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Modeling Domestic Price Volatility for Cereal Crops in Ethiopia

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Abstract: The volatility in the domestic prices of maize and teff crops has been found to vary over time from month to month. Thus, Families of time series models namely, ARCH with their extensions to generalized ARCH, GARCH and EGARCH models with ARIMA mean equations were considered to the data. The best fitting model among each family of models was selected based on how well the model captures the variations in the data. The optimal lag specification for the models are accessed via AIC and SBIC. Comparisons of the symmetric and asymmetric selected models were carried out based on the significance of asymmetric term in the EGARCH model. Thus, statistically significance of asymmetric term and least forecast error from the model established that the EGARCH model with GED for residuals was superior to the GARCH model. Therefore, the ARIMA(2,0,3)-EGARCH(1,1) and ARIMA(0,0,3)-EGARCH(2,3) were chosen to be the best fitting models among the ARIMA(p, d, q)-GARCH(P, Q) family for monthly domestic price volatility of maize and teff crops, respectively. However, the volatility in the domestic price of wheat and barley was found to be not changing over time. Hence, the variance of the ARIMA process was used as the measure of volatility in the prices of these two crops which were 0.00112 and 0.0004, respectively. Moreover, it was found that from candidate exogenous variables, import prices for maize crop, fuel oil price, exchange rate (dollar-birr), inflation from non-food items, past shock and volatility on the domestic price had statistically significant effect on the current month domestic price volatility for maize and teff crops.

Keywords: Domestic Price Volatility, Time Series Data, ARCH, GARCH, EGARCH

1. Introduction

The food price volatility has strong and long-lasting effects on emerging economies and poor people and also ensuring food security to a growing human population is a top priority among the challenges facing the world today. Managing food price instability is a long standing policy challenge, which, with mixed experiences of agricultural price policy reforms, has re-emerged as a contemporary policy issue. This is particularly true for Ethiopia, where managing food price stability continues to be a formidable policy challenge. Ethiopia, like most developing countries, is an agrarian economy with a very small industrial sector and then the agricultural sector, on average, accounts for around 50 percent of GDP, 80 percent of rural employment and 90 percent of the total foreign exchange earnings [1] Out of the total grain crop area, cereals cover 80 per cent of the cropped land and contribute 86 percent of crop production and they are staple food crops of the country. For the average Ethiopian food consumption, cereal accounts 58 percent of total consumption and one-fourth of average expenditure across various household groups and also they are significant part of economy in the country in terms of rural livelihood, food security and as well as national income. The contribution of cereals to national income is about 30% of GDP [2].

Despite infrastructural improvements and liberalization, price volatility in markets for teff, wheat, and maize remains high in the country. A households with low levels of assets have been particularly adversely affected by the food price shock in the country and the recent hike in relative prices has increased the urban cost of living by 8-12 percent and worsens income inequality significantly [3, 4]. The dire consequences of price instability on consumers, producers, as well as on overall economic growth [5]. For poor consumers, consequences of price instability are severe; since a large share of their income is spent on food, an unusual price increase forces them to cut down food intake, take their children out of school, or, in extreme cases, simply to starve. Even when such price shocks are temporary, they can have long term economic impacts in terms of nutritional well-being, labor productivity, and survival chances. It appears that that rising food prices in Ethiopia has been the outcome of monetary policy misalignment, the balance of payment problems resulting from sharp increases in fuel prices, as well as overestimated cereal production [2].

Volatility in commodity prices, particularly for food commodities, affects poor agricultural laborers and labor engaged in unorganized sector adversely because their wages are not index-linked and also commodity price volatility poses problems for the governments and exporters of the primary commodity-producing developing countries. For governments, unforeseen variations in export prices can complicate budgetary planning and jeopardize attainment of the debt targets. For exporters, price volatility increases cash-flow variability and reduces collateral value of inventories. The importance of identifying determinants for price volatility especially in Ethiopia, which is an economy in transition, is the fact that price shocks have a greater negative impact on the economic growth of developing economies [6]. The accurate measurement of the stochastic component in the prices may contribute to the decision maker being able to make more informed decisions when choosing one crop over another. It may also contribute to policy decisions regarding the possible implementation of commodity price stabilization program. Moreover, examining the underlying causes of cereal price instabilities and coffee price volatility has great role for managing price instability for producers, consumers, whole sellers and agricultural price policy reforms for the country as well [7].

Therefore, it is crucial to examine the pattern of domestic price volatility and identify its determinants on agricultural crops under consideration. Hence, this study has employed financial time series econometric methods to explore the nature and causes of domestic price volatility in selected cereal crops under consideration in Ethiopia by developing separate GARCH and EGARCH model with Box-Jenkins model for conditional mean specification.

2. Methodology

2.1. The Data

To assess the pattern and determinants of domestic price volatility for selected agricultural crops namely maize, teff, wheat and barley in Ethiopia, the data for the study were obtained from Central Statistical Association (CSA), National Bank of Ethiopia (NBE), Ethiopia Feul and Oil Agency (EFOA) and Ethiopian Import and Export Authority as secondary data on monthly basis. They were domestic prices of cereal crops collected from selected 119 sample market place in the country, Exchange rate, interest rate, fuel oil price, general inflation rate, inflation rate from food items and non-food items and import price for maize crop observed from September 2003 to February 2011 GC.

2.2. Variables in the Study

This study was considers average monthly domestic closing price returns (Y_t) and conditional variance (σ_t^2) at time t for each agricultural crops maize, teff, barley and wheat as dependent variables and the factors listed below as explanatory variables.

Dependent variables: Average monthly domestic closing price returns (Y_t) for mean equation and conditional variance (σ_t^2) at time t for each agricultural crops under consideration.

