ANALYSIS OF INFLATION VOLATILITY FOR FISH AND MEAT MARKETS IN NIGERIA USING ARMA AND GARCH TYPES

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Abstract

This paper analyzed Consumer Price Index data (2009M9 -2016M10) on fish and meat in Nigeria. Findings reveal that the values of coefficient of variation of Consumer Price Index for fish and meat are 26% and 22% respectively. The experiment to model the absolute and log returns series of fish and meat inflation was carried out using 80 out of the selected 85 observations. This enabled the paper to access the adequacy of the models to forecast the remaining 5 observations. Using Akaike Information Criteria (AIC) and Schwarz information Criterion (SIC) to select model's goodness of fit, Autoregressive Moving Average - ARMA (4,3) is selected for Fish Absolute Returns (FAR) and Fish Log Returns (FLR) while Autoregressive Exponential Generalized Autoregressive Conditional Heteroscedasticity - AR-EGARCH (1,1) is selected for Meat Log Returns (MLR) series. Similarly, Autoregressive Generalized Autoregressive Conditional Heteroscedasticity - AR-GARCH (1, 1) and AR-EGARCH (1,1) are both selected for Meat Absolute Returns (MAR) series. In forecasting the inflation returns, the dynamic forecast selects ARMA (4,2) and AR (1) as equations that best forecast the out of samples for MLR and MAR series respectively. The static forecast chooses AR-EGARCH (1,1) model for the MLR and MAR series. The returns from the models selected by the dynamic forecast yield near accurate CPI. The better performance of dynamic forecast attest to the marginal effect of seasonality in fish and meat production in Nigeria. The paper concludes that the presence of high volatility persistence indicates volatility today will significantly have a long term influence on meat price.

Keywords: CPI, Inflation volatility, ARMA, GARCH, Food insecurity

Introduction

Food Price instability increases investment risk in the food sector and consequently, distorts consumption habit. This phenomenon poses a serious threat to achieving food security status particularly, in the pro poor countries. This is because of either way price swing, it affects both farmers and consumers which can propel dropping off some relatively expensive foodstuffs such as animal protein from household food basket thereby, resulting into malnourishment and imbalanced diets. In Nigeria, the consciousness of the effect of balanced diet on health and growth has raised the importance of fish and meat in household food consumption. Consequently, recent debates about these markets have shown increasing imbalance between supply and demand (Anyanwu, Anyanwu and Obianuju, 2013; Chauvin, Mulangu and Porto, 2012; and Amao, Oluwatayo and Osuntope 2006;) . The time has come to understand the systematic risk embedded in the markets of reference. Although fish production from aquaculture has grown tremendously and has, over the years, contributed to total fish production in Nigerian fish market is not unconnected to an imbalance in supply and demand dynamics. Investment in the fish and meat sub-sectors in Nigeria has continued to increase slowly with the aspiration to meet both local and international demand.. Production grew from 0.61 million tons in 2000 to 0.55 million tons in 2003 and as at 2014 estimates, it has grown to 1.123m Mt. However, demand has also risen from 1.5 million Mt in 2003 to 3.32m Mt in 2014 (Fishery Committee for the West Central Gulf of Guinea, 2016; FDF, 2003; 2015; Dada, 2003; Adewumi, and Fagbenro, 2010). This is an evidence that fish supply has consistently fallen below consumers' demand for fish. Fish importation has augmented the supply deficit over the years. Similarly, as population grows, meat demand has also been on the increase (Raghavendra, 2007) thereby opening up means of livelihood for all class of people across urban and rural sectors. The meat consumed in Nigeria is largely sourced from cattle, sheep, goats, pig and poultry. Consumption of game meat is not uncommon too. Consumption of beef is about the most popular. In the last two decades, Nigeria has continued to witness increasing influx of cattle from neighbour countries in the Sahel region. Despite this growing opportunities in the cattle market, policy makers have not done enough to improve the market. According to FAO report on Nigeria, 30 percent of meat consumed in Nigeria is imported. Even at that, the level of beef demand is hardly met by the level of supply. Finding has shown that the present beef supply in ECOWAS can only meet 2kg out of the 8kg per annual meat requirements per person (Guibert, Banzhaf, Soulé, Balami, Idé, 2009).

Literature is replete with studies on the associated risk about fish market and possible factors of influence (Dahl and Oglend, 2014; Bockstael and Opaluch 1983; Mistiaen and Strand, 2000; Smith and Wilen, 2005; Eggert and Martinsson, 2004; Eggert and Tveteras, 2004; Holland and Sutinen 2000). In a similar vein, Rezitis and Stravropoulos, (2010) have documented the effects of increasing cost of feeds, global economy challenges and other farm inputs on meat market instability. Connor, Keane and Barnes (2009) applied ARMA and GARCH to capture the price volatility of both World and European Union (EU) prices for dairy commodities. Consumer Price Indices (CPIs) of some food price returns series in Nigeria have been successfully modelled (Ojogho and Egware, 2015; and Osarumwense and Waziri, 2013). The outcomes of their studies also concur with other evidence in the literature that GARCH models are good enough to fit agricultural price series. According to Fisher (1966); and Scholes and Williams (1977), non-synchronous financial data allows for autocorrelations in returns. This statistical property and others collectively referred to as stylized facts have endeared researchers to develop some models that can predict the heteroscedastic behaviour in time series data including Consumer Price Index (CPI) for Fish and Meat. In this study, the ARCH and GARCH models developed by Engle (1982) and Bollerslev (1986) were explored to predict and forecast out of samples of the selected series

