Mathematical Theory and Modeling
ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.6, No.6, 2016

Modelling the Volatility of Maize Prices Using Autoregressive Integrated Moving Average Model

Jacob Kirimi

Department of Physical Science and Statistics, Chuka University, Box 109 -60400 Chuka- Kenya

ABSTRACT

This paper examined the monthly prices of maize using Autoregressive Integrated Moving Average (ARIMA) models so as to determine the most efficient and adequate model for analyzing the volatility of the maize prices in Kenya. An exploratory research design and purposive sampling method was adopted for a sample of 55 observations. The monthly maize price data for 90kg bag of maize for a period of five years obtained from Kenya National Bureau of Statistics and National Cereals and Produce Board archives. Time series Analysis was done using R-Gui software. The results indicate that Autoregressive Integrated Moving Average models ARIMA (1,2,2) is the most adequate and efficient model. This was ascertained by comparing the various model selection criterion and the diagnostic tests for various models among them Akaike Information Criteria A better understanding of a country's maize price situation and future prices will facilitate users to make appropriate decisions regarding buying and selling patterns hence adequate policy for maintain stable maize prices. The forecasted results suggest that there are expectations of increasing maize prices in the next five months. This requires the government to take appropriate measures to ensure that this trend of increasing prices is regulated

Key words: ARIMA Model, Volatility, Akaike Information Criteria, Maize Prices

1.0 INTRODUCTION

Agriculture is the core sector in Kenyan economy with the majority of Kenyan, population depending directly or indirectly on agriculture for survival. The government of Kenya has over the years strived to promote agriculture to achieve food security, employment, foreign exchange among many benefits that accrue to agriculture. Food crop farming is the mostly practiced form of agriculture in Kenya with the main staples being maize, beans, rice, and wheat. Maize is the key staple crop in Kenya, constituting 3% of Kenya's Gross Domestic Product (GDP), 12% of the agricultural GDP and 21% of the total value of primary agricultural commodities. Maize is both a subsistence and a commercial crop, grown on an estimated at 1.5 million hectares by large-scale farmers (25%) and smallholders (75%). Maize is the major staple agricultural commodities in many domestic homes in Kenya and consequently attracts public attention whenever there are abnormalities in production, marketing, pricing or external trade. Given the ability to attract public attention, the maize subsector does elicit interest in equal measure in times of deficit as well as surplus. Supplies of maize products to manufacturers and consumers in Kenya come form both domestic production and imports. The price of maize is not stable for it keeps on changing due to factors such as changes in demand and supply, seasonality in production, influence by NCPB and political noise as well as changes in market trends. Maize prices have been fluctuating over time and space. Fluctuation over time causes farmers price insecurity thereby hampering investment decisions, while fluctuation over space, combined with limited knowledge of that fluctuation, reduces market opportunities for their surplus. Thus fluctuations in maize prices have a direct impact to the producers, manufacturers and consumers in the country. The main objective of this study was to analyze the maize market, maize prices trend and to forecast the maize prices using Autoregressive integrated Moving Average (ARIMA) model. The study was guided by the following specific objectives; to fit an ARIMA to the data on the prices of maize and evaluate the efficiency of the ARIMA model on forecasting the maize prices in Kenya.

2.0 LITERATURE REVIEW

2.1 Importance of maize

Maize accounts for about 40 percent of daily calories and per capita consumption is 98 kilograms. The poorest households spend 28 percent of the annual household-income on maize purchase. Because of this importance, stabilization of maize prices will be crucial to solving Kenya's food security problems and alleviating poverty. Maize is the main staple food for rural and urban households in Kenya. It is associated with household food security such that a low-income household is considered food insecure if it has no maize stock in store and or when its prices are beyond the means of common citizen, regardless of other foods the household has at its disposal. Maize also doubles as a main source of income for the producers in the maize surplus regions. Maize is produced in almost all the agro-ecological zones either under mono-crop or an intercrop system. It is grown on 1.5 million hectares and has an annual production of an estimated 30 to 34 million bags (Ariga, 2010).