Independent variables: variables that are assumed to affect domestic price volatility are: exchange rate in dollar/birr ($X_{11}, X_{12}, \dots X_{1t}$), saving interest rate ($X_{21}, X_{22}, \dots, X_{2t}$), *f*uel oil price ($X_{31}, X_{32}, \dots, X_{3t}$), general inflation rate ($X_{41}, X_{42}, \dots, X_{4t}$), inflation rate from food items ($X_{51}, X_{52}, \dots, X_{5t}$), inflation rate from non-food items ($X_{61}, X_{62}, \dots, X_{6t}$), import price ($X_{71}, X_{72}, \dots, X_{7t}$), seasonal dummies ($X_{81k}, X_{82k}, \dots X_{8tk}$), past shock of dependent variable ($\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \dots, \varepsilon_{t-Q}^2$) and past conditional variance ($\sigma_{t-1}^2, \sigma_{t-2}^2, \dots, \sigma_{t-P}^2$), where, X_{it} is i^{th} explanatory variable at time t and X_{itk} is i^{th} explanatory variable at time t for k^{th} seasonal dummies for k = 1, 2,…, 11 by taking September as reference.

2.3. Model Specification

To come up with the objectives of the study, after identifying the presence of ARCH effects, separate GARCH and EGARCH models was employed with joint estimation of a mean and a conditional variance equation in which both mean and variance equations are conditional on available information up to time t-1 as model specifications are given below.

The ARMA (r, s) mean model [8] is given as:

$$Y_t = \phi_0 + \sum_{i=1}^{r} \phi_i Y_{t-i} - \sum_{i=1}^{s} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (1)$$

where $\varepsilon_t = \sigma_t^2 \upsilon_t$ for υ_t is identically and independently distributed normal residual with zero mean and unit variance and Y_t is average monthly domestic price returns at time t for each selected cereal crops under study and σ_t^2 is conditional variance of residuals at time t (ε_t) given in equation (2) and (3) below.

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{Q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2 \quad (2)$$

Restriction on $\alpha_o > 0, \alpha_i \geq 0 \; and \; \beta_j \geq 0$ for $i = 1,2,\dots,Q$ and $j = 1,2,\dots,P$ are imposed in order for the variance σ_t^2 to be positive. As literature on GARCH(P, Q) model indicated, Non-negativity constraints might be violated and the model cannot account for leverage effects. Then as possible solutions in handling financial data, Nelson proposed the EGARCH to respond asymmetrically to allow for asymmetric effect between positive and negative values of the returns and uses logged conditional variance to relax the positivity constraint of model coefficients [9]. Thus, EGARCH(P, Q) model for the variance of residuals at time t is given as:

$$\log(\sigma_t^2) = \alpha_o + \sum_{i=1}^{Q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{Q} \delta_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{P} \beta_j \log(\sigma_{t-j}^2) \quad (3)$$

No restriction imposed on the coefficients in the model since logarithm of conditional variance overcomes the positivity constraint of coefficients in EGARCH model.

More specifically, the general inflation rate, inflation rate from food and non-food items, saving interest rate, exchange rate (dollar-birr), import price for maize, fuel oil price, monthly seasonal dummies was introduced into the conditional variance equation as exogenous variables in order to determine the volatility spillover of these variables on commodity average monthly domestic prices and volatility for each crops under consideration. Thus, conditional variance equation GARCH(P, Q) with explanatory variables for each agricultural crop under consideration is given as:

$$\sigma_{mt}^2 = \alpha_o + \sum_{i=1}^{Q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{P} \beta_j \sigma_{t-j}^2 + \gamma_1 X_{1t} + \gamma_2 X_{2t} + \gamma_3 X_{3t} + \gamma_4 X_{4t} + \gamma_5 X_{5t} + \gamma_6 X_{6t} + \gamma_7 X_{7t} + \sum_{k=1}^{11} \gamma_{8k} X_{8tk} \quad (4)$$

where σ_{mt}^2 is variance of random shock at time t for crop *m*, $k = 1,2....,11$ for the monthly dummies that account for monthly seasonal effects at time t, $(\gamma_1 - \gamma_{8k})$, $(a_0, a_1, \dots, a_Q, \beta_1, \dots, \beta_P)$ and $(\phi_0, \phi_1, \dots, \phi_r, \theta_1, \theta_2, \dots, \theta_s)$ are parameters of explanatory variables including seasonal dummies, lagged shock, lagged volatility and in mean equation (1), respectively which needs to be estimated. Then, estimated coefficients $\gamma_1 - \gamma_{8k}$ shows the effect of explanatory variables, α_o shows long term volatility and the seasonal effect of remaining 12th month's, $a_1, \dots, a_Q$ examines the effect of past shocks irrespective of sign and $\beta_1, \dots, \beta_P$ shows the influence of past volatility on the current volatility of the domestic price for the crops possessing volatility clustering.

Moreover, assuming that domestic price volatility for the increase and decrease of domestic price for maize, teff, wheat and barley crops changes asymmetrically, (i.e. volatility on the domestic price for lagged negative and positive shocks do not respond equally). Then the EGARCH(P, Q) variance equation with explanatory variables for each crop can be given as:

$$log(\sigma_{mt}^2) = \alpha_o + \sum_{i=1}^{Q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{Q} \delta_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{P} \beta_j log(\sigma_{t-j}^2) + \gamma_1 X_{1t} + \gamma_2 X_{2t} + \gamma_3 X_{3t} + \gamma_4 X_{4t} + \gamma_5 X_{5t} + \gamma_6 X_{6t} + \gamma_7 X_{7t} + \sum_{k=1}^{11} \gamma_{8k} X_{8tk} \quad (5)$$

where σ_{mt}^2 is variance of random shock at time t for crop *m*, $k = 1,2,....,11$ for seasonal dummies that account for monthly seasonal effects at time t,$(\gamma_1 - \gamma_{8k})$, $(a_0, a_1, \dots, a_Q, \beta_1, \dots, \beta_P)$ and $(\phi_0, \phi_1, \dots, \phi_r, \theta_1, \theta_2, \dots, \theta_s)$ are parameters to be estimated. Then, the estimated coefficients $\gamma_1 - \gamma_{8k}$ shows the effect of explanatory variables, α_o shows long term volatility and seasonal effect of remaining 12th month's, $a_1, \dots, a_Q$ and $\delta_1, \delta_2, \dots, \delta_Q$ examines the asymmetric effect and $\beta_1, \dots, \beta_P$ shows the influence of past volatility on the current volatility of the domestic prices for the crops under consideration in Ethiopia.