Although some social experiments have been carried out on food commodity markets in Nigeria, the literature on fish and meat price volatility is still scanty. There is a growing concern that in the recent time, food price volatility has been unacceptably high. Hence, having a model that can predict the market will help in arriving at enduring policy strategies that can sustain a relatively stable fish and meat markets in Nigeria. This paper did not intend to close that debate with this singular attempt but, will want to add to the robustness of the debate by assessing fish and meat inflation volatility in Nigeria. In order to achieve this, this paper makes attempt to, among other objectives, assess the volatility of the returns of consumer price index for fish and meat (inflation rates); select models, among selected ARMA and GARCH variants, that best fit the behavior of the fish and meat inflation series; and subsequently, the forecasting power of the models are investigated and analyzed using the inflation rate for fish and meat in Nigeria. In addition to that, the appropriateness of log returns and absolute returns of the CPI to be modelled with ARMA, GARCH, and EGARCH variants, and the accuracy of using same to forecast actual future inflation rate as well as predicting the future CPI series are also tested. The output of the models is analyzed within the conceptual construct for the models.

Data Description and Methodology

The data on composite consumer price indices for meat and fish were obtained from the sites of Nigerian National Bureau of statistics. The period, 2009M9 - 2016M10, was selected because of; the consistent order of the data collected during the period (no missing data in between the series); and, it offers the opportunity to extend the assessment of the price variability of fish and meat to the more recent period not captured in the previous studies of Ojogho and Egware (2015). Subsequently, the CPI growth rates (returns) for the selected series were derived. Both log and absolute returns were considered in this study to observe how both can be properly modelled using the ARMA and GARCH models as well as their ability to predict the actual CPI data accurately. ARMA and GARCH are known to perform well with stationary series hence, unit root test was carried out on each of the series to ensure its stationary status before being fed into the model proper. Each of the series has 86 data points (2009M9 -2016M10), but after taking the returns, each lost a data point thereby resulting to 85. After Unit Root Test, other analyses are structured into two main parts: Modelling the Volatility of Fish and Meat Returns; and Forecasting Accuracy of ARMA and GARCH Models. In each case, the model adequacy is testing using the post diagnostic procedure as explained by (Tsay, 2002; Gourieroux, 2001; Engle 1982; and Bollerslev, 1986).

Simple Returns and Log Returns

In this paper, the absolute and log returns are obtained as: $R_t(k) = \left(\frac{P_t - P_{t-k}}{P_{t-k}}\right) * 100$ and $R_t(k) = logP_t - logP_{t-k} = log\left(\frac{P_t}{P_{t-k}}\right) * 100$ respectively. R_t, P_t and P_{t-k}represent CPI returns, CPI value at month (t) and CPI values at the previous month (t-1) in that order.

In this study, both absolute and log returns for CPI series are used as A and L respectively. For example, FAR and FLR will read as Fish price absolute returns and Fish price log returns respectively.

Autoregressive Moving Average (ARMA) Model

ARMA was developed and made popular by Box and Jerkins (1976). They developed this refined method to identify, fit, check and integrate autoregressive (AR) and moving average (MA) time series. The model takes the advantage of the long memory of time series to model the future values as a linear function of its lagged series and the past errors. ARMA performance is hinged on stationary series. For this paper, given that R's are the known returns of the selected time series while $\varepsilon's$ are the series of the unknown residuals, the ARMA model is stated as:

$$R_t = \alpha + \sum_i^p \beta_i R_{t-i} + \varepsilon_t + \sum_i^q \alpha_i \varepsilon_{t-i} \qquad 2.1$$

where $\varepsilon_t \sim WNiid(0, \sigma^2)$.

Given that R_t is the independent variable, R_{t-i}, for i=1,2,…,p are lagged dependent variables; ε_t stands for error term (white noise); ε_{t-j}, j=1,2,…q β *and* α are autoregressive and moving average parameters to be estimated.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Variants

GARCH

Bollerslev (1986) incorporated lagged terms of the conditional variance in the ARCH model to generate an infinite order of ARCH model called generalized ARCH (GARCH). GARCH model is split into Conditional and Variance equations. The conditional mean equation

$$R_t = c + \sum_{i=1}^q \emptyset_i R_{t-i} + \varepsilon_t, \qquad 2.2$$

while the ARMA equation is stated as

$$R_{it} = c + \sum_{i=1}^p \emptyset_i R_{t-i} + \sum_{j=1}^q \theta_i \varepsilon_{t-j} + \varepsilon_t. \qquad 2.3$$

The return of the CPI rate series in the month (t) and the return of the CPI rate series in the previous month (t-1) are R_t and R_{t-i} for i=1,2,…,p respectively. Similarly, $c, \varepsilon_t \emptyset_i$, and θ_i represent the intercept, error term and other parameters to be estimated for the mean equations. ε_{t-j} stands for the lagged error terms for, j=1,2,…q. The lag lengths for AR and MA are represented by p and q respectively.

Assuming the conditional variance equation for GARCH model is expressed as;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \propto_i \varepsilon_{t-1}^2 + \sum_{i=1}^p \beta_i \sigma_{t-1}^2, \qquad 2.4$$

then the GARCH (1,1) is defined as

$$\sigma_{it}^2 = \alpha_0 + \propto_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 . \qquad 2.5$$

Equation 2.4 has the ARCH (q) and GARCH (p) terms, where p and q are lag lengths. In equation 2.5, ε_{it-1}^2 and σ_{it-1}^2 are the ARCH and GARCH terms. The ARCH term feeds the system information about the previous month, and the GARCH term accounts for the previous period forecast variance. Both combine to determine the one period ahead forecast. $\alpha_0, \propto_i$ and β_i are non-negative parameters which are often restricted to ensure the non-negativity of the conditional variance.

