Horn of Africa Journal of Business and Economics (HAJBE), 2023, 6(2), PP: 150-171
ISSN: 2617-0078 (Print), 2617-0086 (Online)

Agricultural Commodity Price Volatility Models and Prediction Performance of GARCH Family Models

Elias Dessie[1], Tesfahun Brhane[1*], Abdu Mohammed[1], AssayeWalelign[1]

[1]Department of Mathematics, Bahir Dar University, Bahir Dar, Ethiopia,

[*]Corresponding author Tel.: +251-911-89-13-26 E-mail: tesfahunb2002@gmail.com.

Abstract

Agricultural product price volatility leads to future retail price uncertainties for producers and consumers. This paper examines modeling and forecasting price volatility of four widely produced, highly household consumed and traded agricultural commodities, namely Teff, Wheat, Barley and Maize at Debre Markos of Ethiopia using time series retail price data from September 2010-August 2022. We compare the performance of GARCH family models against different error distributions for each price return and AIC, BIC,log likelihood and significant p-value were applied to identify the best fit GARCH family models and the results showed thatARCH(1,1)GED for Teff and Barley and EGARCH(1,1)STD for Wheat and Maize are appropriate models. Moreover, based on the sign and magnitude of the parameters (coefficients of residuals) there is asymmetry in the news, in which bad news has larger effect on volatility than good news for two cereals price returns. Furthermore, the forecasting performance of the models are evaluated using the root mean square error and mean absolute errors and four weeks ahead prediction performance in MAE are 0.0082, 0.0066, 0.0065 and 0.0144 for Teff, Wheat, Barley and Maize return models respectively which reveals that they perform well. They can be concluded that GARCH(1,1)GED for Teff and Barley and EGARCH(1,1)STD for Wheat and Maize are more accurate price return volatility forecast for risk management. Therefore, consumers and producers are recommended to use these models for future price predictions.

Key words: *Heteroscedasticity, price volatility, log-return, GARCH family*

1. Introduction

Volatility is the variability of the prices around their central value i.e., the tendency for individual price observations to vary far from its mean value. Thus, volatility is often defined as high deviations from a global tendency (Huchet-Bourdon, 2011) Volatility has three usual characteristics called stylized facts. The first one is volatility clustering that refers to the observation that large changes in price tend to be followed by large changes and small changes tend to be followed by small changes. (Cont, 2007; Niu, 2013; Tseng, 2012). The second is leverage effect which refers to the observed tendency of an asset's volatility to be negatively correlated with the asset's returns (AL-Najjar, 2016; Wang, 2004; Yu, 2005). The last stylized fact is kurtosis which is a statistical measure used to describe the degree of score clusters in the tail or peak of a frequency distribution.

Agricultural commodity price volatility is one of the major problems in the world, especially for those countries whose dominant economy depends on agricultural products. Policymakers as well as all the participants along the food supply chain have an interest in the question of cereal price volatility and need to better understand the expected future price variation. Agricultural commodity producers and consumers, employ them to protect themselves against price movements and volatility (Staugaitis & Vaznonis, B, 2022) . For example, farmers in some countries face a number of risks which is related to markets and price policies (Huchet-Bourdon, 2011).

Future market information in prices of cereal crops may have important implications for resource allocation as well as consumer and producer welfare. However, fluctuation in price has a negative impact at the macroeconomic level on growth and poverty reduction in poor countries (Aizenmen & Marion,N.P., 1993; Kose, Prasad,E.S., & Terrones,M.E., 2006). (Santeramo, 2018) asserted that the prices of the most important cereals, such as wheat and maize, dramatically increased during the period from 2003 to 2008, before tumbling down during the global financial crisis, and the food crisis of 2007 and 2008 produced the largest price changes in agricultural commodity history. (Haji, Gelaw,F., Bekele,W., & Tesfaye,G., 2011) affirmed that there was rapid growth of price in the main food crops such as maize, wheat, and edible oil including rice. Specifically, in Ethiopia, since the end of 2005 food prices have shown unexpected increments. For instance, in 2006, 2007, and 2008, successive increments have been recorded as 15.1%, 28 %, and 57.4 %, respectively (Dinku, 2021) ; the problem is not the increments but the variation of increments which indicates that agricultural commodity price in Ethiopia was unstable.

Food price inflation in Ethiopia has shown highest, level starting from third quarter of 2010 up to second quarter of 2012. The annual food inflation rate jumps from single digit to double digit (Hailegebrial., 2015). The trend of food inflation showed the highest growth rate from February 2011 and reached its peak of 51.7% in October 2011. The food inflation level shows some increment trend since November 2014 till May 2015 it was 10.2% (Hailegebrial., 2015). Ethiopia's food inflation rate increases persistently high, reaching 41.9 % in February 2022 that shows food price are volatile (Global Agricultural information Network, GAIN). Thus, modeling and predicting the price volatility of cereal crops is the demanding issue and econometric models play a prominent role in quantifying and forecasting price volatility.

Autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models are particularly valuable in modeling time series that exhibit stylized properties of financial time series such as fat-tailless, volatility clustering (Alentorn, 2004; Birau, Trivedi,J, & Antonescu, 2015; Frimpong & Oteng-Abayie, 2006; Niyitegka & Tewar,D, 2013; Yip, Brooks,R, & Nguyen, 2020). Several GARCH extension models have been made which proved to be useful in modeling and analyzing financial time series. For example, (Nelson & Cao,C.Q., 1992) proposes the EGARCH (exponential GARCH) specification, modeling the leverage effect. Threshold GARCH that was proposed by (Zakoian, 1994) is the other pioneering one that allows for asymmetric shocks to volatility in which positive and negative shocks of equal size to have different impacts on volatility.