2.4. Basic Procedures for GARCH Family Model Building

The basic framework that was followed to investigate the pattern of domestic price volatility and its determinants on maize, wheat, teff and barley crops follows Box and Jenkins approach of time series modelling namely: testing for the presence of unit root, testing for ARCH effect, order selection for GARCH family model, estimation of the model parameter, checking model adequacy and forecasting [8].

2.4.1. Testing for the Presence of Unit Root (Non-Stationarity)

The non-stationarity of a series can strongly influence its behavior and properties like persistence of shocks, gives spurious regressions that is if two variables are trending over time, a regression of one on the other could have a high R^2 even if the two are totally unrelated [10]. Consequently, unit root tests were first performed to examine the stationarity of data under study using ADF test proposed by Dickey and Fuller and Phillips-Perron test proposed by Phillips and Perron non-stationarity test [10, 11]. Both ADF and PP test, tests the null hypothesis that a time series has unit root problem against the alternative that it is stationary, assuming that the dynamics in the data have an ARMA structure. Once the presence of unit root (non-stationarity) is confirmed the data needs to be differenced to make it stationary. The ADF test is then applied on the differenced data sets to test whether differencing the data made it stationary. This process is to be repeated until it yields a stationary series that can be used in further analyses.

2.4.2. Test for ARCH Effect

The Box-Jenkins approach is based on the assumption that the residuals are homoskedastic (remain constant over time) for ARMA or ARIMA model [8]. But in financial data, ARCH effect is commonly found [12, 13]. Thus, the presence of ARCH effect (whether or not volatility varies over time) has to be tested in series through the squared residuals of the series which is known as ARCH effect [14]. According to Tsay, there are two available methods to test for the ARCH effects and then the methods to test for the ARCH effects [14] and their details are discussed below.

i) The Ljung-Box Test

It was developed by Box and Pierce [15] and modified by Ljung and Box and tests the joint significances of serial correlation in the standardized and squared standardized residuals for the first k lags insteady of testing individual significance. They suggested to test hypothesis:

$H_0: \rho_1 = \rho_2 = \dots = \rho_k = 0$ (The first k lags of ACF of the squared residuals series is zero) against H_1: $not\ all\ \rho_j =$

0, where ρ_j is the ACF at lag j = 1, 2,..., k.

They suggested the statistic:

$Q(k) = n(n+2)\sum_{j=1}^{k}\frac{d_j^2}{n-j}$, where n denotes the length of the series after any differencing and d_j denote the squared residuals from equation (1). They showed that under null hypothesis Q (k) is asymptotically distributed as chi-square with (k − r − s) degrees of freedom, where k is time lags, r and s are the orders of the AR and MA from equation (1), respectively. Thus, reject null hypothesis at alpha level of significance if Q (k) is greater than critical value from chi-square distribution with (k-r-s) degree of freedom indicating significant serial autocorrelation in the squared residuals and presence of ARCH effect in the data for the application of GARCH family model.

ii) The LM Test

This test was suggested by Engle and used to test significances of serial correlation in the squared residuals for the first q lags [16]. Steps to derive test statistic for LM test are:

a. Estimate the mean equation as Engle [16] and Bollerslev [17] suggested by using OLS to estimate parameters initially to estimate errors in the model(1)
b. Then, regress current squared residual on lagged squared residuals and constant as follows:

$$\hat{\varepsilon}_t^2 = \alpha_o + \sum_{i=1}^{q}\theta_i\hat{\varepsilon}_{t-i}^2 \quad (6)$$

The hypothesis to be tested is:

$H_0: \theta_1 = \theta_2 = \cdots = \theta_q = 0$ (There is no serial autocorrelation for the first q lags of square residuals) against $H_1: \theta_i \neq 0$ for some i=1, 2,3, …, q.

Test statistic:

LM= R^2*T, where R^2 is coefficient of multiple correlation and T is number of observations.

Moreover, Engle [16] was suggested the test statistic LM under null hypothesis follow chi-square distribution with q degree of freedom. Thus, if the value of observed test statistic (LM) is greater than the critical value from chi-square distribution with q degree of freedom, then reject the null hypothesis at alpha level of significance indicating the evidence for the ARCH (q) effects.

2.4.3. Order Selection for GARCH Family Model

Once the ARCH effects are determined, then the next step involves identifying the appropriate orders for GARCH(P, Q) family model, i.e. identifying the ARCH (Q), GARCH(P) or EGARCH(P) parts for both symmetric and asymmetric GARCH models. In the presence of several competing models with different number of parameters, to select the model with appropriate order, AIC proposed by Akaike [18] and SBIC proposed by Schwartz [19] was employed to identify the optimal lag specification for the model to describe domestic price volatility for agricultural crops under study that possesses volatility clustering. The formal expressions for the above criteria in terms of the log-likelihood are:

$$AIC = -2\ln(loglikelihood) + 2r$$

$$SBIC = -2\ln(\text{loglikelihood}) + \text{r}(\ln\text{N}),$$

where r and N are number parameters and observations, respectively.

From information criteria, AIC penalizes parameters the least, and SBIC the most. Thus, in order to prevent over-fitting the models, the SBIC criterion was used to choose the lag length of the expansion in this study. In general, a desirable model is one that minimizes the AIC or SBIC. Moreover, studies indicated that GARCH(1,1) model is the most convenient specification in the financial literature [17] to fit the data with parsimonious model (model with small number of parameters). As a result, the EGARCH(1,1) and GARCH(1,1) model was compared to various higher-order models based on information criteria's given above.