Poterba and Summer (1986) has explained that if the variance equation gives a parameter estimate that indicates high volatility persistence such that the sum of $\propto_i$ and β_i close to unity, then it implies that the shocks will decay slowly. Therefore, it will take as long as it takes to decay to significantly influence the price under consideration.

Exponential GARCH (EGARCH) Model

GARCH has its limitation in the inability to capture the asymmetric effect of news on conditional variance; the restrictions of non-negativity imposed on the parameter to be estimated, and clumsiness in revealing persistence in stationary series. EGARCH model has taken care of all these shortcomings including achieves covariance stationarity when the GARCH term is less than 1 (Shephard, 1996). The model was developed by Nelson (1991).

For the purpose of this study, the conditional variance of EGARCH model (1,1) model is specified as

$$log\sigma_t^2 = \alpha_0 + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] + \beta log\sigma_{t-1}^2 + \gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} . \qquad 2.6$$

As presented in equation 2.6,

γ captures leverage effect;

γ< 0 means Volatility responds to -ve shock more than +ve shock;

γ> 0 means Volatility responds to +ve shocks more than –ve shocks;

α describes the magnitude (size) of shocks (standardized residuals) on the conditional variance; and

β denotes the volatility persistence.

The efficiency of Maximum Likelihood Method (MLM) has been tested in its estimations of parameters for normalized shocks (innovations). However, in the absence of this normality, MLM has also been deployed to achieve Quasi Maximum Likelihood Estimators (QMLE). In this case, an adaptation is made to achieve efficient estimators and such properties have been properly researched for ARMA-GARCH and EGARCH errors (Ling and McAleer, 2002; Bollerslev, 1986; Tsay, 2002).

Model Adequacy and Model Selection (Ranking)

At this stage of checking for model adequacy, Talkle (2003) suggests that attention should be on the goodness of fit based on Ljung Box and ARCH tests. The tests are carried on the squared residuals to confirm that each of the models is able to account for all the structure in the each of the series. The approach, therefore, is that a decision threshold of 5% was set for the P values to either reject or not to reject the null hypothesis for the Ljung-Box (Null: there is no serial correlation) and ARCH/GARCH tests (Null: no ARCH effect not accounted for in the series). Also, the propositions about the residual obtained for each fitted series is that, whether it follows a normal or t distribution, it must be independently and identically distributed (Tsay, 2002 and Gourieroux, 2001). The expectation of well-fitted model is that the null hypothesis in each of the cases for all the models should not be rejected. In addition, AIC and SIC are considered as the selection criteria to rank the performance of the models in fitting the selected series. The AIC and SIC are ranked and the ranks are converted to scores. The scores are summed for each of the models and later ranked in the ascending order. The model with the highest rank (least value of AIC and SIC) is considered as the best model for each of the pair of series. For the purpose of selecting the best models that best forecast the out of samples of the selected series, the Root Mean Square Errors (RMSE), Mean Absolute Errors (MAE) and Mean Absolute Percentage Errors(MAPE) are ranked in a similar pattern to the AIC and SIC to select the model with the least values of RMSE, MAE and MAPE. The objective is to see which of the models' forecast gives zero or near zero errors. Both the dynamic and static forecast are observed. A number of studies that have been conducted in relation to testing the forecasting power of GARCH variants provided some guide (see Gabriel, 2012; Miron and Tudor, 2010; and Poon and Ganger, 2003)

Results and Discussion

Below are the results of each of the experiments conducted on the selected time series data. It is arranged in the order in which the experiment was carried out and the table on the assessment of the forecasting power concludes the table list.

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Statistical Properties of Data

Table 1 presents the summary of the statistical properties of the returns. The upper and lower parts of the table show the distribution of the absolute and log returns for fish and meat. The distribution provides some sort of motivations for this study. The standard deviation of FAR and MAR are 1.97% and 1.51% respectively. Also, the FLR and MLR have deviations from the mean of 0.85% and 0.65% accordingly. Each of the series has a standard deviation that is greater than its mean. This gives a hint about notable spikes in the return series. More importantly, the coefficient of variation reveals that though fish market looks attractive than the meat market in terms of high expected returns, it has investment risk than a meat market. Both FAR and MAR have the same pattern of fat tailed skewness (positively skewed) with noted peaked density (kurtosis) which is well above three (3), an indication for non-normal distribution. It is, however, different in FLR and MLR. The latter has its skewness towards the right while the former has its skewness towards left. The fact that the skewness of the returns series is non-zeros is an indication of violation of normality in the distribution. Similarly, the Jarque-Bera statistics rejects the null hypothesis for all, which confirms that the returns series are not normally distributed.

