.e. $\gamma \neq 0$). Negative and statistically significant of the parameter $\gamma$ is an indication of asymmetry and greater impact of negative shocks in price volatility.

Table (10) below reports parameter estimates, AIC and BIC criteria of conditional volatility TGARCH (1,1) model for agricultural commodity prices under the analysis. For the commodity prices returns series, TGARCH (1,1) shows that the parameter $\gamma$ is positive and not statistically significant for surgham commodity, which indicates the series is asymmetry and greater impact of positive shocks on the price volatility, while for seasem and millet commodities the parameter $\gamma$ is negative and not statistically significant, meaning that the series has not asymmetry and greater impact of negative shocks on the price volatility. For wheat commodity the parameter $\gamma$ is negative and statistically significant which indicates that wheat commodity prices series has a asymmetry and greater impact of negative shocks on the price volatility. Furthermore, the sum of ARCH and GARCH coefficients in TGARCH (1,1) model is not close to one indicating that volatility shocks is not quite persistent on the conditional variance.

Table (10) Estimated TGARCH (1,1) models for surgham, seasem, millet and wheat commodity prices respectively

<table>
<thead>
<tr>
<th>commodity</th>
<th>$\mu$</th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\alpha + \beta$</th>
<th>$\alpha + \gamma$</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>surgham</td>
<td>0.0150</td>
<td>0.008</td>
<td>0.028</td>
<td>0.234</td>
<td>0.277</td>
<td>0.305</td>
<td>-1.377</td>
<td>-1.282</td>
</tr>
<tr>
<td>seasem</td>
<td>-0.010</td>
<td>0.015</td>
<td>0.750</td>
<td>0.372</td>
<td>0.712</td>
<td>0.378</td>
<td>-0.968</td>
<td>-0.873</td>
</tr>
<tr>
<td>millet</td>
<td>0.017</td>
<td>0.021</td>
<td>0.300</td>
<td>0.113</td>
<td>0.147</td>
<td>0.187</td>
<td>-1.009</td>
<td>-0.914</td>
</tr>
<tr>
<td>wheat</td>
<td>0.003</td>
<td>0.015</td>
<td>0.110</td>
<td>0.555</td>
<td>0.144</td>
<td>0.665</td>
<td>-0.760</td>
<td>-0.665</td>
</tr>
</tbody>
</table>
Table (11) bellow contains a summary of the empirical results for the agricultural commodity prices series and TGARCH (1,1) specifications, in terms of the hypotheses under analysis (volatility, persistence, changes in volatility, and asymmetry in volatility) as well as other aspects that help to understand the structure of price volatility in the primary commodities studied.

Table (11) A summary of the empirical results of TGARCH (1,1) model for the agricultural commodity prices returns series

<table>
<thead>
<tr>
<th>Item for analysis</th>
<th>Consequences</th>
<th>Product with the characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant of F- statistic</td>
<td>Result are consistent</td>
<td>All commodities</td>
</tr>
<tr>
<td>Significant of coefficients</td>
<td>Result are consistent</td>
<td>seaseme</td>
</tr>
<tr>
<td>$\alpha + \beta$ close to one</td>
<td>Persistence of volatility</td>
<td>None of commodities</td>
</tr>
<tr>
<td>Significant of $\gamma$</td>
<td>Asymmetry in volatility</td>
<td>wheat</td>
</tr>
<tr>
<td>A large $\alpha + \gamma$</td>
<td>Impact of bad news on volatility</td>
<td>None of commodities</td>
</tr>
<tr>
<td>Large and significant of $\alpha$</td>
<td>Impact of good news on volatility</td>
<td>seaseme</td>
</tr>
</tbody>
</table>

A closer look to table (11), it can be seen that TGARCH (1,1) models for agricultural commodities under the study, have a significant F-statistics, the significant of coefficients is not apparent except for seaseme commodity. The parameter $\gamma$ is not statistically significant except for wheat commodity, indicating that agricultural commodity prices have not a symmetric effect except seaseme commodity. None of agricultural commodity has an impact of bad news on the price volatility, while good news on the price volatility is presents in seaseme commodity.