2.4.4. Parameter Estimation for GARCH(P, Q) Family Model

Under the presence of ARCH effects, the OLS estimation is not efficient since variance of residuals is not constant and volatility models used in financial econometrics are non-linear in conditional variance. Also OLS involves minimizing the sum of squares of residuals, sum of squares of residuals depends on the coefficient of the mean not on conditional variance. Therefore, as many studies indicated, the commonly used method known as the maximum-likelihood estimation was employed to estimate parameters of GARCH family model. In maximum likelihood estimation the distributional assumption on residual is the core point. Thus, in this study, normal, student-t and the GED were considered to estimate parameters as financial time series data possess volatility clustering and leptokurtosis characteristics which led to the use different distributional assumption for residuals [17]. However, appropriate distribution for the residual was identified based on in-sample forecast error statistics to check predictive ability of the model under specified error distributions and final analysis was done based on selected distribution for residuals in the mean equation.

Moreover, in ML estimation method the conditional maximum likelihood estimates for the parameters are obtained by maximizing the conditional log-likelihood function. However, maximization of the log-likelihood function of the model analytically in terms of its parameter is impossible because of non linearity of GARCH model. As a result, maximization of the log-likelihood function was done through numerical iteration method using statistical package Eviews software version-6 which is uniquely developed for financial time series data.

2.4.5. Model Adequacy Checking

When a model has been fitted to a time series, it is advisable to check that the model really does provide an adequate description of the data. As with most statistical models, this is usually done by looking at the Residuals and then goodness of fit of the ARCH-GARCH model are based on residuals and more specifically on the standardized residuals [20].

The Ljung-Box test is one of the widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model and developed by Box and Pierce [15] Thus, Ljung-Box test statistic uses the Q (k)-statistic to test whether there is a group of significant k autocorrelations, to test whether the model of the mean is appropriately specified and to test for the remaining GARCH effects under the null hypothesis that there is no autocorrelation among k lags of standardized residuals and squared standardized residuals for mean and GARCH specification, respectively. Thus, if the statistic Q (k) at all lags was found to be non-significant indicating absence of autocorrelation in the residuals, then this is a further supporting evidence that the model selected fits the data well.

Evaluating the performance of different forecasting models plays a very important role in choosing the most accurate model. There are several criteria for assessing the predictive accuracy of an ARCH-GARCH family model and the most widely used statistical evaluation measures are MAE, RMSE and MAPE. These are applied to measure forecasting accuracy of the ARCH-GARCH model in this study. Their formal expressions are given below:

1. $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t^2 - \hat{\sigma}_t^2)2}$

2. $MAE = \frac{1}{T}\sum_{t=1}^{T}|y_t^2 - \hat{\sigma}_t^2|$

3. $MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{(y_t^2-\hat{\sigma}_t^2)}{y_t^2}\right| * 100$, where, $\hat{\sigma}_t^2$ for t = 1,..., T is the estimated conditional variance obtained from fitting ARCH-GARCH model and in general, the smaller the error statistic is, the better the forecasting ability of that model under consideration.

2.4.6. Forecasting by GARCH Family Model

Conditional variance forecasts from GARCH family models are obtained with similar approach to forecasts from ARMA models by iterating with the conditional expectations operator. In other words, when the estimation of the unknown parameters is done, estimates of the standard deviation series can be calculated recursively via the definition of the Conditional variance for the GARCH(P, Q) family process which helps to examine past behavior of domestic price volatility for each agricultural crops under consideration that possesses volatility clustering.

3. Results

3.1. Descriptive Statistics

The return series are constructed from monthly domestic prices to allow a market wide measure of volatility to be examined. They were calculated as the continuously compounded returns which are the first difference in logarithm of closing prices of cereals on successive months and summary results are displayed in Table 1.

Table 1. *Summary Results for Average Monthly Domestic Prices per kg (in birr) and Its Return for Cereal crops.*

Statistics	Price for Maize	Return Series	Price for Barley	Return Series	Price for teff	Return Series	Price for wheat	Return Series
Mean	2.455	0.003	3.714	0.005	5.032	0.002	3.505	0.005
Maximum	6.550	0.126	7.410	0.104	9.520	0.120	7.340	0.182
Minimum	1.040	-0.091	1.675	-0.045	2.100	-0.059	1.643	-0.154
Sd. Dev.	1.259	0.034	1.731	0.019	2.479	0.021	1.561	0.033
Skewness	1.167	0.500	0.466	1.702	0.404	2.330	0.521	0.488
Kurtosis	3.918	5.207	1.872	9.996	1.570	14.503	1.835	16.923
JB test	23.327	21.777	7.943	224.475	10.000	571.267	9.057	722.429
P-values	0.000	0.000	0.019	0.000	0.007	0.000	0.011	0.000

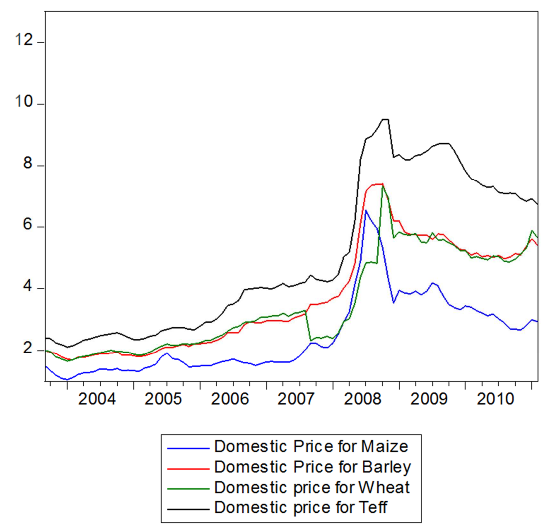

Figure 1. *Domestic Price Trend of four selected Cereals from September 2003 to February 2011.*

Table 1 displays summary descriptive statistics and normality test for the monthly domestic price series and its returns for cereals under study. Thus, the empirical result shows that the average monthly domestic price per kg (in birr) for maize, teff, wheat and barley were 2.455, 5.032,3.505 and 3.714 with standard deviation of 1.259, 2.479, 1.561 and 1.731, respectively. Literature suggested that the distribution of agricultural price returns exhibit the following features: skewness, leptokurtosis and volatility. Thus, the evidence for return series in the Table 1 indicates positive skewness and longer tails than does the normal distribution for monthly price return series as the coefficients of skewness 0.500, 1.702, 2.330 and 0.488 were indicates that the series typically have asymmetric distributions skewed to the right. Also the excess kurtosis coefficients 5.207, 9.996, 14.504 and 16.923 were indicates that the distribution of monthly domestic price return series for maize, barley, teff and wheat, respectively possess leptokurtic characteristic. Moreover, the implication of non-normality is supported by the Jarque-Bera (JB) test statistic which points out that the null hypothesis of normal distribution is rejected at 5% level of significance for all monthly return series since its respective p-values for all return series are less than 5% level of significance. Hence, the price returns appropriately contain financial and agricultural time series characteristics such as, long tails and leptokurtosis.