Table 1: Summary of Statistical Properties of Data

Statistics	Fish Absolute Returns (FAR)	Meat Absolute Returns (MAR)
Std Dev	1.973396	1.512118
Coefficient of Variation (CV)	1.7935	1.6575
Skewness	0.14948	0.428232
Kurtosis	21.3893	10.50842
Jarque-Bera	1197.989	202.2641
Probability	0.0000	0.0000
Observations	85	85
Statistics	**Fish Log Returns (FLR)**	**Meat Log Returns (MLR)**
Std Dev	0.849639	0.649359
Coefficient of Variation (CV)	2.1807	1.6668
Skewness	-0.46189	0.220165
Kurtosis	22.57836	10.37984
Jarque-Bera	1360.587	193.5732
Probability	0.0000	0.0000
Observations	0.3532	0.3514

Source: Data Analysis, 2017

Modelling Fish and Meat Price Returns Using ARMA

Table 2 presents the output of ARMA for fish and meat returns series. The stability of returns series is the primary key to the estimation of ARMA and GARCH models to avoid spurious output (French, Schwert and Stambaugh, 1987). Hence, all the returns series were confirmed to be stationary at 1% level of significance before estimation. The modelling was done with 80 out of 85 observations. This is to enable the paper assesses the efficiency of the model to forecast the remaining 5 observations. Determination of the lag length takes precedence in the attempt to select the model that best predict and forecast the fish and meat log price returns. Therefore, the correlograms plots from autocorrelation and partial autocorrelation function, as well as the AIC, were relied upon to select the lags for autoregression (AR) and moving average (MA) terms respectively. Among the twenty-five (25) simulations that were carried out but, the lags with the least AIC values 2.4972 and 4.1885 were selected for FLR and FAR respectively. The equation selected for both is ARMA (4,3). For the MLR and MAR, with least AIC values of 1.7369 and 3.4329, the equations selected are ARMA (4,2) and ARMA (3,2) accordingly.

Table 2: Output of ARMA for Fish and Meat Returns

Variables	AR	Coefficients	P value	MA	Coefficients	P value	AIC	SIC
FLR:	1	-0.10002	0.6332	1	-0.11256	0.7213	2.4972	2.7651
ARMA (4,3)	2	-0.09981	0.5801	2	0.113774	0.7015		
	3	-0.65238	0.0000	3	0.864822	0.066		
	4	-0.45012	0.0000					
Constant		0.4519	0.0000					
FAR:		-0.0935	0.6591		-0.1138	-0.4210	4.1885	4.4564
ARMA (4,3)		-0.0972	0.5893		0.0993	0.4223		
		-0.6554	0.0000		0.8611	2.5259		
		-0.4449	0.0000					
Constant		1.0669	0.0000					
MLR:	1	1.2809	0.0000	1	-1.9968	0.8897	1.7369	2.0150
ARMA (4,2)	2	0.2096	0.0995	2	0.9991	0.9447		
	3	-0.4932	0.0153					
	4	-0.0517	0.6865					
Constant		0.3720	**0.0000**					
MAR:	1	-0.53122	0.0000	1			3.4329	3.4929
ARMA(1,0)								
Constant		1.3358	0.0000					

Source: Data Analysis, 2017

Post Estimation Diagnostics and Adequacy of ARMA Model

After the estimation of fish and meat price returns using ARMA model, the residuals obtained are checked for both random walk (zero correlation) and ARCH effects. In the case of FLR and FAR, the P-values for the correlograms of the squared residuals, show clear evidence that at each point, there is no sufficient evidence to reject the null. Therefore, there is no autocorrelation (white noise) remaining in the squared residuals of the returns series. However, the case is totally different for MLR and MAR. The P-values of the correlograms of the squared residuals are predominantly below 5% hence, the null hypotheses are rejected for the two models. Therefore, it is concluded that there is autocorrelation in the squared residuals of the series. Further test such as ARCH test needed to be carried out to confirm the inadequacy or otherwise for ARMA to capture the heteroscedastic property in the MLR and MAR.

Testing for ARCH Effects

The ARCH test helps to confirm the presence of, or otherwise, heteroscedastic properties in FLR, FAR, MLR and MAR. The result of the test is on Table 3. Based on the results below, the null hypotheses (no ARCH effect) are not rejected for the residuals of the fitted FLR and FAR models. It is an indication that ARMA model was adequate to fit those return series. However, the null hypotheses are rejected for MLR and MAR. The rejection indicates that there are still some elements of clustering volatility in the residuals of the ARMA models estimated for MLR and MAR not accommodated by ARMA. It can be concluded therefore that, ARMA model does not properly fit for MLR and MAR series. This gave the motivation to develop GARCH models for the two returns series (MAR and MLR).

Table 3: ARCH Test on ARMA Output

Variable	**F statistics**	**Prob. F(1,77)**	**Obs. R-squared**	**Prob. (Chi-square(1)**
FLR	0.0038	0.9509	0.0039	0.9501
FAR	0.0023	0.9717	0.0023	0.9611
Variable	**F statistics**	**Prob. F(1,76)**	**Obs. R-squared**	**Prob. (Chi-square(1)**
MLR	11.7535	0.0010	10.4618	0.0012
MAR	11.5722	0.0011	10.3073	0.0013

Source: Data Analysis, 2017.

GARCH and EGARCH Models

These models were initially set up for the estimation of all the four returns series but, the model was not considered good for FPR and FAR because the post diagnostic ARCH tests carried out on the residuals after fitting the series using ARMA model showed no ARCH effect which automatically disqualifies GARCH variants as suitable model for the series. The standardized series of FLR and FAR indicated constant variance of the errors hence, not a good series that can be captured with GARCH models. The Quasi Maximum Likelihood Estimation (QMLE) of the parameter estimates was carried out under the assumptions of Gaussian, t and Generalized Error Distributions but only the Gaussian and Generalized Error Distributions were selected because their estimates are relatively useful here than t-distributions'.

AR-GARCH Model

Meat Log Returns (MLR) Series: The MPR is estimated using AR-GARCH (1,1) and the results are presented in Table 4. The results for the two distributions show that all the necessary conditions are met except that the short run volatility persistence is explosive (greater than one) under the Gaussian distribution. That is an indication that shocks influencing the unconditional volatility will persist definitely long into the future. The non-negativity constraints are not violated. The coefficients are significant at 1%. The output under the Generalized Error Distribution (GED) shows a more stable equation. The persistence is close to unity, an evidence of prolonged shocks to meat price inflation volatility.