As per the knowledge of authors, no research has been conducted on weekly retail price volatility of four main cereals in Ethiopia using GARCH family models in different error distributions; thus the aim of this study is modeling and forecasting the price volatility of Teff, Wheat, Barley and Maize based on the performance of generalized autoregressive conditional heteroscedasticity(GARCH) family models in normal, t and generalized error distributions from September 2010 to August 2022 in the study area for risk reduction and market stability.

2. Data description and Methods

2.1 Data source

The data used for modeling price volatility of Teff, Wheat, Maize and Barely is taken from the Ethiopian Statistical Agency (ESA) record as the weekly retail price of Debre Markos town which is found in the most productive zone of these cereal crops in Ethiopia from September 2010 to August 2022. The reason for selecting these cereals is: Their dominant consumption in Ethiopia, their agricultural economic value and worldwide demand of these cereals.

2.2. GARCH family Models

2.2.1 Autoregressive Conditional Heteroscedasticity (ARCH model)

An ARCH model is one of the classical models in time series data for analyzing and forecasting volatility. It is originally proposed by (Engle, Granger,C.W, & Kraft,D., 1984) ,where the prediction accuracy of conditional variance depends on the previous historical shocks and this is expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 \qquad (1)$$

Where $\varepsilon_t = \sigma_t e_t$, $e_t \sim i.i.d(0, 1)$, $\alpha_0 > 0$, $\alpha_i > 0$, σ_t^2 is the conditional variance, ε_t is the innovation of an asset, σ_t is the volatility of the series at time t and, e_t is a white-noise.

$$\sum_{i=1}^{q} \alpha_i < 1 \qquad (2)$$

This sum indicates the measure of volatility clustering depend on the closer to unity; But, it often requires many parameters and a high order of the ARCH term q to capture the dynamic behavior of conditional variance that leads to over predict the volatility and fails to capture the leverage effect (Schmidt, 2021).

2.2.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.

In GARCH the current conditional variance is expressed not only the previous shocks but also the previous conditional variance and mathematically expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \qquad (3)$$

$\alpha_0 > 0, \alpha_i > 0, q > 0, p \geq 0$

When p = 0, equation (3) reduced to equation (1) of the ARCH. When p =1 and q =1 it is called GARCH (1, 1) and the conditional volatility of equation (3)becomes:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{4}$$

The limitation of GARCH is that it still fails to capture the leverage effect due to its symmetric distribution. This model is proposed by (Bollerslev, Engle,R.F, & Nelson,D.B, 1994).

2.2.3. Exponential Generalized Autoregressive Conditional Heteroscedasticity(EGARCH)

This model is proposed by (Nelson ,1991) to take into account the leverage effects of price fluctuation on conditional variance. This means that a negative shock (bad news) can have greater impact on volatility than a positive shock (good news) of the same magnitude. (Koutmos & Booth,G.G, 1995). The conditional variance in EGARCH is given as:

$$log\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{r}\frac{\gamma_i\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \tag{5}$$

Where p, q and r are the ARCH, GARCH and asymmetric orders respectively. As log of the variance σ_t^2 makes the leverage effect exponential. When γ_1 = 0, regardless of the sign of ε_{t-i} the model is symmetric; thus, no leverage effect. When ε_{t-1} is positive (good news) the total effect of ε_{t-1} is $(1+\gamma_1)\,|\,\varepsilon_{t-1}\,|$ on the contrary, ε_{t-1} is negative (bad news) the total effect of ε_{t-1} is $(1-\gamma_1)\,|\,\varepsilon_{t-1}\,|$ for p = q = r=1. Bad news can have larger impact on volatility, and the value of γ_1 would be expected to be negative. When $\sum_{j=1}^{p}\beta_j$<1 it indicates stationary and the sum is the persistence measure. Another advantage of the EGARCH model over the basic GARCH model is that the conditional variance σ_t^2 is guaranteed to be positive regardless of the values of the coefficients in the above equation (5) because the $log\sigma_t^2$ instead of σ_t^2 itself is modeled (Atoi, 2014; Zivot & Wang,G, 2006) .

2.2.4. Threshold Generalized Autoregressive Conditional Heteroskedastic (TGARCH)

The other alternative for modeling the conditional variance with leverage effect is the threshold GARCH model which was proposed by (Zakoian, 1994) that allows asymmetric shocks to volatility with positive and negative shocks of equal size to have different impacts on volatility.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_i\, \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 I) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (6)$$

Where $f(x) = \begin{cases} 1, & if \ \ \varepsilon_{t-i} < 0 \\ 0, & otherwise \end{cases}$

In this model if γ is zero it become GARCH, if γ is negative then bad news decrease volatility which is not likely and it is expected to be positive and good news decrease volatility.

2.2.5. An asymmetric power ARCH model

Another extension of GARCH model is the power ARCH expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, (|\varepsilon_{t-i}| - \varepsilon_{t-i}\gamma_)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^{\delta}$$

(7)

Where γ is the asymmetric parameter and delta is the parameter of the power term.