From Figure 1, the values on the Y-axis are domestic price per kg for cereal crops and the values on the X-axis are years in the sample period from September 2003 to February 2011 GC. Thus, from figure above it can be observed that monthly domestic price per kg for all cereals under study show an increasing trend over the study period from September 2003 to February 2011 GC. In particular, high increase of domestic price for cereals is observed in the year 2008 GC in the country. When we compare domestic price for cereals, maize and teff crops had lower and higher price over the whole study period, respectively.

3.2. Unit Root Test for Non-Stationarity

As many literatures indicated, most of the time series data possesses non-stationarity property or unit root problem. Thus, in order to check for non-stationarity of monthly domestic price series and its returns for crops under study, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests was used and test results are presented below.

Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) Unit Root Test

Null hypothesis: An Average Monthly Domestic Prices and its Returns have a unit root at Level.

Table 2. *ADF and PP Unit Root Test at Level for Average Monthly Domestic Prices.*

Crop	ADF test Statistic	Critical value at 5% sign. Level	P-values
Maize	-2.522880	-3.461686	0.3167
Wheat	-2.495562	-3.461094	0.3297
Teff	-1.824970	-3.461686	0.6843
Barley	-2.477061	-3.461686	0.3386
	PP test Statistic	Critical value at 5% sign. Level	P-values
Maize	-1.630690	-2.894332	0.4628
Wheat	-2.488554	-3.461094	0.3331
Teff	-1.706209	-3.461094	0.7405
Barley	-2.041335	-3.461094	0.5707

One-sided p-values (MacKinnon, 1996)

Table 2 displays ADF and PP unit root test for average monthly domestic prices for the crops under study. Empirical test results from Table 2 reveals that all the price series in levels (before it was transformed in to return series), for four cereal crops under study appeared as non-stationary. This is because of their corresponding p-values from both ADF and PP test statistic were greater than 5% level of significance to test null hypothesis of non-stationarity was failed to reject. Thus, there is no evidence to reject null hypothesis of non-stationarity at 5% level of significance. However, all monthly domestic price appeared stationary after first difference of logarithmic transformation in to return series for all the crops under study which were required for further analysis.

3.3. Mean Equation Specification to Test for ARCH Effects

Based on equation (1), twenty five combinations of (AR 0-4) by (MA 0-4) were computed for each price return series of cereal crop under study over the study period. The optimal lag length was selected based on SBIC provided that no serial autocorrelation in the residuals from specified mean model. Therefore, mean equation for monthly domestic price return series for maize, wheat, teff and barley crops were ARIMA(2,0,3), ARIMA(1,0,3), ARIMA(0,0,3) and ARIMA(2,0,3), respectively, selected among twenty five combinations and this results were verified through automatic lag selection procedure called tramo/seat which was adopted in Eviews software for monthly and quarterly time series data. To verify the adequacy of selected mean equation, the Ljung-Box Q (k)-test was performed to check for absence of autocorrelation in the residuals for correct specification as the residuals from a model that fits the data well should be uncorrelated [21]. Then, the test result showed that the autocorrelations are statistically insignificant at 5% level of significance for first 48 lags from the selected mean model as p-values from respective lags are greater than 5% significance level. Therefore, the result of no serial autocorrelation under the Ljung-Box Q (k)-test, using the selected terms for the mean equation, indicates that mean model is correctly specified to proceed with the estimation of the conditional variance for the errors using GARCH family models after testing for presence of ARCH effects.

3.4. Test for the Presence of ARCH Effects

To proceed with volatility modelling through financial time series econometric models for those monthly domestic price return series for selected cereal crops under study, ARCH effects (whether or not volatility varies over time) in the residuals from selected ARIMA models was tested using the squared residuals to fit ARCH equation in (6). As ARCH effect is commonly found in many financial time series data [12] and tested through squared residuals of the series from selected mean equation [14]. When fitting ARCH equations, Engle-LM and F-tests were used to test the null hypothesis of no ARCH effect in the residuals from mean equation in steady of testing individual lagged squared residual coefficients. Therefore, the summary results of ARCH effect test using chi-square and F-test statistic with respective time lags q=3, 6, 9 from equation (6) for each selected mean equations are depicted in Table 3.

Table 3. *Summary Results for ARCH Effect Test.*

Crop	chi-square statistic (q)	P-values	F-statistic	P-values	SBIC
Maize (ARCH3)	15.44091	0.0015	6.005878	0.0010	-9.858931
Wheat (ARCH3)	1.382428	0.7097	0.446384	0.7205	-8.202408
Teff (ARCH3)	24.40392	0.0000	10.82927	0.0000	-11.21065
Barley (ARCH3)	4.881744	0.1807	1.645383	0.1855	-11.83948
Maize (ARCH6)	16.06259	0.0134	3.050711	0.0101	-9.675711
Wheat (ARCH6)	1.553980	0.9558	0.241463	0.9613	-8.003212
Teff (ARCH6)	28.28242	0.0001	6.547145	0.0000	-11.09347
Barley (ARCH6)	6.608270	0.3586	1.095579	0.3731	-11.66338
Maize (ARCH9)	17.17212	0.0461	2.132985	0.0382	-9.489777
Wheat (ARCH9)	1.606418	0.9963	0.159133	0.9972	-7.793323
Teff (ARCH9)	27.84097	0.0010	4.151551	0.0003	-10.89771
Barley (ARCH9)	8.797570	0.4562	0.960523	0.4801	-11.48774

From Table 3, ARCH order for lagged square residuals are selected to be three for all crops under study since SBIC is minimized for order three. The test for null hypothesis of no ARCH effects using Engle LM test having chi-square test statistic and F-test statistic confirmed the presence of ARCH (3) effects in the residuals from mean equations for maize and teff crops monthly domestic price returns. This was because of p-values for both test statistic (0.0015 and 0.0010) and (0.0000 and 0.0000) were less than 5% level of significance indicating that there is no evidence to accept null hypothesis of no ARCH effect at 5% level of significance, respectively. The confirmation of the presence of ARCH effect indicates that the volatility in the average monthly domestic price of these crops is time varying and appropriateness of employing GARCH family models.

However, no similar evidence was found for the domestic price series of wheat and barley crops as their respective p-values for both test statistic (0.7097and 0.7205) and (0.1807 and 0.1855) were greater than 5% level of significance. Therefore, there is no evidence to reject null hypothesis of no ARCH effect at 5% level of significance. Measure of volatility in the monthly domestic prices of wheat and barley were taken to be variance of ARIMA models which were selected as mean equation for both crops. Thus, volatility of domestic price for wheat and barley crops were 0.00112 and 0.0004, respectively using variance as volatility measure.

3.5. Optimal Order Selection and Parameter Estimation of GARCH Family Model

Once the ARCH effects are determined, and then the optimal lag specification for a GARCH family models were determined prior to the construction of the final model to investigate the determinants of domestic price volatility, Even though there is consensus that GARCH(1,1) family model is the most convenient specification in the financial literature [13, 17] to fit data with parsimonious model. As a result, the GARCH(1,1) family model is compared to various higher-order models from 1,2,3,4 or four months relationship of volatilities, since GARCH family model was used for short-term forecasting based on AIC and SBIC. After testing for different orders of P and Q, it was found that EGARCH(1,1) for domestic price volatility of maize crop under specified error distributions and EGARCH(1,3) under normal and student-t distributional assumptions for residuals and EGARCH(2,3) under GED for residual for domestic price volatility of teff crop were selected to be best model to describe the data as they possess minimum SBIC. Then, the summary results for selected lag order based on SBIC for the volatility models under different innovations (errors) assumptions are displayed in Table 4 below.

Table 4. *Optimal lag Selected Based on SBIC under Different Distributional Assumptions of Residuals for Maize and Teff Crops.*

Model for Maize Crop	Error distribution	SBIC	Asymmetric term at 5% Sign. level
ARIMA(2,0,3)-EGARCH(1,1)	Normal	-4.290392	not significant
ARIMA(2,0,3)-EGARCH(1,1)	Student-t	-4.425728	Significant
ARIMA(2,0,3)-EGARCH(1,1)	GED	-4.276507	Significant
Model for Teff Crop			
ARIMA(0,0,3)-EGARCH(1,3)	Normal	-5.291670	significant
ARIMA(0,0,3)-EGARCH(1,3)	Student-t	-5.491176	Significant
ARIMA(0,0,3)-EGARCH(2,3)	GED	-5.449244	Significant

From Table 4 shows optimal lag specification for EGARCH(P, Q) models and result revealed that asymmetric terms are statistically significant at 5% level of significance for all selected models under specified error distributions except monthly domestic price return series under the assumption of normal distribution for residuals. This indicates that asymmetric GARCH class models are appropriate to assess the determinants of domestic price volatility for maize and teff crops. Moreover, to select appropriate error distribution for selected asymmetric GARCH class models assuming normal, unrestricted Student's t and GED distributions for the error terms from mean equation, the three error statistics: MAE, RMSE and MAPE was applied to evaluate the forecast ability of models using in-sample forecast. Thus, empirical result showed that EGARCH(1,1) and EGARCH(2,3) model with GED for residuals performs best than distributional assumptions for residuals under student-t and normal since in all cases RMSE, MAE and MAPE of EGARCH(1,1) and EGARCH(2,3) for monthly domestic price returns of maize and teff, respectively formulates the model with the smallest measure of forecast error. Finally, analysis was done to identify the determinants of monthly domestic price volatility and as summary of results for estimated parameters and their corresponding p-values of test statistics are presented in Table 5.

Table 5. *Maximum Likelihood Parameter Estimates of the Volatility Models for Selected Orders with the Incorporated Exogenous Variables.*

Variable	Maize		Teff	
	Mean	Variance	Mean	Variance
Constant		-6.349130*[0.0018]		-5.406499*[0.0189]
AR(1)	0.198603[0.1694]			
AR(2)	0.066021[0.6054]			
MA(1)	0.484729*[0.0000]		0.102247[0.0696]	
MA(2)	-0.241499[0.1298]		-0.124394*[0.0017]	
MA(3)	-0.42602*[0.0000]		0.313282*[0.0000]	
ARCH(-1)		1.875444*[0.0001]		1.346641*[0.0000]
ARCH(-2)				0.035205[0.9249]
Asymmetric(-1)		-0.36732*[0.0316]		1.143767*[0.0000]
Asymmetric (-2)				-0.410221[0.1829]
EGARCH(-1)		0.440357*[0.0015]		0.280984[0.0512]
EGARCH(-2)				0.513875*[0.0000]
EGARCH(-3)				-0.360074*[0.0230]
General inflation rate		0.027253[0.2706]		0.004630[0.8971]
Inflation rate food items		-0.012349[0.4020]		0.008332[0.8252]
Inflation rate non-food items		0.075921*[0.0002]		0.104767*[0.0015]
Import price for maize		0.843562*[0.0000]		NA
Fuel oil price		0.000228*[0.0004]		0.000453*[0.0027]
Exchange rate		1.828733*[0.0027]		1.169975*[0.0093]
Saving interest rate		-0.317928[0.4429]		-0.004122[0.9886]
October		0.931095[0.3187]		-2.56097*[0.0404]
November		2.266032*[0.0137]		0.073476[0.9533]
December		1.624323[0.1179]		2.655653*[0.0027]
January		-0.699863[0.4505]		-1.102994[0.4478]
February		1.704795*[0.0240]		-1.356802[0.3545]
March		2.098190*[0.0264]		-0.282331[0.8141]
April		0.542172[0.5242]		-3.353766[0.0626]
May		2.814432*[0.0090]		2.263063*[0.0002]
June		1.582045* [0.0437]		-2.089246[0.1255]
July		0.970500[0.3214]		-2.905949*[0.0418]
August		1.546001[0.0536]		-0.849565[0.3992]

Note that: In Table 5, coefficients marked by * are statistically significant at 5% level of significance and values inside the bracket "[ ]" denotes p-values corresponding to test statistic.