Table 4: AR-GARCH Output for MLR

GARCH Mean Equation	Coefficient	P-Values	GARCH	Coefficient	P-Values
c	0.33744	0.0000	c	0.4108	0.0000
ϕ	0.0113	0.9276	ϕ	-0.1633	0.0226
Variance Equation					
α	0.0010	0.5843	α		
$\propto$	1.5882	0.0000	$\propto$	0.363223	0.0000
β	0.3347	0.0000	β	0.636777	0.0000
AIC		0.4696	AIC		0.3846
SIC		0.6196	SIC		0.5046
Normal (Gaussian)			GED		0.0000

Source: Data Analysis, 2017.

Meat Absolute Returns (MAR) Series: An attempt to observe the adequacy of AR-GARCH model in accommodating the structure in MAR was explored. The results are presented in Table 5. The parameters ($\propto$ *and* β) estimated under the Gaussian are statistically significant at 1%. The results of the AR-GARCH estimation under the GED shows that the parameter estimates that capture the influence of new information that was not available when the previous forecast was made ($\propto$) and the forecast variance of the previous months (β) are statistically significant at 5%. However, since the shock to volatility is explosive because $\propto + \beta > 1$ under the assumptions of the two distributions, it implies that persistence volatility is explosive. The conditional volatility cannot be determined within the model.

Table 5: AR-GARCH Output for MAR

MAR	Coefficient	P-Values	MAR	Coefficient	P-Values
c	0.7848	0.0000	c	0.9459	0.0000
ϕ	0.0047	0.9700	ϕ	-0.1587	0.0747
Variance Equation					
α	0.0053	0.5885	α	0.0151	0.4883
$\propto$	1.5756	0.0000	$\propto$	1.3918	0.0448
β	0.3371	0.0000	β	0.3632	0.0130
AIC		2.1529	AIC		1.9522
SIC		2.3029	SIC		2.1322
Normal (Gaussian)			GED		0.0000

Source: Data Analysis, 2017

ARMA-GARCH (4,2)(1,1)

The paper explores the possibility of modeling the MLR using ARMA (4,2)-GARCH(1,1). The results are presented in Table 6. The AR(1) in the mean equation in the previous model is replaced by ARMA (4,2) to assess its performance in capturing the structure of the MLR series under the assumptions of Gaussian and Generalized Error distributions. In the variance equations, though the parameter estimates, $\propto$ and β are statistically significant at 1% and 5% respectively, the shocks to volatility are considered to be explosive hence, the two models suffer stability.

Table 6: ARMA-GARCH (1,1) Estimation of MLR

MLR	**Coefficient**	**P-Values**	**MLR**	**Coefficient**	**P-Values**
c	0.3372	0.0000	c	0.3431	0.0000
$\emptyset_1$	0.2715	0.3196	$\emptyset_1$	0.4885	0.0016
$\emptyset_2$	-0.2718	0.4355	$\emptyset_2$	-0.3473	0.0471
$\emptyset_3$	-0.1248	0.4714	$\emptyset_3$	-0.1660	0.0001
$\emptyset_4$	-0.1296	0.3565	$\emptyset_4$	-0.1120	0.1538
θ_1	-0.3079	0.2248	θ_1	-0.6625	0.0002
θ_1	0.4943	0.0535	θ_1	0.4871	0.0075
Variance Equation					
α	0.0011	0.4413	α	0.0057	0.3418
$\propto$	1.2075	0.0014	$\propto$	1.8803	0.0377
β	0.3537	0.0002	β	0.1957	0.0363
AIC		0.4462	AIC		0.3541
SIC		0.7439	SIC		0.6816
Normal Distribution			GED		0.0000

Source: Data Analysis, 2017.

AR-EGARCH (1,1) Model

i. Meat Log Returns (MLR) Series: Table 7 shows the results of the AR-EGARCH developed to model the MLR. The estimation of EGARCH model using MLR is simulated under the Gaussian and GED assumptions. The results show that the persistence parameter estimates (β) are 0.94 and 0.91 under the distribution assumptions of Gaussian and Generalized Error respectively and significant at 1%. The parameter estimates for leverage effects are not statistically significant.

Table 7: Output of AR-EGARCH Estimation for MLR

MLR	**Coefficient**	**P-Values**	MLR	**Coefficient**	**P-Values**
c	0.3316	**0.0000**	c	0.4057	0.0000
$\emptyset$	0.0352	**0.8499**	$\emptyset$	-0.1573	0.0738
Variance Equation					
α	-0.9296	0.0000	α	-0.9277	0.0026
$\propto$	1.1328	0.0000	$\propto$	1.0611	0.0033
γ	0.0471	0.7590	γ	0.0389	0.8810
β	0.9412	0.0000	β	0.9119	0.0000
AIC		0.4678	AIC		0.2578
SIC		0.6477	SIC		0.4677
Normal (Gaussian)			GED		0.0000

Source: Data Analysis, 2017

ii. Meat Absolute Returns (MAR) Series: The output of AR-EGARCH as estimated by QMLE under the Gaussian and GED assumptions are presented in Table 9. The results show that the volatility persistence is high and also statistically significant at 1%. Other parameter estimates are also statistically significant (1%) except the leverage.

Table 8: Output of AR-EGARCH Estimation for MAR

MAR	**Coefficient**	**P-Values**	MLR	**Coefficient**	**P-Values**
c	0.7412	0.0000	c	0.9600	0.0000
$\emptyset$	0.0811	0.6452	$\emptyset$	-0.1850	0.0597
Variance Equation					
α	-0.8496	0.0000	α	-0.7869	0.0011
$\propto$	1.1492	0.0000	$\propto$	1.0642	0.0025
γ	0.0385	0.8048	γ	0.0396	0.8734
β	0.9366	0.0000	β	0.9125	0.0000
AIC		2.1469	AIC		1.9464
SIC		2.3268	SIC		2.1563
Normal (Gaussian)			GED		0.0000

Source: Data Analysis, 2017

ARMA-EGARCH

Table 8 presents the results of the estimation of ARMA-EGARCH model for MLR. The model output under the assumption of GED reveals that MLR series has leverage effect but not statistically significant. A similar trend to other estimates, there is high persistence in the series which are found to be statistically significant at 1%.

Table 8: Output of ARMA-EGARCH Estimation for MLR

MLR	**Coefficient**	**P-Values**	MLR	**Coefficient**	**P-Values**
c	0.3371	0.0000	c	0.3422	0.0000
$\emptyset_1$	0.4746	0.2878	$\emptyset_1$	-0.0322	0.9724
$\emptyset_2$	-0.2265	0.4982	$\emptyset_2$	0.0187	0.9714
$\emptyset_3$	-0.2444	0.2262	$\emptyset_3$	-0.0099	0.9207
$\emptyset_4$	-0.0486	0.7850	$\emptyset_4$	-0.0665	0.3024
θ_1	-0.6538	0.0798	θ_1	-0.0306	0.9738
θ_1	0.5516	0.1100	θ_1	0.0349	0.9474
Variance Equation					
α	-1.0720	0.0000	α	-1.0119	0.0087
$\propto$	1.3200	0.0000	$\propto$	1.1414	0.0103
γ	0.0912	0.6054	γ	-0.0041	0.9885
β	0.9587	0.0000	β	0.9110	0.0000
AIC		0.4471	AIC		0.3910
SIC		0.7746	SIC		0.7483
Normal (Gaussian)			GED		0.0000

Source: Data Analysis, 2017

Post Estimation Diagnostics and Adequacy of GARCH and EGARCH Models

Table 9 presents the results of the ARCH tests. According to the results by Ljung-Box (not included here because of space), there is no serial correlation detected on any lag in the standardized residuals $(\hat{\varepsilon}_t \hat{\sigma}_t)$ while the ARCH test statistics show that there is no ARCH/GARCH effect remaining in the squared standardized$(\hat{\varepsilon}_t^2 \hat{\sigma}_t^2)$. This is applicable for all the models. Therefore, there are no enough reasons to reject the null hypotheses. This is an indication that all structure in the series has been properly taken care.

Table 9: Results of ARCH Tests

MLR **Gaussian**	**F statistics**	**Prob. F(1,81)**	**GED**	**F statistics**	**Prob. F(1,77)**
AR-GARCH (1,1)					
ARMA-GARCH (4,2)(1,1)	**0.0047**	**0.9458**		**0.5048**	**0.4795**
AR-EGARCH	0.0168	0.8971		0.0364	0.8492
ARMA-EGARCH (4,2)(1,1)	0.1661	0.6848		0.0447	0.8331
MAR					
Gaussian	**F statistics**	**Prob. F(1,77)**	**GED**	**F statistics**	**Prob.**
AR-GARCH (1,1)	**0.0289**	0.8653		0.0169	0.8968

Source: Data Analysis, 2017

Model Selection

Table 10 presents the results of the model selection. In the case of FLR and FAR series, the only model reported in this paper is the one with the least AIC and SIC which is ARMA (4,3). While AR-EGARCH (1,1) is selected as the model best fit MLR series, AR-GARCH (1,1) and AR-EGARCH (1,1) are selected for MAR series.

Table 10: Results of Model Selection

MLR		AIC		SIC		Score	Remarks
ARMA (4,2)	Normal Gaussian	1.7369	(9)	2.0150	(9)	18	
AR-GARCH (1,1)	Normal Gaussian	0.4696	(8)	0.6196	(3)	11	
	GED	0.3846	(3)	0.5046	(2)	5	
ARMA-GARCH (4,2)(1,1)	Normal Gaussian	0.4462	(5)	0.7439	(6)	11	
	GED	0.3541	(2)	0.6816	(5)	7	
AR-EGARCH (1,1)	Normal Gaussian	0.4678	(7)	0.6477	(4)	11	
	GED	0.2578	(1)	0.4677	(1)	2	Best
ARMA-EGARCH (4,2)(1,1)	Normal Gaussian	0.4471	(6)	0.7746	(8)	14	
	GED	0.3910	(4)	0.7483	(7)	11	
MAR							
ARMA (1,0)	Normal Gaussian	3.4329	(5)	3.4929	(5)	10	
AR-GARCH (1,1)	Normal Gaussian	2.1529	(4)	2.3029	(3)	7	
	GED	1.9522	(2)	2.1322	(1)	3	Best
AR-EGARCH (1,1)	Normal Gaussian	2.1469	(3)	2.3268	(4)	7	
	GED	1.9464	(1)	2.1563	(2)	3	Best

Source: Data Analysis, 2017

Out of Sample Forecast Adequacy

Table 12 presents the result of the forecast accuracy. The model that best forecast each of the four returns series are selected by allowing all the models which the predictive powers had been tested with 80 of the 85 observations to forecast the last 5 observations. The tables of the selection in both the Static and dynamic forecast as well as the forecast output are in the appendix. For the dynamic forecast, ARMA (4,2) and AR (1) are selected as the best models that forecast the out of samples for MLR and MAR series respectively. In the static forecast, AR-EGARCH (1,1) model which estimation follows a Gaussian distribution is the best that forecast the MLR and MAR series. For the FLR and FAR, only ARMA (4,3) is reported here because of space. In the realization of the actual CPI from the forecasted returns, the dynamic forecast performs better than the static forecast as the sum of the differences between the actual and the predicted values of the 5 observations is closer to zero in the output of the former than the latter.