2.3. Distributional Assumptions

In the analysis three conditional error distribution functions for the price returns are considered; Normal (Gaussian)(ND), student's t(STD) and generalized error distribution (GED). And the mathematical expressions are:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (8)$$

for normal distribution

$$f(x) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{(\nu-2)\pi}} (1 + \frac{x^2}{\nu-2})^{-\frac{\nu+1}{2}} \quad (9)$$

Where Γ is the usual gamma function and $\nu > 2$ is the number of degree of freedom for students' t distribution.

For generalized error distribution, we have

$$f(z, \mu, \sigma, \nu) = \frac{\sigma^{-1}\nu e^{\frac{-1}{2}\left|\frac{z-\mu}{\sigma\lambda}\right|^{\nu}}}{\lambda 2^{\left(1+\frac{1}{\nu}\right)} \Gamma(\frac{1}{\nu})} \quad ,1 < z < \infty \quad (10)$$

Where $\nu > 0$ *is* the degree of freedom and $\lambda = \sqrt{2^{\left(\frac{-2}{\nu}\right)}\Gamma\left(\frac{1}{\nu}\right)\Gamma\left(\frac{3}{\nu}\right)}$ is the parameter. If $\nu = 2$, the GED yields the normal distribution. If $\nu < 1$ the density function has thicker tails than the normal density function, If $\nu > 2$ it has thinner tails.

(Kuhe, 2019)

2.4. Forecasting performance measure

We select two forecasting performance measures, the root means square error (RMSE) and the mean absolute error (MAE), to evaluate the predictive performance of our proposed models. RMSE indicates the magnitude of the error in square root of the average square of the predicted and observed values, whereas MAE shows the magnitude of absolute difference average of predicted and observed value. These equations are as follows:

Root mean square error $RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(\widehat{\sigma_t} - \sigma_t)^2}$ (11)

$$MAE = \frac{1}{n}\sum_{n=1}^{n}|\widehat{\sigma_t} - \sigma_t| \quad (12)$$

Where $\widehat{\sigma_t}$ is the forecast volatility, σ_t is the observed volatility value in time period t and n is number of out sample periods.

2.5. Diagnostic checking

For developing GARCH family models: Plot the graphs and check the stationary and volatility cluster or use Augmented Dickey-Fuller (ADF) test and check that existence of unit root to determine stationarity.The distribution of returns in financial time series data is not usually characterized by normality but fat-tails, high peakedness and skewness. The

kurtosis and skewness are defined as:

$$K(R) = E[\frac{(R-\mu)^4}{\sigma 4}] \quad (13)$$

$$S(R) = E[\frac{(R-\mu)^3}{\sigma 3}] \quad (14)$$

where μ and σ are the mean and standard deviation of the return price. When K(R) is greater than three it indicates that the distribution has heavy tail properties. Negative values of S(R) shows skewed to the left and positive value indicates the skewed to the right.

Jarque-Bera test is a normality test based on skewness and kurtosis. The test statistic is defined by:

$$JB = \frac{n}{6}\left(\frac{(K-3)^2}{4} + S^2\right) \qquad (15)$$

The assumption of normality under H0 is rejected when the p-value of JB test is less than the significance level. (normal distribution when it is less than 5%).

The presence of heteroscedasticity in the time series data can be checked using ARCH-LM test. Using the significance of the coefficient of determination(R-squared) and F-statistics), we determine whether the standardized residuals exhibit ARCH effect or not in the time series data

3. Results and Discussion

To understand the price dynamic behavior and the price return of the time series it is necessary to plot the original series and its log return of Teff, Wheat, Barley and Maize price and their log returns. The price dynamics and returns are depicted in the Figure 1 and 2.

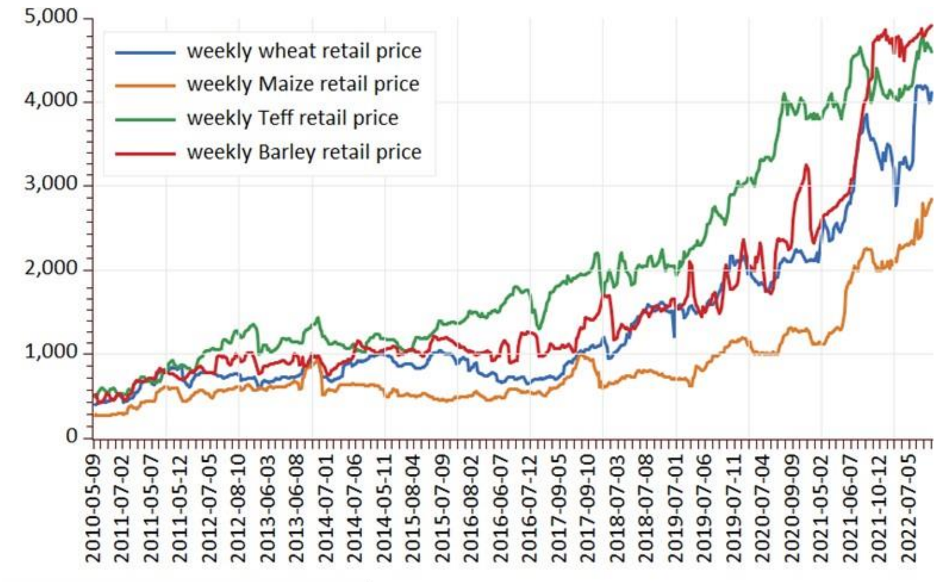

Figure 1: Weekly retail price of crops

For better description of volatility, we use return of retail price at time t and it is calculated as:

$$R_t = \ln(\frac{p_t}{p_{t-1}}) \quad (16)$$

Figure 1, weekly retail price of Teff, Wheat, Barley and Maize in which all of them are non-stationary while the return series of Teff, Wheat, Barley and Maize on Figure 2, shows stationary. However, the plot of the figure is not sufficient but it gives us a clue and we checkby unit root test. Moreover, from Figure 2, the variability of the changes, small changes are followed by small changes and large changes are followed by large changes which shows that the existence of volatility clustering in all of the crops. The results in Table 1, shows that all the weekly return prices are stationary since the magnitude of the t-statistics is greater than the magnitude at 5 % levels; thus, it is mean reverting.