Table 5 displays empirical results of parameter estimates of ARIMA(2,0,3)-EGARCH(1,1) and ARIMA(0,0,3)-EGARCH(2,3) models for domestic price volatility of maize and teff crops, respectively. The parameters of interest in the variance equations from Table 5 are the coefficients on explanatory variables, past shocks and volatility from monthly domestic price return series.

Thus, at the national level a positive and statistically significant coefficient is evident for exchange rate (dollar-birr). This is because of its corresponding p-value of 0.0027 and 0.0093 to test null hypothesis of coefficient for exchange rate is zero in the variance equation of domestic price for maize and teff crops, respectively were less than 5% level of significance. Thus, there is no evidence to accept null hypothesis at 5% level of significance and the link between exchange rate and increase in domestic price volatility at current month was likely to be through the impact that exchange rate affect the purchasing power of domestic money. This result was consistent with findings by Loening et al. (2009), Gilbert (1989), Chambers (1984) [22-24]. Therefore, a unit increase in the exchange rate of the U.S. dollar's in to birr serves to increases domestic price volatility for maize and teff crops by 1.83 and 1.17 units, respectively. Likewise, coefficients of fuel oil price is positive and statistically significant at 5% level of significance, indicating that the change in fuel oil price was also determinant of current month volatility of domestic price for maize and teff crops in the country over the study period. The link between fuel oil prices and maize and teff crops domestic price volatility is likely to be through the fact that a fluctuation on the fuel oil prices affects the costs of transportation. This finding was consistent with findings by Swaray (2007) and Baffes (2007) [25, 26] in the domestic price volatility for agricultural crops. Therefore, a unit increase in the fuel oil price serves to increase current month domestic price volatility for maize and teff crops by 0.000228 and 0.000453 units, respectively.

Past volatility of domestic price for maize and teff crops was statistically significant predictor of current month domestic price volatility over the study period at 5% level of significance. This is because of p-values 0.0015 corresponding to EGARCH(-1) term in the variance equation for maize crop and 0.0000 and 0.0230 corresponding to EGARCH(-2) and EGARCH(-3) in the variance equation, respectively, for domestic prices of teff crop, respectively were less than 5% level of significance, indicating that fail to accept null hypothesis of coefficients are zero. Therefore, current month volatility of domestic price for maize is affected by its previous one month's lagged volatility and a unit increase of its previous variance for domestic price causes current volatility to increase by 0.44035 units. Whereas domestic price volatility for teff crop at current month affected by its previous two and three month's lagged volatility. Thus, a unit increase of the two month's lagged volatility causes domestic price volatility to increase by 0.513875 units. Likewise, one month's lagged shock (ARCH (-1) term) in the variance equation for the domestic price of maize and teff crops also had statistically significant effects on the current month volatility at 5% level of significance as corresponding p-values 0.0001 and 0.0000 were less than 5% level of significance to test null hypothesis of coefficients are zero fail to accept, respectively.

The coefficient of import price for maize in the variance equation was positive and statistically significant at 5% level of significance since its corresponding p-value was less than 5% level of significance to test null hypothesis of coefficient for export price is zero was rejected at 5% level of significance. Thus, there is transmission of import price for maize to the domestic price volatility in the country over the study period. This result also inline findings by Ahmed (2008) that import price was one of the determinants of domestic price volatility [27], but not in line findings by Rashid et al (2007) [2]. Therefore, a unit increase in the import price serves to increases domestic price volatility at current month for maize crop by 0.84 units. Among the seasonal dummies added to the EGARCH model, price during November, February, March, May and June months all had positive coefficients and statistically significant at 5% level of significance, indicating that domestic prices during those months had increasing effects on the current month variability of domestic price for maize crop. However, price during September month had negative coefficient as reflected through constant parameter in variance equation for maize crop and statistically significant at 5% level of significance. As p-value of 0.0018 was less than 5% level of significance, indicating that null hypothesis of constant parameter is zero was rejected. The link between price during those months and domestic price volatility increase was likely to be related with seasonal pattern for maize crop that causes price to go up and down as reported by Jordaan et al. (2007) that maize price characterized by lower prices at harvest and go up gradual [7]. Similarly for teff crops, among the seasonal dummies added to the EGARCH model, price during September, October, May and July months had negative coefficients, but price during December had positive coefficient and statistically significant at 5% level of significance, implying that domestic price during September, October, May and July months had decreasing effect, but price during December month's had increasing effects to the current month variability of domestic price.

Moreover, one of the important features of EGARCH models is that the model can fit the data that responds asymmetrically. Table 5 reports the results of testing for asymmetric effects in the model and then the test results signify that domestic prices volatility for maize crop responds asymmetrically (asymmetric in the news) as the coefficient on asymmetric term(-1) in the variance equation for maize crop was negative and statistically significant at 5% significance level. Thus, bad news (an unexpected increase in the domestic prices) has less impact on the volatility of domestic prices than good news (an unexpected decrease of domestic price). However, in the case of domestic price volatility for teff crop, coefficient of asymmetric term was positive and statistically significant at 5% level of significance as p-value of 0.0000 corresponding to coefficient of asymmetric shocks (asymmetric term (-1)) was less than 5% level of significance. Thus, bad news (an unexpected increase of domestic price) had larger impact on the domestic price volatility than good news (unexpected decrease in the domestic prices). This result was consistent with finding by Greene (2002). The significance of asymmetric term in the volatility model also suggests that the EGARCH model could be a favoring model than a symmetric GARCH model to fit data with asymmetric effects.

In this study, from candidate explanatory variables general inflation rate and inflation rate from food items had no statistically significant impact on the current volatility of domestic price at 5% level of significance. This is because of p-values corresponding to both variables (0.2706 and 0.4020) and (0.8971 and 0.8252) in the variance equation for maize and teff crop, respectively were greater than 5% level of significance to test null hypothesis of coefficients are zero fail to reject at 5% level of significance. This result was not in line findings by Chambers (1984). The link between insignificance of general inflation and inflation rate from food items was likely to be the declining of general inflation and inflation rate from food item since 2009 GC. Saving interest rate also had no statistically significant impact on the volatility of domestic price for maize and teff crops at 5% significance level as p-values of 0.4429 and 0.9886 corresponding to saving interest rate were greater than 5% level of significance in the variance equation for maize and teff crops, respectively. Therefore, there is no evidence to reject null hypothesis of coefficient for saving interest rate was zero at 5% level of significance. The link between saving interest rate and domestic price for maize and teff crops was likely to be due to less fluctuation nature of saving interest rate from month to month and agricultural investors in the country.

3.6. Checking Adequacy of Fitted Model

Diagnostic tests were performed to establish goodness of fit and appropriateness of the fitted model. First, it was examined whether the standardized residuals and squared standardized residuals of the estimated models were free from serial autocorrelation. Then, the Ljung-Box Q (k) test indicates that autocorrelations in the standardized residuals are zero for the first 22 lags as their respective p-values for all first 22 lags are greater than 5% level of significance to test null hypothesis of serial autocorrelation for the first 22 lags are zero was fail to reject. Thus, the result of no autocorrelation in the standardized residuals suggests that residuals are uncorrelated (white noise). The test for the remaining ARCH effect at time lag three of squared standardized residuals showed that no remaining ARCH effect in the residual as p-values from Engle-LM chi-square and F-test statistic were greater than 5% level of significance. This indicates that there is no evidence to reject null hypothesis of no ARCH effect at 5% level of significance for volatility models of maize and teff crops. This result was consistent as documented by Siourounis (2002) that the best fit model should not have autocorrelation in standardized residuals sequence and any remaining ARCH effects for GARCH family model [28]. Furthermore, the coefficient estimation for asymmetric term was statistically significant at 5% significance level, suggesting the adoption of the asymmetric GARCH than symmetric GARCH model. Therefore, EGARCH(1,1) and EGARCH(2,3) assuming a GED distribution was selected as the final specification to investigate the determinant of domestic price volatility for maize and teff crops, respectively. These result was consistent with finding by Asteriou and Hall (2007) that the EGARCH model has several theoretically superiority than a GARCH model in which it allows an investigation of asymmetries and the conditional variance is always positive [12].

3.7. In-sample Forecast of Domestic Price Volatility by EGARCH Models

Incorporating the most adequate choice of the volatility models for domestic price of maize and teff crops, the volatility of domestic prices using variance as volatility measures was forecasted using the in-sample observations under static forecasting as results are presented in Figures below.

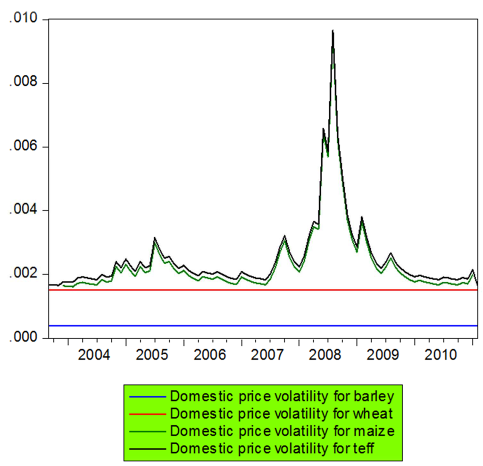

Figure 2. *In-Sample Forecast of Domestic Price Volatility for four Cereal Crops.*

From above Figure 2, it can be observed that domestic price volatility for barley and wheat remains constant over time, whereas in the case of maize and teff crops volatility varies from month to month. When we compare volatility among four cereal crops, domestic price for maize and teff had higher volatile price than volatility of domestic price for barley and wheat which were constant over time and highest domestic price volatility for both crops observed in the year 2011 GC, this may be likely to be due to high inflation from food items during that year in the country.

4. Conclusions

From empirical results, it can be concluded that the volatility in the domestic prices of wheat and barley crops have been found to constant over time, but the volatility in the domestic prices of maize and teff crops vary over time from month to month, suggesting the use of the GARCH approach. Asymmetric EGARCH model was found to be better than GARCH for assessing the determinants and forecasting domestic price volatility of maize and teff crops. Thus, ARIMA(2,0,3)-EGARCH(1,1) and ARIMA(0,0,3)-EGARCH(2,3) models were found to be the best models to fit the data on the domestic price return series for maize and teff crops, respectively, over the study period. There was evidence to conclude that the variance of the domestic price at current month influenced by its previous one month's lagged volatility and by its previous two month's lagged volatility for maize and teff crops, respectively.

In monthly series, there is convincing evidence from the study that many of the candidate variables had an impact on the domestic price volatility. In particularly, it can be concluded that fuel oil price had a positive impact on domestic price volatility. Likewise, there is evidence to conclude that appreciation of exchange rate had positive influence on domestic price volatility and also inflation rate from non-food items had positive impact on monthly domestic price volatility for maize and teff crops over the study period in the country.

Moreover, price of import for the maize crop had statistically significant effect on its domestic price volatility. However, there is no evidence to conclude that saving interest rate, general inflation rate and inflation rate from food items had influence on the monthly domestic price volatility for the selected cereal crops over the study period.

Availability of Data and Materials

The dataset supporting conclusions of this article is available by contacting the author.

Competing Interests

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Author Contribution

The author designed the study, analyzed the data, drafted the manuscript, and critically reviewed the article.

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