Appropriateness of Log and Absolute Returns

The results in Appendices III-VI show that the all the forecasted log returns, except FLR and FAR forecasted by ARMA (4,3), perform better than the forecasted absolute returns in terms of predicting the actual CPI data. The differences between the actual and predicted values are close to zero in other log returns as found on Appendices IV-VI. However, in the case of Appendix III, the absolute returns is more appropriate. On the average, the log returns are more appropriate for modeling volatility returns and forecasting the consumer price index for fish and meat in Nigeria.

Conclusions

The paper investigated the consumer price index of fish and meat in Nigeria in the period, 2009M10-2016M10. The paper adopted the AIC and SIC as selection criteria to select the models that best fit the returns series. The post diagnostic tests (Ljung and ARCH tests on the residuals) were also performed to ascertain if the models were able to capture all the structures in the returns series. Findings reveal that ARMA (4,3) is selected for FLR and FAR (results not presented here because of space but can be produced on request). However, ARMA could not account for the heteroscedastic structure in MLR and MAR series. In view of this, we proceeded to models the returns with AR-GARCH (1,1), ARMA-GARCH (4,2)(1,1), AR-EGARCH(1,1) and ARMA-EGARCH (4,2)(1,1) as appropriate for MLR and MAR series. The results of the model selection indicate that AR-EGARCH(1,1) models under the assumption of the generalized error distribution fit the MLR best while AR-GARCH (1,1) and AR-EGARCH(1,1) are selected as models that best fit MAR series. The Ljung and ARCH tests confirmed the adequacy of the models to account for all the structure in the series. In the realization of the actual CPI from the forecasted returns, the paper finds that the dynamic forecast performed better than the static forecast. For the dynamic forecast, ARMA (4,2) and AR (1) were selected as the best models that forecast the out of samples for MLR and MAR series respectively. In static forecast, it is AR-EGARCH (1,1) model for the MLR and MAR series. Finally, the findings from this study show that the log returns performs better to appropriately reveal the behavior and structure of the inflation rate in all the models except the ARMA (4,3) estimated for FLR and FAR. In this case, absolute returns reveal the volatility in fish inflation better, and it also predicts the actual CPI better. Findings from the study also reveal that both MAR and MLR in all the models show high persistent volatility. It implies innovations to volatility decays very slowly, and by that, it means shocks to volatility will have to persist for long before inflation volatility can affect the meat price.

Therefore, the paper recommends ARMA and GARCH variants as appropriate forecasting tools to predict future expectations of fish and meat price inflation volatility with a view to knowing the future expectations with respect to the foodstuff of reference, and provide adequate policy strategies to address this in the annual budgets as currently being practiced in Nigeria and other countries in the sub-Saharan Africa. However, further studies need to be carried out to determine the culpability of fuel, power and other macroeconomic uncertainties on fish and meat price volatility.

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Appendix

Appendix I: Results of the Dynamic Forecast Selection

	Distribution	RMSE	MAE	MAPE	Score	Remarks
FLR						
ARMA (4,3)		0.3663	0.3339	57.64	NR	
FAR						
ARMA (4,3)		0.8158	0.7553	56.71	NR	
MLR						
ARMA (4,2)		0.2475 (1)	0.2139 (1)	32.19 (1)	3	Best
AR-GARCH (1,1)	Normal Gaussian	0.3131 (5)	0.2788 (8)	42.23 (8)	21	
	GED	0.3122 (3)	0.2723 (3)	40.82 (4)	10	
ARMA-GARCH (4,2)(1,1)	Normal Gaussian	0.3332 (9)	0.3026 (9)	46.63 (9)	27	
	GED	0.3194 (7)	0.2754 (7)	41.71 (7)	21	
AR-EGARCH (1,1)	Normal Gaussian	0.3094 (2)	0.2682 (2)	40.58 (2)	6	
	GED	0.3148 (6)	0.2748 (6)	41.25 (6)	18	
ARMA-EGARCH (4,2)(1,1)	Normal Gaussian	0.3127 (4)	0.2724 (4)	40.83 (5)	13	
	GED	0.3234 (8)	0.2746 (5)	40.75 (3)	16	
MAR						
ARMA (1,0)		0.7149 (2)	0.5922 (1)	37.61 (1)	4	Best
AR-GARCH (1,1)	Normal Gaussian	0.7315 (4)	0.6507 (5)	42.45 (5)	14	
	GED	0.7291 (3)	0.6348 (3)	40.99 (3)	9	
AR-EGARCH (1,1)	Normal Gaussian	0.7034 (1)	0.6254 (2)	40.77 (2)	5	
	GED	0.7381 (5)	0.6428 (4)	41.52 (4)	13	

Source: Author’s Computations, 2017.

Appendix II: Results of the Static Forecast Selection

	Distribution	RMSE	MAE	MAPE	Score	Remarks
FLR						
ARMA (4,3)		0.4028	0.3550	58.50	NR	
FAR						
ARMA (4,3)		0.8998	0.8085	57.97	NR	
MLR						
ARMA (4,2)		0.4499 (9)	0.4455 (9)	73.81 (9)	27	
AR-GARCH (1,1)	Normal Gaussian	0.3108 (2)	0.2760 (2)	41.75 (2)	6	
	GED	0.3427 (5)	0.3083 (4)	46.96 (3)	12	
ARMA-GARCH (4,2)(1,1)	Normal Gaussian	0.3286 (3)	0.3080 (3)	48.18 (4)	11	
	GED	0.3428 (6)	0.3155 (6)	48.75 (5)	17	
AR-EGARCH (1,1)	Normal Gaussian	0.2868 (1)	0.2497 (1)	37.41 (1)	3	Best
	GED	0.3556 (7)	0.3112 (5)	47.42 (3)	15	
ARMA-EGARCH (4,2)(1,1)	Normal Gaussian	0.3416 (4)	0.3201 (7)	50.06 (6)	17	
	GED	0.3736 (8)	0.3362 (8)	51.23 (8)	24	
MAR						
ARMA (1,0)		0.9682 (5)	0.8752 (5)	57.98 (5)	15	
AR-GARCH (1,1)	Normal Gaussian	0.7292 (2)	0.6479 (2)	42.25 (2)	6	
	GED	0.8050 (3)	0.7342 (3)	47.55 (3)	9	
AR-EGARCH (1,1)	Normal Gaussian	0.6675 (1)	0.5806 (1)	37.46 (1)	3	Best
	GED	0.8282 (4)	0.7483 (4)	49.27 (4)	16	

Source: Author's Computations, 2017.

Appendix III: Results of the Appropriateness of FLR and MAR (ARMA (4,3) – DF

Date	FLRF	CPI	CPI_f	Diff	Date	FARF	CPI	CPI_F	Diff
2016M5	.4454	230.45	**227.45**	**3.00**	2016M5	1.1640	230.45	**227.75**	**2.70**
2016M6	.3316	234.33	**232.21**	**2.12**	2016M6	.8409	234.33	**232.38**	**1.95**
2016M7	.2248	237.90	**235.55**	**2.35**	2016M7	.4885	237.90	**235.48**	**2.42**
2016M8	.4637	241.00	**240.46**	**.54**	2016M8	1.0262	241.00	**240.35**	**.65**
2016M9	.5548	242.64	**244.10**	**-1.46**	2016M9	1.2320	242.64	**243.97**	**-1.33**
2016M10	.6427	244.84	**246.26**	**-1.42**	2016M10	1.5353	244.84	**246.36**	**-1.52**
				5.13					**4.87**

Source: Author's Computations, 2017.

Appendix IV: Results of the Appropriateness of MLR and MAR (ARMA (1,0) - DF

Date	MLRF	CPI	CPI_F		Date	MARF	CPI	CPI_F	
2016M5	.4120	195.59	**193.46**	**2.13**	2016M5	.6356	195.59	**192.86**	**2.73**
2016M6	.4903	198.84	**197.81**	**1.03**	2016M6	.9982	198.84	**197.54**	**1.30**
2016M7	.4062	201.41	**200.71**	**.70**	2016M7	.8056	201.41	**200.45**	**.96**
2016M8	.4107	204.12	**203.33**	**.79**	2016M8	.9079	204.12	**203.24**	**.88**
2016M9	.3684	206.23	**205.86**	**.37**	2016M9	.8535	206.23	**205.86**	**.37**
2016M10	.3525	208.79	**207.91**	**.88**	2016M10	.8824	208.79	**208.05**	**.74**
				5.90					**6.98**

Source: Author's Computations, 2017.

Appendix V: Results of the Appropriateness of FLR and FAR, AR-EGARCH (1,1) – SF

Date	FLRF	CPI	CPI_f	Diff	Date	FARF	CPI	CPI_F	Diff
2016M5	.4454	230.45	**227.45**	**3.00**	2016M5	1.1640	230.45	**231.25**	**-.80**
2016M6	.2140	234.33	**231.58**	**2.75**	2016M6	.5971	234.33	**233.64**	**.69**
2016M7	.1350	237.90	**235.06**	**2.84**	2016M7	.2870	237.90	**235.89**	**2.01**
2016M8	.4954	241.00	**240.63**	**.37**	2016M8	1.0531	241.00	**243.74**	**-2.74**
2016M9	.4762	242.64	**243.66**	**-1.02**	2016M9	1.0414	242.64	**246.85**	**-4.21**
2016M10	.6727	244.84	**246.43**	**-1.59**	2016M10	1.6267	244.84	**251.90**	**-7.06**
				6.35					**-12.11**

Source: Author's Computations, 2017.

Appendix VI: Results of the Appropriateness of MLR and MAR, AR-EGARCH (1,1) – SF

Date	MLRF	CPI	CPI_f		Date	MARF	CPI	CPI_F	
2016M5	.3664	195.59	**193.26**	**2.33**	2016M5	**.7874**	195.59	**193.15**	**2.44**
2016M6	.3911	198.84	**197.36**	**1.48**	2016M6	**.8131**	198.84	**197.18**	**1.66**
2016M7	.3779	201.41	**200.58**	**.83**	2016M7	**.7994**	201.41	**200.43**	**.98**
2016M8	.3655	204.12	**203.11**	**1.01**	2016M8	**.7865**	204.12	**203.00**	**1.12**
2016M9	.3673	206.23	**205.86**	**.37**	2016M9	**.7883**	206.23	**205.73**	**.50**
2016M10	.3567	208.79	**207.93**	**.86**	2016M10	**.7774**	208.79	**207.83**	**.96**
				6.88					**7.66**

Source: Author's Computations, 2017.