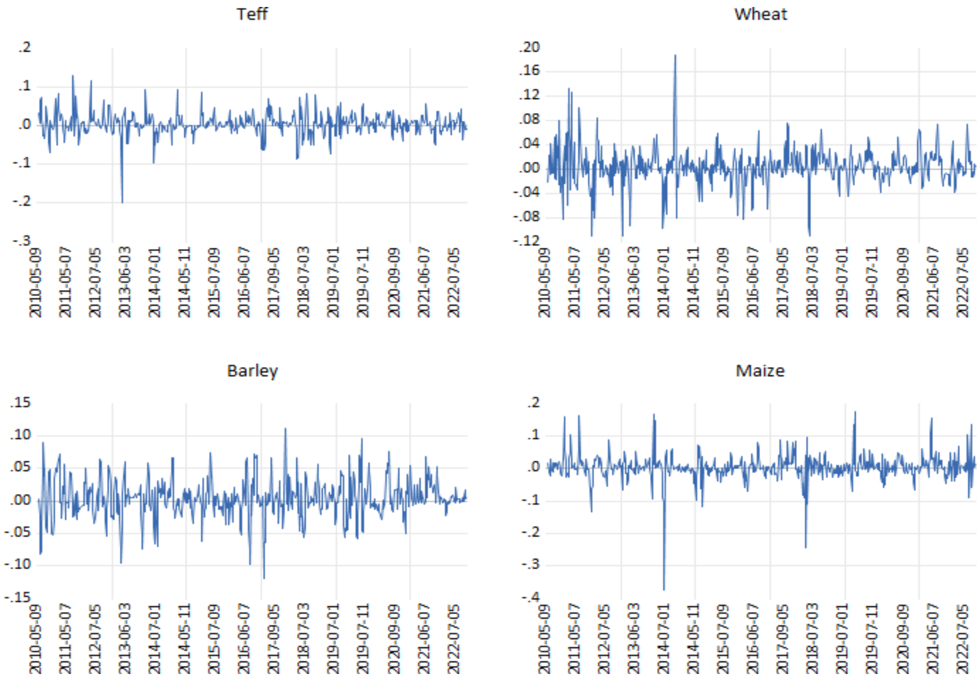

Figure 2: Log price return of crops in the study period

From the descriptive statistics on Table 2 weekly log return price of Teff, Wheat, Barley and Maize the means are 0.0039, 0.0041, 0.0041 and 0.0039 respectively. The maximum values are 0.2346, 0.2257, 0.1730 and 0.1281 for Wheat, Barely, Maize and Teff respectively that indicates high return deviations from the mean. Similarly, the minimum values are -0.3739, -0.2437, -0.2056 and -0.1989 for Maize, Wheat, Barley and Teff respectively which shows high weekly variability of log returns.

Table 1: Unit root tests for Log-return series of selected cereals

		ADF test	critical values		
Variables	t-statistics	1%	5 %	10 %	p-value
Teff	-16.2573	-3.4415	-2.8664	-2.5694	0.0000
Wheat	-19.3078	-3.4415	-2.8664	-2.5694	0.0000
Barely	-13.8412	-3.4415	-2.8664	-2.5694	0.0000
Maize	-12.9560	-3.4415	-2.8664	-2.5694	0.0000

Table 2: Weekly price Log-return statistics of selected cereals

Parameter	Teff	Wheat	Maize	Barley
Mean	0.003895	0.004056	0.004099	0.003915
Median	0.004158	0.004488	0.003752	0.004073
Maximum	0.128121	0.234647	0.173019	0.225738
Minimum	-0.198851	-0.243662	-0.373966	-0.205590
Std.Dev	0.026947	0.034557	0.038920	0.039305
Skewness	-0.461898	-0.840425	-1.438414	-0.185334
Kurtosis	10.72215	16.800029	23.77059	9.744343
Jarque-Bera	1449.119	4630.504	10534.32	1093.065
Probability	0.000000	0.0000000	0.000000	0.000000

The skewness of the normal distribution is 0. However, Table 2 reveals that the skewness of Maize is -1.4384 that is negatively skewed and all the remaining three cereals are also negatively skewed. The kurtosis of Maize, Wheat, Teff and Barely weekly price returns of the series are 23.7706, 16.8000, 10.7222 and 9.7443 respectively that are greater than 3 which reveals leptokurtic. That has fat-tails and high peakedness distributions for each cereal.

The value of Jarque-Bera for each cereal in Table 2, are 1449.119, 4630.504, 10534.32 and 1093.065 Teff-return, Wheat-return, Maize-return and Barely-return series respectively significantly greater than the p-value 0. Therefore, (Tseng, 2012) reject the null hypothesis (normality) and the distributions are not normally distributed.

From Table 3 the LM - statistic of Teff, Wheat, Maize and Barely returns respectively are 24.96, 36.35, 6.85 and 10.05 respectively whereas the p- values are 0.0000, 0.0000, 0.0088 and 0.0015 which are statistically significant. This shows that the null hypothesis (Homoscedasticity) is rejected and reveals the presence of heteroscedasticity (time varying volatility).

Table 3: Heteroscedasticity test of return price for selected cereals

	Teff	Wheat	Maize	Barley
F-statistic	26.0142(0.0000)	38.6794(0.0000)	6.9055(0.0088)	10.1938(0.0015)
Obs*R-squared	24.9677(0.0000)	36.3524(0.0000)	6.8469(0.0089)	10.0501(0.0015)

values in parenthesis are p-values

Therefore, it is better to estimate GARCH family models. To determine the order of GARCH type family models Akaike information criterion (AIC), Schwarz information criterion (SIC) and error distribution are used for each model.

Table 4: Teff-return GARCH extension model candidate

Model	Error distribution	AIC	SIC	Log likelihood	MAE	RMSE.
GARCH(1,1)*	ND	-4.6605	-4.6226	1342.56	0.0166	0.0251
GARCH(1,1)*	STD	-4.9015	-4.8560	1412.73	0.0165	0.0250
GARCH(1,1)*	GED	-4.9002	-4.8547	1412.35	0.0165	0.0250
TGARCH(1,1)*	ND	-4.6576	-4.6121	1342.74	0.0165	0.0250
TGARCG(1,1)	STD	-4.9009	-4.8478	1413.55	0.0165	0.0250
TGARCH(1,1)	GED	-4.8977	-4.8446	1412.64	0.0165	0.0250
EGARCH(1,1)*	ND	-4.6514	-4.6059	1340.96	0.0166	0.0251
EGARCH(1,1)	STD	-4.8932	-4.8401	1411.34	0.0165	0.0250
EGARCH(1,1)	GED	-4.8923	-4.8393	1411.10	0.0165	0.0166
PARCH(1,1)	ND	-4.6588	-4.6057	1344.08	0.0167	0.0251
PARCH(1,1)	STD	-4.9074	-4.8467	1412.14	0.0165	0.0251
PARCH(1,1)	GED	-4.9057	-4.8374	1416.93	0.0165	0.0250

* all parameters are significant (p-value <0.05)

From Table 4 we observed that GARCH(1,1), TGARCH(1,1), EGARCH(1,1) and PARCH(1,1) models under normal distribution(ND), student's t-distribution(STD) and generalized error distribution(GED) assumptions of Teff-return were selected as the candidate models using minimum Akaike information criteria(AIC), minimum Schwarz information criterion(SIC), maximum likelihood with significant p value of parameters(p-value less than 5%) and mean reversion from the sum of coefficients.

Table 5: Computation of $\alpha_0, \alpha_1, \beta_1$ in EViews

Dependent Variable: TEFF_RETURN
Method: ML ARCH - Generalized error distribution (GED) (Marquardt / EViews legacy)
Date: 24/05/23 Time: 14:09
Sample (adjusted): 3 576
Included observations: 574 after adjustments
Convergence achieved after 16 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002664	0.000904	2.945819	0.0032
AR(1)	0.426149	0.033545	12.70383	0.0000
		Variance Equation		
C	0.000204	4.98E-05	4.100770	0.0000
RESID(-1)^2	0.547447	0.167219	3.273827	0.0011
GARCH(-1)	0.252437	0.120569	2.093715	0.0363
GED PARAMETER	0.891026	0.065944	13.51184	0.0000

R-squared	0.132426	Mean dependent var	0.003842
Adjusted R-squared	0.130909	S.D. dependent var	0.026940
S.E. of regression	0.025115	Akaike info criterion	-4.900094
Sum squared resid	0.360803	Schwarz criterion	-4.854596
Log likelihood	1412.327	Hannan-Quinn criter.	-4.882347
Durbin-Watson stat	2.058856		

Thus, based on the minimum information criteria, maximum likelihood and significant coefficients,GARCH (1,1) with GED assumption for Teff-return model is identified as the best performing model among the selected candidate models. The distribution is GED that reveals it isleptokurtic.

The conditional variance equation of Teff-return in GARCH (1, 1) GED is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (17)$$

$$\sigma_t^2 = 0.00020 + 0.54583\varepsilon_{t-1}^2 + 0.25463\sigma_{t-1}^2$$

(18)

From equation (18) above indicates that the volatility of returns is persistent, with the sum of α_1 and β_1 being 0.80046(close to unity). Although the volatility of Teff price return haslong memory, it is still mean reverting. Moreover, stationarity condition of $\alpha_1 + \beta_1 < 1$ is satisfied and it shows that the conditional variance process of Teff log returns series is stable and predictable.

Table 6: Wheat-return GARCH extension model candidate

Model	Error Distribution	AIC	SIC	Log likelihood	MAE	RMSE
GARCH(1,1)*	ND	-4.5236	-4.4856	1303.268	0.01962	0.02884
GARCH(1,1)*	STD	-4.6474	-4.6019	1339.815	0.01934	0.02846
GARCH(1,1)*	GED	-4.6201	-4.5746	1331.99	0.01937	0.02854
TGARCH(1,1)*	ND	-4.5379	-4.4924	1308.402	0.01952	0.02877
TGARCG(1,1)	STD	-4.6520	-4.5988	1342.134	0.01933	0.02848
TGARCH(1,1)*	GED	-4.6287	-4.5756	1335.456	0.01934	0.02854
EGARCH(1,1)*	ND	-4.5334	-4.4879	1307.093	0.01946	0.02866
EGARCH(1,1)*	STD	-4.6489	-4.5958	1341.231	0.01929	0.02833
EGARCH(1,1)*	GED	-4.6267	-4.5736	1334.86	0.01932	0.02848
PARCH(1,1)*	ND	-4.5346	-4.4815	1308.434	0.01980	0.02896
PARCH(1,1)	STD	-4.6510	-4.5904	1342.860	0.01938	0.02856
PARCH(1,1)	GED	-4.6261	-4.5654	1335.78	0.01971	0.02882

* all parameters are significant (p-value <0.05)

Using minimum AIC and SIC and maximum log likelihood having significant parametric values from Table 6 EGARCH (1,1) in STD identified as the best fit model for the conditionalvariance of wheat price return in the study period. The distribution is STD that shows it isleptokurtic (has fat tails). The conditional variance of the wheat price return after EViews computation is presentedas:

$$log\sigma_t^2 = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \frac{\gamma_1 \varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \sigma_{t-1}^2 \quad (19)$$

$$log\sigma_t^2 = -4.88688 + 0.90951 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \frac{-0.21516\varepsilon_{t-1}}{\sigma_{t-1}} + 0.41601\sigma_{t-1}^2 \quad (20)$$

The coefficient of the asymmetric term γ_1 is negative (-0.21516) and statistically significantat 1% level which reveals that negative return (bad news) has larger volatility than positive return (good news). The total effect of bad news on $log\sigma_t^2$ is (1 + 0.2151) | ε_{t-1} | where as the total effect of good news on $log\sigma_t^2$ is

(1-0.2151)ε_{t-1}. The GARCH term β_1 = 0.4160 which shows weak persistence to die out as far from unity

Table 7: Barely-return GARCH family model selection

Model	Error distribution	AIC	SIC	Log likelihood	MAE	RMSE.
GARCH(1,1)*	ND	-4.5404	–4.5029	1308.116	0.01879	0.02610
GARCH(1,1)*	STD	-4.6589	-4.6134	1343.129	0.01875	0.02610
GARCH(1,1)*	GED	-4.6576	-4.6121	1342.747	0.01861	0.02620
TGARCH(1,1)	ND	-4.5382	-4.4927	1308.483	0.01879	0.02610
TGARCH(1,1)	STD	-4.6556	-4.6025	1343.177	0.01875	0.02610
TGARCH(1,1)	GED	-4.6545	-4.6014	1342.841	0.01861	0.02621
EGARCH(1,1)	ND	-4.5446	-4.4991	1310.308	0.01876	0.02609
EGARCH(1,1)	STD	-4.6608	-4.6074	1344.584	0.01873	0.02609
EGARCH(1,1)	GED	-4.6625	-4.6094	1345.149	0.01861	0.02621
PARCH(1,1)	ND	-4.5385	-4.4854	1309.562	0.01877	0.02685
PARCH(1,1)	STD	-4.6612	-4.6006	1345.773	0.01875	0.02609
PARCH(1,1)	GED	-4.6569	-4.5933	1344.559	0.01860	0.02622

* All parameters are significant

In the same way, minimum AIC and SIC and maximum log likelihood having significant parametric values from candidate models of Table 7 many asymmetric models are not significant which at least one of the parameters are not significant (p-value greater than 5%). The conditional variance of Barley is symmetrical to bad news and good news. Although GARCH (1, 1) in STD shows minimum in AIC and BIC but it is not best predictive and not mean reverting as $\alpha + \beta > 1$.

Thus GARCH (1,1) GED is identified as the best model for the conditional variance of Barley price return.

The conditional variance of the Barley price return is presented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (21)$$

$$\sigma_t^2 = 0.00006 + 0.2855\varepsilon_{t-1}^2 + 0.6722\sigma_{t-1}^2 \quad (22)$$

From equation (22) above indicates that the volatility of returns is persistent, with the sum of α_1 and β_1 being 0.9577 which shows that price return has long memory but it is still mean reverting. Moreover, stationarity condition of $\alpha_1 + \beta_1 < 1$ is satisfied and it indicates that the conditional variance process of Barley log returns series is stable and predictable.

Table 8: Maize-return GARCH extension model candidates

Model	Error distribution	AIC	SIC	Log likelihood	MAE	RMSE.
GARCH(1,1)*	ND	-4.1469	-4.1090	1195.16	0.02302	0.03866
GARCH(1,1)*	STD	-4.3588	-4.3133	1256.97	0.02259	0.03821
GARCH(1,1*)	GED	-4.3520	-4.3065	1255.05	0.02250	0.03817
TGARCH(1,1)*	ND	-4.1485	-4.1030	1196.62	0.02299	0.03864
TGARCG(1,1)	STD	-4.3594	-4.3063	1258.16	0.02258	0.03821
TGARCH(1,1)	GED	-4.3531	-4.3000	1256.35	0.02251	0.03819
EGARCH(1,1)*	ND	-4.1498	-4.1043	1196.99	0.02282	0.03844
EGARCH(1,1)*	STD	-4.3745	-4.3214	1262.48	0.02254	0.03820
EGARCH(1,1)*	GED	-4.3635	-4.3104	1259.32	0.02248	0.03819
PARCH(1,1)	ND	-4.1546	-4.1015	1199.34	0.02278	0.03839
PARCH(1,1)*	STD	-4.3733	-4.3127	1262.16	0.02250	0.03820
PARCH(1,1)	GED	-4.3633	-4.3027	1260.29	0.02248	0.03819

*All parameters are significant (p-value < 0.05)

From Table 8 having all significant parameters and the criteria of minimum AIC, SICand maximum likelihood EGARCH (1, 1) with students' t distribution is the best conditional variance model of Maize price return and the equation is

$$log\sigma_t^2 = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \frac{\gamma_1 \varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \sigma_{t-1}^2 \quad (23)$$

$$log\sigma_t^2 = -2.3999 + 0.8798 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \frac{-0.21545\varepsilon_{t-1}}{\sigma_{t-1}} + 0.71129\sigma_{t-1}^2$$
(24)

From equation (24) γ_1 is negatives that shows bad news has high volatility than good news. That is the current volatility depends not only on one lag of the magnitudeof the return but also the sign of one lag log returns of Maize. The result is synonyms with (Musunuru, Yu,M, & Larson,A, 2013). As GARCH term β_1 = 0.71129 its volatility persistence is moderate and it satisfies stationary condition.

The empirical result has emphasized that for these agricultural commodities, a negative return increases conditional variance by more than a positive return of the same magnitude does which is the leverage effect. The pivotal point implies that negative (shocks to) commodity returns ought to be followed by an increase in conditional variance, or at least that negative returns ought to affect subsequent conditional variance more than positive returns do.

Table 9: ARCH-LM test for standardized residuals of fitted models

Teff	F-statistics	1.5448	Prob.F(1,571)	0.2144
	Obs*R-squared	1.5460	Prob.Chi-square(1)	0.2137
Wheat	F-statistics	0.0498	Prob.F(1,571)	0.8235
	Obs*R-squared	0.0499	Prob.Chi-square(1)	0.8231
Barely	F-statistics	0.4210	Prob.F(1,571)	0.5167
	Obs*R-squared	0.4222	Prob.Chi-square(1)	0.5158
Maize	F-statistics	0.7915	Prob.F(1,571)	0.3740

Obs*R-squared	0.7931	Prob.Chi-square(1)	0.3731

From Table 9 standardized residuals of the fitted models did not exhibit any additional ARCHeffect for all series as both the F statistics and observed R squared are not significant. Moreover, by correlogram squared residual diagnostics both the autocorrelation function (ACF) and partial autocorrelation function (PACF) of all the p value are more than 5% (0.05) or lies within the confidence interval which justifies

that there is no serial correlation in the residuals. Therefore, the selected models for price volatility were well justified.

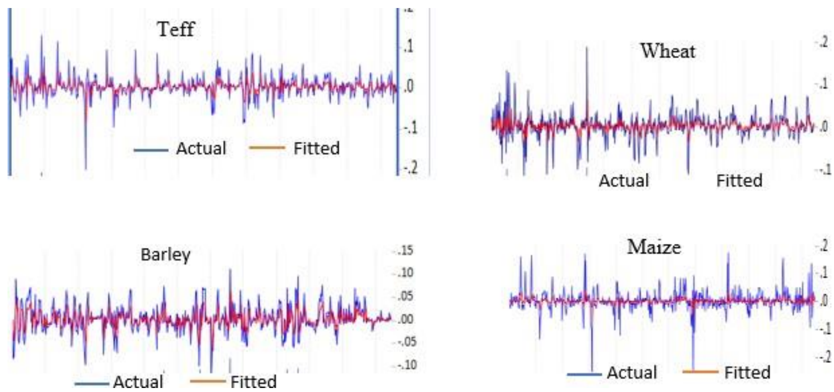

Figure 3: Actual-fitted log return for selected models

Table 10: Actual and fitted Log-return price for last four weeks

Teff Actual	Fitted	Wheat Actual	fitted	Barley Actual	Fitted	Maize Actual	fitted
0.0107	0.0042	-0.0123	0.0001	0.0.0062	-0.0004	0.0111	0.0033
-0.0107	0.0060	-0.0074	-0.0023	0.0175	0.0035	0.0363	0.0037
-0.0021	0.0008	0.0074	-0.0007	0.0030	0.0095	0.0035	0.0081
-0.0086	-0.0092	0.0049	0.0042	0.0040	0.0017	0.0141	0.0021

Table 11: Forecasting performance of better fitted price volatility models

Log-Return	Model	Error dis.	RMSE	MAE
Teff	GARCH (1,1)	GED	0.0101	0.0082
Wheat	EGARCH (1,1)	STD	0.0078	0.0066
Barely	GARCH (1,1)	GED	0.0078	0.0065
Maize	EGARCH (1,1)	STD	0.0180	0.0144

From Table 11 we see that the four weeks ahead forecasting performance of GARCH (1,1) GED for Teff-return, EGARCH (1,1) STD for Wheat-return, GARCH (1,1) GED for Barely-return and EGARCH (1,1) STD for Maize-return in mean absolute error are 0.0082, 0.0066, 0.0065 and 0.0144 respectively and it indicates that they better perform.

4.Conclusions

Price volatility is usually perceived as a measure of risk, researchers have been concerned with modeling the time variation in the volatility of commodities. The aim of this study was to model and forecast price volatility for dominant agricultural commodities in Debre Markos town of Ethiopia. Specifically, it determines better fitted GARCH extension models and forecast price volatility of agricultural commodities. The data for the study is weekly price data of Teff, Wheat, Barley and Maize from September 2010 to August 2022 collected from Ethiopian Statistical Agency (ESA). For better statistical properties the raw data was changed into log-return. After checking the stationarity by unit root test of price log return time series data we have been compared the GARCH family in normal, students' t and generalized error distributions. To identify best fitted model for each cereal, we took GARCH (1,1), TGARCH (1,1), EGARCH (1,1), and PARCH (1,1) as the candidate models andapply Akaike information criterion (AIC), Schwarz information criteria (SIC), Log-likelihood and significance of the parameters for the selection of appropriate model. As result of these GARCH (1,1) GED for Teff and Barley and EGARCH (1,1) STD models for Wheat and Maize returns are selected.

Based on the sign and magnitude of the parameters (coefficients of residuals) there is asymmetry in the news, in which bad news has larger effect on the volatility than good news for Wheat and Maize and this indicates that the negative shocks imply higher future price variance.

We conclude that GARCH and EGARCH models are best fit for modeling and forecasting the price volatility of Teff, Wheat, Barley and Maize that suggests next period information on market price fluctuation for producers, consumers and traders and adjust market decision to reduce the volatility of these cereal price

Bibliography

Aizenmen, J., & Marion,N.P. (1993). Policy uncertainity, persistence and growth. *Review of international Economics*, 145-163.

Alentorn, A. (2004). *Modeling the implied volatility surface :an emperical study for ftse options*. Retrieved from www.theponytail.net/CCFEA.

AL-Najjar. (2016). Modeling and Estimation of volatility using ARCH/GARCH models in Jordan's Stock market. *Asian journal of Finance and Acounting*, 152-167.

Atoi, N. (2014). Testing voltility in Nigeria stock market Using GARCH models. *CBN Journal of Applied Statistics(JAS)*, 4.

Birau, R., Trivedi,J, & Antonescu. (2015). Modelig S &P bomby stockexchange bankex volatility paterns using garch model. *Procedia Economics and Finnance*, 520-525.

Bollerslev, T., Engle,R.F, & Nelson,D.B. (1994). ARCH models. *Hand book of Econometrics*, 2959-3038.

Cont, R. (2007). Volatiity Clusteringin financial markets:emperical facts andagent based models. *Long memory in economics*, 289-309.

Dinku, T. (2021). Modeling price volatility for selected Agricultural commodities in Ethiopia: Application of GARCH modls. *International Journal of Environmental Science*, 6.

Engle, R., Granger,C.W, & Kraft,D. (1984). Combining competing forecasts of inflation using a bivariate arch model. *Journal of Economic Dynamics and control*, 151-165.

Frimpong, J., & Oteng-Abayie. (2006). Modeling and Forecasting volatility of returns on Gana stock exchange using Garch models.

Hailegebrial., Z. (2015). Determinants of food price inflation in Ethiopia . *Food Science and Quality management*, 30-43.

Haji, J., Gelaw,F., Bekele,W., & Tesfaye,G. (2011). The 'black-box' of Ethiopian Agricultural produces price formation and its determinants within the current liberized market policy. *Drylands Coordination group,Mijihuset G*, 9.

Huchet-Bourdon. (2011). Agricultural price volatility:an overview.

Kose, M., Prasad,E.S., & Terrones,M.E. (2006). How do trade and financial integration affct the relation ship between growth and volatility. *Journal of International Economis*, 176-202.

Koutmos, G., & Booth,G.G. (1995). Asymmetric volatility transmission in international stock markets. *Journal of international Money and finance*, 747-762.

Kuhe, D. (2019). Modeling volatility of agricultural commodity food price indexin Nigeria using ARIMA-GARCH models. *Mediterranean Jornal of Basic and Applied Sciences*, 55-75.

Musunuru, N., Yu,M, & Larson,A. (2013). Forecasting Volatility of reurnsfor corn Using GARCH models. *Texas Journal of Agriculture and Natural Resources*, 42-55.

Nelson, D., & Cao,C.Q. (1992). Inequality constraints in the univariate GRCH model. *Journal of Business & Economic Statistics*, 229-235.

Niu, H. a. (2013). Volatility clusterng and long memory of financial time series and financial price model. *Digital signal processing*, 489-498.

Niyitegka, O., & Tewar,D. (2013). Volatility clustering at Johannesburg stock exchange: Investigation and Analysis. *Mediterranean Journal of Social Sciences*, 621-642.

Santeramo, F. (2018). Emerging trends in european food ,diets and food industry. *Food research international*, 39-47.

Schmidt, L. (2021). Volatility forecasting performance of garch models: Astudy on nordic indices during Covid-19.

Staugaitis, A., & Vaznonis, B. (2022). Short-Term Speculation Effects on Agricultural Commodity Returns and Volatility in the European Market Prior to and during the pandemic. *Agriculture (MDPI)*, 1-26.

Tseng, J. a. (2012). Quantifying Volatility clustering in Financial time series. *International Review of Financial Analysis* , 11-19.

Wang, C. (2004). Emperical evidence of the leverage effect in international bulk shiping market. *Maritime policy &management*, 109-124.

Yip, P., Brooks,R, & Nguyen. (2020). Dynamic volatility spillover effects between oil and agricultural products. *International Review of Finanial Analysis*.

Yu, J. (2005). On leverage in stochastic volatility model. *Journal of Econometrics*, 165-17.

Zakoian, J. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, 931-955.

Zivot, & Wang,G. (2006). Modeling financial time series withS-PLUS. *Springer*.