Table (12) bellow reports parameter estimates, AIC and BIC criteria of conditional volatility APARCH (1,1) model for agricultural commodity prices under the analysis . For the commodity prices returns series, APARCH (1,1) shows that the parameter $\gamma$ is negative and statistically significant for surgham commodity, which indicates that the series is asymmetry and grater impact of negative shocks on the price volatility, while for seaseme and millet commodities the parameter $\gamma$ is positive and not statistically significant, meaning that the series has not asymmetry and grater impact of positive shocks on the price volatility. For wheat and millet
commodities the parameter $\gamma$ is negative and not statistically significant which indicates that the prices series has a asymmetry and greater impact of negative shocks on the price volatility. Furthermore, the sum of ARCH and GARCH coefficients in APARCH (1,1) model for the surgham and wheat commodities are very close to one, indicating that volatility shocks is quite persistent on the conditional variance.

Table (12) Estimated APARCH (1,1) models for surgham, seaseme, millet and wheat commodity prices respectively

<table>
<thead>
<tr>
<th>commodity</th>
<th>$\mu$</th>
<th>$\omega$</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>$\delta$</th>
<th>$\alpha + \beta$</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>surgham</td>
<td>0.018</td>
<td>0.042</td>
<td>0.065</td>
<td>0.849</td>
<td>-0.975</td>
<td>0.458</td>
<td>0.914</td>
<td>-1.374</td>
<td>-1.261</td>
</tr>
<tr>
<td>seaseme</td>
<td>-0.017</td>
<td>0.090</td>
<td>0.341</td>
<td>0.572</td>
<td>0.023</td>
<td>0.314</td>
<td>0.913</td>
<td>-0.930</td>
<td>-0.816</td>
</tr>
<tr>
<td>millet</td>
<td>0.015</td>
<td>0.024</td>
<td>0.219</td>
<td>-0.185</td>
<td>-0.116</td>
<td>1.949</td>
<td>0.034</td>
<td>-0.996</td>
<td>-0.882</td>
</tr>
<tr>
<td>wheat</td>
<td>-0.000</td>
<td>0.029</td>
<td>0.037</td>
<td>-0.227</td>
<td>-0.971</td>
<td>2.034</td>
<td>-0.190</td>
<td>-0.830</td>
<td>-0.716</td>
</tr>
</tbody>
</table>

Table (13) below contains a summary of the empirical results for the agricultural commodity prices series and APARCH (1,1) specifications, in terms of the hypotheses under analysis (volatility, persistence, changes in volatility, and asymmetry in volatility) as well as other aspects that help to understand the structure of price volatility in the primary commodities studied.

Table (13) A summary of the empirical results of APARCH (1,1) model for the agricultural commodity prices returns series

<table>
<thead>
<tr>
<th>Item for analysis</th>
<th>Consequences</th>
<th>Product with the characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant of F- statistic</td>
<td>Result are consistent</td>
<td>All commodities</td>
</tr>
<tr>
<td>Significant of coefficients</td>
<td>Result are consistent</td>
<td>None of commodities</td>
</tr>
<tr>
<td>$\alpha + \beta$ close to one</td>
<td>Persistence of volatility</td>
<td>Seaseame, surgham</td>
</tr>
<tr>
<td>Significant of $\gamma$</td>
<td>Asymmetry in volatility</td>
<td>surgham</td>
</tr>
<tr>
<td>Significant of $\delta$</td>
<td>Leverage effect is not present</td>
<td>None of commodities</td>
</tr>
</tbody>
</table>

A closer look to table (13), it can be seen that APARCH (1,1) models for agricultural commodities under consideration, have a significant F-statistics, the
significant of coefficients is not apparent in all commodities. The parameter $\gamma$ is not statistically significant for surgham commodity, indicating that surgham commodity has a symmetric effect on the price volatility. None of agricultural commodities has a significant value of $\delta$ this means that leverage effect is not present on the conditional variance.