2.2 Organization of the Maize Marketing System

Kenya's maize marketing system has evolved considerably since independence. With this evolution, the participation and roles of various marketing institutions have changed considerably. Today several types of market intermediaries exist. Seven major categories of market intermediaries can be identified: assemblers or bulk builders, wholesalers, retailers, dissemblers or bulk breakers, posho millers, large-scale millers, and the NCPB. Another category of traders could be identified by the use of intermediate means of transport (bicycles, oxcarts, donkeys, handcarts, and head load). These agents also purchase and bulk maize at the farm level and deliver it to assemblers, retailers, and posho millers. In contrast to the current marketing organization, Schmidt (1979) noted that during the era of market controls, the maize marketing system was separated into two interrelated subsystems. There was the formal state marketing agency, which was subject to controls, and the informal subsystem, which consisted of relatively small traders, mainly women, operating on a local level in the open-air markets where prices were not controlled. Other intermediaries identified by Schmidt (1979) included the posho miller, large-scale millers, cooperatives, wholesalers, retail shops, and brewers.

2.3 National cereals and produce board (NCPB)

The National Cereals and Produce Board (NCPB) was created in 1979, to regulate maize markets through the administration of prices, the purchase of domestic maize production and the management of a public buffer stock. With the liberalization reform, between 1995 and 2000, the NCPB scaled back its purchases, providing greater scope for the private sector to operate. However, since 2000, the government has gradually increased NCPB's purchases, (Ariga, Jayne et al. 2010). The NCPB remains a dominant player in the maize market, purchasing in normal or good years around 25-35% of the total domestically marketed maize, most of all from large scale farmers (Jayne, Yamano et al. 2001).The evolution of maize trade and marketing policies in Kenya has been marked by frequent and usually unanticipated changes in trade tariffs, NCPB prices set and volumes purchased (Ariga, Jayne et al. 2010). Empirical studies showed that these discretionary policies raised market uncertainties for private stakeholders and led to inefficiencies (Chapoto and Jayne 2009; Tschirley and Jayne 2010).

2.4 The regulation of maize market in Kenya

Except in good harvest years, Kenya requires substantial maize imports. These imports mainly come from Uganda and Tanzania accounted for more than 10% of domestic consumption in the last ten years'(World Bank 2009). Government imposed tariffs on maize imports from 1994, but these tariffs have fluctuated since then. Imports from countries that are not part of either the East African Community or the Common Market for Eastern and Southern Africa are typically taxed at the rate of 50%, but this tariff can be waived and re-imposed without prior notification and is a source of major uncertainty for market participants. If the tariff rate is waived unexpectedly, local prices could quickly become higher than the cost of importing. While the tariff waiver normally triggers imports by the private sector, it can take many months before sufficient volumes are able to be move through a port and transport system with constrained supply capacities to push local prices back down to import parity (Jayne and Tschirley 2009). In addition to these tariffs, numerous non-tariff barriers to regional trade remain, as food quality and safety standard certificates (Ariga, Jayne et al. 2010).

2.5 Overview Literature Review of ARIMA Model

Forecasts have been made using parametric Univariate time series models, known as Autoregressive Integrated Moving Average (ARIMA) model popularized by Box and Jenkins (1976). These approaches have been employed extensively for forecasting economics time series, inventory and sales modeling (Brown, 1959). Ljung and Box (1978) and Pindyck and Rubinfeld (1981) have also discussed the use of Univariate time series in forecasting. Rachana et al. (2010), used ARIMA models to forecast pigeon pea production in India. Badmus and Ariyo (2011), forecasted the area of cultivation and production of maize in Nigeria using ARIMA model. They estimated ARIMA (1, 1, 1) and ARIMA (2, 1, 2) for cultivation area and production respectively. Falak and Eatzaz (2008), analyzed future prospects of wheat production in Pakistan. They obtained the parameters of their forecasting model using Cobb-Douglas production function for wheat, while future values of various inputs are obtained as dynamic forecasts on the basis of separate ARIMA estimates for each input and for each Province. The ARIMA technique have been used extensively by a number of researchers to forecast demands in terms of internal consumption, imports and exports to adopt appropriate solutions, Sohail et al., (1994)

3.0 METHODOLOGY

3.1 Research Design

The study adopted exploratory research design and purposive sampling method to obtain a sample of 55 observations. The monthly maize price data for 90kg bag of maize for a period of five years obtained from Kenya National Bureau of Statistics and National Cereals and Produce Board archives.

3.2 Data analysis

The data were model using Autoregressive Integrated Moving Average (ARIMA) model as proposed by Box and Jenkins (1976). An ARIMA (p,d,q) model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. The ARIMA model denoted as ARIMA (p, d, q) has the general form given by;

$$Y_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \ldots + \emptyset_p X_{t-p} + e_t - \Theta_1 e_{t-1} - \Theta_2 e_{t-2} - \ldots - \Theta_q e_{t-\mathbf{q}}$$

Where: Y_t is the dependent variable at time t

$X_{t-1}, X_{t-2}, \ldots, X_{t-p}$ are response variables at time lags t-1, t-2, …, t-p

$\emptyset_1, \emptyset_2, \ldots, \emptyset_p$ are coefficients of past variables

$e_{t-1}, e_{t-2}, \ldots, e_{t-q}$ are past errors

and $\Theta_1, \Theta_2, \ldots, \Theta_q$ are coefficients of past errors

The above equation simply means that any given series X_t can be modeled as a combination of past errors e_t or past values X_t or both. Four steps are to be followed when analyzing data using ARIMA model. Firstly, the original series X_t is to be transformed in order for it to become stationary in its mean and variance. Stationarity condition is achieved when the series becomes constant in its mean and variance. Secondly, is the specification of order p and q; this is done by selecting the order that has the least values of log-likelihood, AIC, SBC and Hannan-Quin. Thirdly, is the estimation of the parameters $\emptyset_1, \emptyset_2, \ldots, \emptyset p$ and/or $\Theta_1, \Theta_2, \ldots, \Theta q$ using non-linear optimization procedure which will minimize sum of square roots. Finally the seasonal series is modeled practically and the of the order of the models specified. This stage includes carrying out diagnostic checks that show random residuals after which the model can be adopted for purposes of forecasting. The data was subjected to first and second log-differencing in order to attain the stationarity condition necessary for ARIMA. Stationarity transformations also involved plotting time series ACF plots and a review of descriptive summary statistics. Suitability of the model is achieved through Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), Log-likelihood Estimation and Hannan-Quinn Information Criterion. Diagnostic checks are carried out with the aid of tests for normality of residuals. Data were analyzed using R-Gui software.

4.0 EMPIRICAL RESULTS AND DISCUSSION

4.1 Preliminary Analysis

The series was transformed to attain Stationarity by taking the first difference of the natural logarithms of the values in each series. The equation representing the transformation is given by $Y_t = \text{In}(\frac{P_t}{P_{t-1}})$ where Pt represent the monthly maize prices. The resulting plot for the return is presented in Figure 1

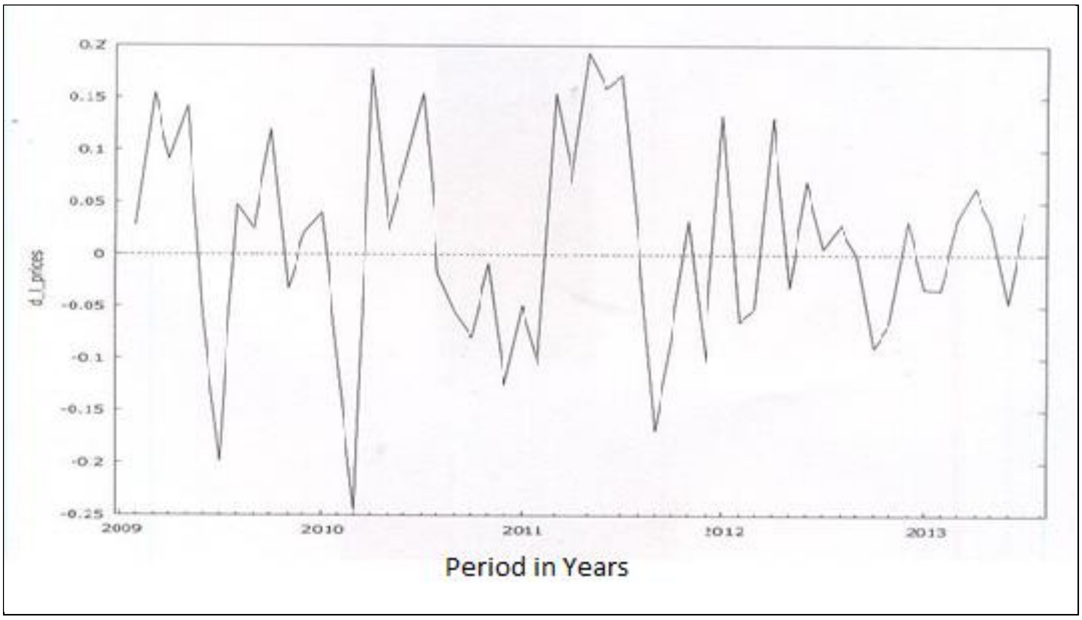

Figure 1: Time plots for Log differenced Prices of 90Kgs/Bag of maize

The time plot of series now depicts stationarity. The mean and variance show the property of being constant. In 2010 there is a shock on prices movements caused by a sharp fall in maize supply that resulting of famine that stroke Kenya in 2010/2011.

4.2.1 Summary Statistics

The analysis involved a total of 55 observations being used. This data displayed a mean of 2718.2 and a standard deviation of 541.26.Standard deviation of 541.26 shows that the maize prices are fluctuating from the estimated sample mean by 541.26. The differenced data had a kurtosis of -0.94905 and Jarque Bera test of 2.06559.1t was positively skewed with a Skewness of 0.012765.This means that there were more observations on the right hand side.

4.2.2 Auto-correlation Function (ACF)

Apart from inspection method of checking for stationarity, the ACF of the maize price series showed non-stationary as ACF did not fall as quickly as the number of lags increased shown in figure 2. The figure provides very useful information that is typical of a non-stationary process.

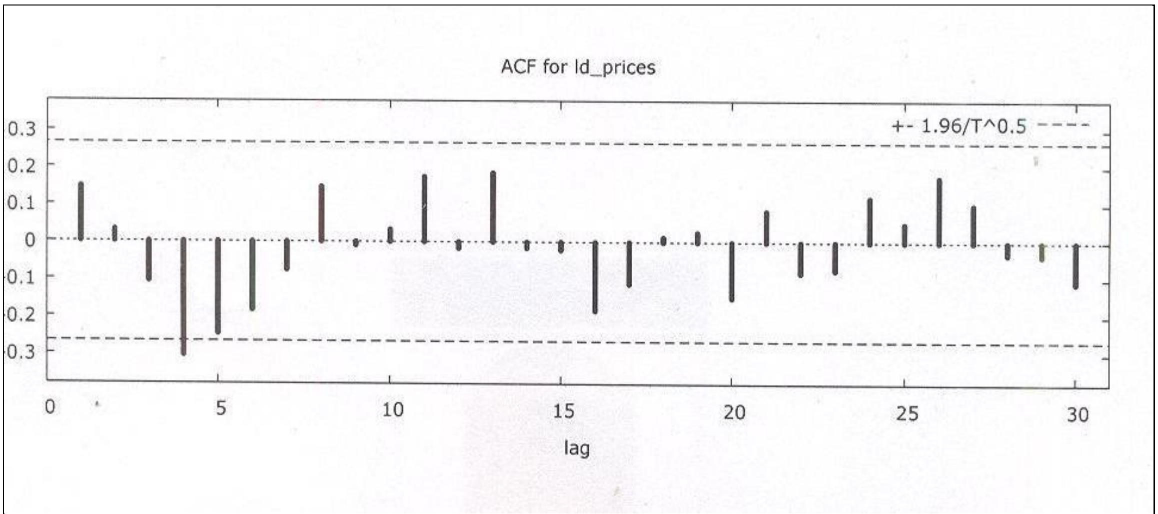

Figure 2: Auto-Correlation Function of maize prices

To check the further stationary, first difference of the second series for maize prices was taken. The auto correlation formulation of the first different series and correlogram shows some more stationary than that of the first series. This is shown in the Figure 3

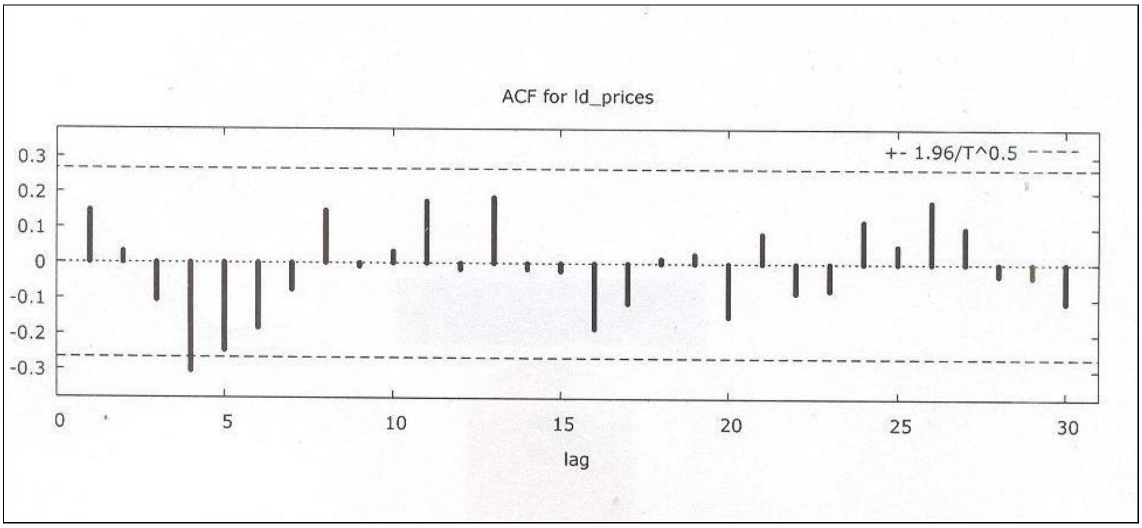

Figure 3: ACF of log differenced prices

Figure 3 shows the ACF and PACF of the transformed data. By log differencing the maize prices, stationarity of the prices was achieved. The auto correlation function of transformed data showed that the auto correlation function finally depicted a white noise which is condition for stationarity.

Model Estimation and Testing
Results of Estimation

Ordinary Least Squares method is used to generate results for the model. Results are summarized in Table 1

Table 1: Results of Estimation

Variable	**Estimation**	**Standard Error**	**Z**	**p-value**
Intercept	0.000356	0.02126	-0.0982	0.902
AR1	-0.04329	0.1302	-0.0219	0.825

Dependent Variable: Student Population

According to the results AR2, MA1 and MA2 coefficient are zero and autoregressive coefficient of order 1 is provided as well as standard error and z value. The p-value estimated above is not statistically significant at 5% level of significance.

Mathematical Theory and Modeling
ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.6, No.6, 2016

Comparison to other ARIMA Models

Table 2: Comparison to other ARIMA Models

	ARIMA (2, 2, 2)	ARIMA (2, 2, 1)	ARIMA (1, 2, 2)	ARIMA (2, 2, 0)	ARIMA (0, 2, 2)	ARIMA (1, 2, 1)	ARIMA (0, 2, 1)	ARIMA (1, 2, 0)
Log likelihood	-282.59	-283.01	-283.01	-284.07	-284.07	-283.06	-284.07	-284.07
Schwarz Criterion	509.54	506.31	506.30	504.38	504.38	502.37	500.31	500.35
Akaike Criterion	597.16	596.03	594.02	596.15	596.13	596.13	594.13	594.12
Hannan-Quinn	602.00	600.03	599.35	600.35	599.35	597.35	596.54	596.54
Ljung-Box Q'	18.73	18.99	16.99	20.04	20.02	19.18	20.10	20.04

ARIMA model (1, 2, 2) is measured against other models as in Table 2, criterion for model suitability being the one with least figures of all. This condition is tested using Log Likelihood, Bayesian Schwarz, Hannan-Quinn and Akaike criterions. In all cases ARIMA (1, 2, 2) surpasses rival models making it the most suitable. ARIMA model has thus transformed to AR (1) model.

Fitting the best Model

Having met all conditions for best fitting model, ARIMA (1, 2, 2) is considered best for forecasting the student population for University of Kabianga. The model fitted with values from results of estimation given in Table 1 now appears as follows:

$Y_t = 0.000356 - 0.04329X_{t-1} + e_t$

The negative estimate for **Ø**$_1$, means that lags bear an inverse relationship with previous variables in previous periods.

Diagnostic Checks

Data is tested for normality and uses the statistics: Doornik-Hansen test, Shapiro-Wilk W, Lilliefors test and Jarque-Bera test. Normal QQ plot is also drawn and residual kutorsis as well as skewness of the series reviewed as summarized below:

Table 3: Test for normality

Statistic	Estimate	p-value
Doornik-Hansen test	105.56	2.33e-011
Shapiro-Wilk	0.717	0.056512
Lilliefors test	0.363	0.0000001
Jarque-Bera test	116.002	0.000099

Jarque-Bera test has an estimate of 116.002 with p-value that rejects the null hypothesis of normality in the residuals. All other statistics have p- values less than 5% implying residuals in the series do not satisfy normality condition. For normality Skewness of series has to be zero which is not the case for this data. Model independence was evaluated through inspection of sample residual autocorrelations to see if they resemble those of white noise which they do as observed in Figure 3 The Durbin Watson Statistic for this series is 1.7335 which is nearing 2, hence the series is free of negative or positive autocorrelation.

5.0 CONCLUSION AND RECOMMENDATION

Using proposed model, the results of forecasting showed that the maize prices have fairly increasing trend over the five months forecasted. The main recommendation from this study is that the national cereals and produce board should adopt a stable form of fixing maize prices that are fairly in line with price in the maize market and not putting up prices that are above the normal market prices. Domestic maize prices increases over time due to Kenya

National Cereal and Produce Board inefficiency in its intervention in maize market to fix prices for both sale and purchases. Government initiative through NCPB to promote free and fair trade in commodities and their timely accessibility put pressure on maize prices both at wholesale and retail levels. The forecasted results in this case showed that there are expectations of increasing maize prices in the next five months. This requires the government to take appropriate measures to ensure that this trend of increasing prices is regulated.

REFERENCES

Allen, P.G.(1994).Economic Forecasting in Agriculture. International Journal of Forecasting. Vol. (4).No.10.81-135.

Ariga, J et al, 2010. Staple Food Policies in Kenya, a Paper Prepared for the COMESA policy seminar on Variation in Staple Food Prices: Causes, Consequence, and Policy Options.

Ariga, J., and T. S. Jayne. 2010. "Maize Trade and Marketing Policy Interventions in Kenya." In Food Security in Africa: Market and Trade Policy for Staple Foods in Eastern and Southern Africa, edited by A. Sarris and J. Morrison. Rome: Food and Agriculture Organization of the United Nations (FAO): 221-251.

Badmus, M.A. and O.S. Ariyo, 2011. Forecasting cultivated areas and production of maize in Nigeria using ARIMA model. Asian J. Agric. Sci., 3(3): 171- 176.

Bo;c, G.E.P. and G.M. Jenkins, 1976. Time series Analysis, Forecasting and Control. San Francisco, Holden Day, California, USA.

Brown, R.G., 1959. Statistical Forecasting for Inventory Control. McGraw Hill Book Co., Inc., NY, USA.

Chapoto, A., and T. S. Jayne. 2009. The Impacts of Trade Barriers and Market Interventions on Maize Price Predictability: Evidence from Eastern and Southern Africa. Food Security International Development Working Papers. East Lansing, MI, US: Michigan State University, Department of Agricultural, Food, and Resource Economics.

Chatfield, C. (1996). The Analysis of Time Series. 5th ed. Chaprman and Hall, New York.

Chirwa, E. 2009. The 2007-2008 Food Price Swing: Impact and Policies in Malawi. Discussion Paper. Project on Policies for Good Economic Management of Food Price Swings in Africa. Rome: FAO, Trade and Markets Division.

Cooper, R.L.(1972)The predictive Performance of Quarterly Econometric Models of the United States. Econometric Models of Cyclical Behaviour, New York.

Falak, S. and A. Eatzaz, 2008. Forecasting Wheat production in Pakistan. Lahore J. Econ., 3(1): 57-85. http://ideas.repec.org/p/ags/midivvp/56798.html.

Hussein, Z. (2011). Modelling and Forecasting Volatility Using ARIMA Model. Euro can Journal of Economics, Finance and Administrative Sciences. Vol. (35). No.5.pp 110-124.

Ljung, G.M. and G.E.P. Box, 1978. On a measure of lack of fit in time series models. Biometrika, 65: 67-72.

Muhammed, F., M. Siddique, M. Bashir and S. Ahamed, 1992. Forecasting rice production in Pakistan Using ARIMA models. J. Animal Plant Sci., 2: 27-31.

Minot. N. 2012. Food Price Volatility In Africa. Discussion Paper. www.fao.orgies/esc/foodpriceswing/presentations/FoodPriceSwingsMalawi E-Chirwa.

Organisation for Economic Cooperation and Development (OECD). Agricultural Outlook 2010-2011