**Conclusion:-**

This paper provided a comparative study of performance of the ARMA vs. ARCH/GARCH models to obtain an appropriate model in modelling and forecasting agricultural commodity prices data in the Sudan and investigating its ability to forecast and capture common facts about conditional volatility, such as persistence, change in volatility, asymmetry and leverage effects on agricultural commodity prices data in the Sudan.

Both Box-Jenkins (ARIMA) models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models were applied to four agricultural commodity prices data. The empirical analysis reveals that both Augmented Dickey Fuller (ADF) and correlogram tests conclude that the series levels of all agricultural commodities are not stationary, while the first difference of these series are stationary. Furthermore, the empirical results showed that, following the outcomes of the correlogram and unit root tests, all agricultural commodity prices returns series were found stationary.

According to the paper empirical results, and thesis evaluation criteria the Box-Jenkins models been selected for forecasting agricultural commodity prices data using ARIMA models are ARIMA (1,1,1) for surgham commodity, ARIMA (0,1,0) for seaseme commodity, ARIMA (1,1,2) for millet commodity and ARIMA (1,1,1) for wheat commodity respectively.

Moreover, the thesis were also applied GARCH (1,1), E GARCH(1,1), TGARCH(1,1) and APARCH(1,1) models to four agricultural commodity prices returns series to handle agricultural commodity prices volatility, according to the comparison criteria stage, these models perform adequate forecast than ARIMA (1,1,1) for surgham commodity, ARIMA (0,1,0) for seaseme commodity, ARIMA (1,1,2) for millet commodity and ARIMA (1,1,1) for wheat commodity respectively. The above findings confirm the following results;
(i) All agricultural commodities series levels are shown non stationary, however the first difference are stationary. Furthermore statistical tests conclude that all agricultural commodities prices return series are stationary.

(ii) There is strong evidence, that agricultural commodity prices returns series can be modeled using the GARCH models.

(iii) The findings also conclude that ARIMA (1,1,1), ARIMA (0,1,1), ARIMA (1,1,2) and ARIMA (1,1,2) models are adequate in forecasting surgham, seaseme, millet and wheat commodity prices respectively, therefore, the above models are appropriate in forecasting agricultural commodity prices data.

(iv) Moreover, The application of GARCH (1,1), EGARCH(1,1), TGARCH (1;1), and APARCH (1,1) models on agricultural commodities were shown that:

(i) For GARCH (1,1) models, the estimated coefficients are statistically significant for all commodities, the sum of ARCH and GARCH coefficients is not close to one in all commodities indicating that volatility shocks is not quite persistent.

(ii) For EGARCH (1,1) models, a significant F-statistics, significant of coefficients were found in all commodities except wheat. According to the significant of $\beta$ the persistence of volatility is present in all commodities, asymmetry in volatility is achieved in all commodities except for wheat.

(iii) For TGARCH (1,1) models, a significant F-statistics, the significant of coefficients is not apparent except for seaseme commodity, agricultural commodity prices have not a symmetric effect except seaseme commodity. None of agricultural commodities has an impact of bad news on the price volatility, while good news on the price volatility is present in seaseme commodity.

(iv) And for APARCH (1,1) models the significant of coefficients is not apparent in all commodities, surgham commodity has a symmetric effect on the price volatility, none of agricultural commodities has a leverage effects on the conditional variance.

Furthermore, the results could also conclude that, APARCH (1,1) model, EGARCH (1,1) model and TGARCH (1,1) model are appropriate to capture volatility of surgham, seaseme, millet and wheat agricultural commodity prices data.
Thinking about all of the above, Tansuchat et al. (2009) concluded that “fractionally integrated models performed significantly better than traditional conditional volatility models”. Moreover Engle (2001) concluded that “the applications of ARCH and GARCH in finance have been particularly successful”. On the other hand, Guida and Matring (2004) conclude that “the predictive ability of GARCH models used with agricultural commodities data is not established, they need more specifications”. Consequently, GARCH models are strongly recommended in forecasting Agricultural commodity prices in the Sudan. This finding suggests that for this particular data, because of their ability to capture the volatility, GARCH models are appropriate in modeling and forecasting volatility of agricultural commodities in the Sudan.
References:


