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Modeling and Forecasting Volatility of Food and Non-food Price in Ethiopia: A GARCH Modelling Approach.

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Abstract

This study aimed to model and forecast price volatility of food and nonfood prices in Ethiopia using the Generalized Autoregressive Conditional Heteroscedasticity Model. To achieve the objective, the study employs monthly data on monthly prices of food and non-food inflation from December 2000 to September 2020 collected from the Central Statistical Agency of Ethiopia. It finds that the long-run result showed that a 1% increase *in the Food Price Index is associated with a 42.84% increase in the consumer price index keeping other variables constant. Therefore, stabilization policies to dampen high volatilities and a prudent fiscal policy as a means of avoiding sources of subgroup commodities imbalance are quite apparent to reduce the rapidly rising food prices and non-food prices in the country.*

Keywords: ***Volatility, Correlation, Consumer Price Index, Forecasting, GARCH***

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Introduction

Inflation is officially regarded as a major economic problem and is one of the major concerns of macroeconomic policies. The rapid rise and volatility of food prices, nowadays, are at the highest outline of the global community. The people of developing countries, particularly, are highly exposed to food insecurity as they are economically incompetent to manage to pay for basic food crops (Abebe et al, 2012). (Yonas and Mans, 2012) indicated that the high food price inflation has been the most divergent economic shock that has sustained to undesirably affect the Ethiopian economy where a significant proportion of households had to adjust food consumption in response.

Many other factors contributed to the economic disorder even though supply and demand fundamentals played a significant role in the food price and non-food price disaster. For example, large increases in oil prices have driven food price inflation higher significance and contributed to rising production costs. Globally, according to the World Bank, the food price increases between 2010 and 2016 due to the weakness of the dollar accounted for 22% (Mitchel, 2008). Furthermore, most African countries cross the threshold of global economic disaster from a much stronger basis in terms of macroeconomic immovability gratitude to determinations agreement over the past decades to device painful macroeconomic and trade transformations (James and Léonce, 2010).

Volatility as a relative rate of change in a price displays the range of prices over a specified time frame. A price is deemed to have greater volatility the more ups and downs it experiences, possibly attributed to information flow. The characteristics of financial and economic time series must be faithfully captured by appropriate modeling procedures. These characteristics—fat tails, sharp peaks, and volatility clustering—have been named. Investigating the volatility handles the properties of the movement's prices of many time series data. Alternative estimations considering the food and non-food price inflation were used in the literature, but there was a shortage of work undertaking GARCH analysis as a statistical framework, which was particularly suited for modeling price volatility. Moreover, existing work appears to focus mostly on in-sample modeling of volatility of prices, giving less attention to model forecasting performance.

Most of the existing research focuses on modeling the volatility of food price inflation rather than modeling the volatility of food and non-food price inflations. Several recent papers have investigated the volatility of food price inflation and others have studied the commodity of non-food price inflation mainly due to increased interest in understanding the dynamics of such volatilities in highly volatile times. (Nicholas, 2014) examined the patterns and trends in food price volatility in Africa by using the GARCH model. The finding showed that the prices of teff, millet, and rice were less volatile than the average whether measured as unconditional volatility or conditional volatility.

Similarly, (Gemechu & Struthers, 2013) investigated the effects of market transformation programs in Ethiopia and their impact on the volatility of coffee prices. Using the GARCH model techniques, they argued that there was evidence that Ethiopia experienced a significant increase in coffee price volatility after the agreement of the market-oriented transformation program. These are an important gap according to the Ethiopian context and this work tried to find the contribution to the literature by undertaking a systematic analysis of forecasting the volatility of food and non-food price inflations. The general objective of this study is to model and forecast the volatility of food and non-food prices in Ethiopia using GARCH family models.

Review of Related Literature

The inflation rate is measured as the percentage change in the price index (consumer price index, wholesale price index, producer price index. (Essien, 2015) opine that the consumer price index (CPI), for instance, measures the price of a representative basket of goods and services purchased by the average consumer and is calculated based on periodic surveys of consumer prices. Owing to the different weights of the basket, changes in the price of some goods and services have an impact on measured inflation with varying degrees. There are several disadvantages of the CPI as a measure of price level. First, it does not reflect goods and services bought by firms and/or the government, such as machinery. Secondly, it does not reflect the change in the quality of goods which might have occurred over time. Thirdly, changes in the price of substitutable goods are not captured.

Lastly, the CPI basket usually does not change often. Despite these limitations, the CPI is still the most widely used measurement of the general price level. This is because it is used for indexation purposes for many wage and salary earners (including government employees). Another measure of inflation or price movements is the GDP Deflator. This is available on an annual basis. However, it is rarely used as a measure of inflation. This is because the CPI represents the cost of living and is, therefore, more appropriate for measuring the welfare of the people. Furthermore, because CPI is available on a more frequent basis, it is useful for monetary policy purposes.

In financial trading, one of the central parts is to try to capture the movements of the underlying asset, which is usually known as volatility. In economics, in particular, in the context of inflation, volatility refers to the degree to which inflation itself fluctuates with which there are some periods of small fluctuations and periods of large fluctuations. This phenomenon is known as volatility clustering. Volatility clustering is a property of most heteroscedastic processes used in finance and economics as noted by (Mandelbrot, 1963) that "large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes". In a nutshell, volatility in economics refers to a variable conditional variance of fluctuation (error terms) that measures uncertainty given a model and information set with which its unconditional variance is constant. Hence time time-varying heteroscedasticity occurred resulting in persistent volatility as it does not die through time for a long time.

The volatility is the conditional standard deviation of the return of the underlying asset and is denoted by σt. The volatility has some important features. One of the most important is that the volatility changes over time and that it is not directly visible in daily data since there is only one observation each trading day. The volatility depends on the trading on each day and between the days, the overnight volatility. Understanding and predicting volatilities and correlations of asset returns has been the object of much attention since volatilities and correlations are the two most important elements in financial activities such as asset pricing, asset allocation decisions, portfolio management, and risk assessment (Tsay, 2015).

In the last three decades, there has been an unexpected increase in volatility research. The "Dynamic Volatility Era" began with the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model (Maria, 2016). The ARCH (p) model expresses the conditional variance as pth order weighted average of past squared disturbances and thus can describe volatility clustering in financial series. Following this, an enormous body of research has focused on a generalization of the ARCH model, mainly by providing alternative functional forms for the conditional variance. During the last few decades, a body of research regarding energy price, commodity price, and food price inflation volatility has been presented. A large proportion of this research has focused on a univariate approach for studying volatility clustering and volatility persistent and asymmetric effects in the returns. (Andersen & Bollerslev, 1998) Performed well-known research among econometricians in the study, where they concluded that univariate standard volatility models can perform accurate volatility forecasts. However, only a smaller fraction of the literature has concentrated on a multivariate approach for conditional correlation forecasting and the performance of these models. The empirical literature on volatility forecasting is discussed in the following two sections separately. Correspondingly, (Gemech & Struthers, 2013) empirical investigation into the effects of the market transformation program in Ethiopia and their impact on the volatility of food prices.

The Data and Estimation Strategy

The purpose of the analysis was to track the trends in Ethiopia's nonfood and food pricing indices from December 2000 to September 2020. There are two main categories into which the study's methodology can be separated. The Vector Error Correction (VECM) models for stationary and parameter estimation are covered in the first section. The GARCH Model is used to model volatility in the second portion. The items of food and non-food prices are listed as follows.

Table 1:

Food Items and Non-food Items in Ethiopia

No.	Food items	Non-food items
1	Cereals	Beverages
2	Pulses	Cigarettes and Tobacco
3	Bread and other prepared food	Clothing and Footwear
4	Meat	House Rent, Construction Materials, Water, and Fuel and Power
5	Milk, Cheese, and egg	Furniture Furnishing, Household Equipment and Operation
6	oil and fats	Medical Care and Health
7	Vegetable and fruits	Transport
8	Spices	Communication
9	Potatoes, other Tubers, and stems	Recreation, Entertainment, and Education
10	Coffee, (been, whole) and Tea leaves	Personal Care and Effects
11	Other Foods Items	Miscellaneous Good

Source: Central Statistical Agency

The following Laspeyres formula is used to calculate the food and non-food price items in the current period at time t (Laspeyres, 1871). The Ethiopian CPI was given by:

$$CPIti = \frac{\sum_{t=1}^{T} Wti \left(\frac{Pti}{Po}\right)}{\sum_{t=1}^{T} Wti} * 100 \quad \text{.. (1)}$$

Where; *i* is the items of food and non-food price, *Pti* is the price of items in the current period at time t, P0 is the price of the items in the reference period and Wti is the weight associated with items.

Several model specifications have been used in previous research on related variables, including Hakimipoor (2016). Autoregressive vector models and vector error correction models were calculated to ascertain the link between the consumer price index and producer pricing index for six American countries. Furthermore, the analysis of impulse response was conducted, and the Toda and Yamamoto causality tests were employed. However, (Seifu, 2017) employed a linear regression specification and discovered correspondingly noteworthy outcomes. Following the above-mentioned model specifications, this study assumed the GARCH model used to estimate the volatility of food and nonfood price index and their commodities following as

CPIit = f(FPIt, NFPIt, εt) .... (2)

The model is then transformed to the logarithmic form to smooth out the specification and where the resulting equation is set as follows:

lnCPIt = α + β1ln FPIt+ β2lnNFPIt++εt ....(3)

Where lnCPIt =ln of consumer price index at time t lnFPIt = ln of Food price index at time t, lnNFPIt = ln of Nonfood Price Index at time t, α = Intercept of the regression line. It represents any level of CPI that is at zero of all explanatory variables. **β**i (i = 1, 2, ... 5) are coefficients of the components of the target.

The general expression for the univariate time series model is Yt = f (Y_{t-1}, Y_{t-2}….., Ɛ t). To make this equation operational, three things must be specified: the functional form of Y_t, the number of lags, and a structure for the disturbance term.

To capture the volatility features Autoregressive Conditional Heteroskedasticity (ARCH) models were introduced by (Engle.1982). These models were later extended to Generalized ARCH or GARCH (Bollerslev, 1986). These models were attempts to capture several characteristics of food and non-food price inflation series such as thick (fat tail), volatility clustering, etc. The GARCH model with p number of lagged squared error terms and q number of lagged variance terms denoted as GARCH (p, q), and can be written as:

$\sigma^2_t = \alpha o + P\sum_{i=1}^{p} \alpha i \varepsilon^2_{t-i} + \sum_{j=1}^{q} \beta_j \sigma^2_{t-j}$, $\alpha_0 > 0$, $\alpha_1 > 0$, and $\beta_1 > 0$ .... (4)

Where the volatility term σ^2_{t-j} denotes the variance, j represents the number of lags, and the term ε^2_{t-i} is the squared error for the period t-i.

All model variables' data must be checked for their stationary states in order to perform the econometric technique (Gujarati, 2004; Dickey & Fuller, 1979). If the mean and variance of a stochastic process remain constant throughout time and the covariance value between two time periods solely depends on the lag or gap between them rather than the moment at which the covariance is determined, the process is considered stable.

Econometricians agreed so far, that return series are usually found to be stationary. It is important to ensure the stationarity of the series before analyzing the food and non-food price data. Let Pt, t = 1, 2, 3 …, be a time series of food and non-food price inflation. Instead of analyzing price Pt, often analyze log returns on price Pt since price often displays unit root behavior and thus could not be modeled as stationary (Fryzlewicz, 2007) and given by:

$$Yt = \log\left(\frac{Pt}{Pt-1}\right) = \log(\mathrm{Pt}) - \log(\mathrm{Pt}-1) \quad (5)$$

Where Yt is the return series of food and non-food price inflation, Pt is the current prices of food and non-food price inflation and P_{t-1} is the past prices of food and non-food price inflation.

More specifically, {**Y**t} is stationary if: (a) ε(Yt) = μ that is a mean of both food and non-food price is constant and (b) Cov (Y_t**,** Y_{t-l}) = γ_l, that is, the covariance between food and non-food price is constant. Augmented Dickey-Fuller (**ADF**) test, Phillips-Perron (**PP**) test, and **graphical** analysis of the series are used for testing stationarity, and optimal lag length is also determined with the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

It is generally excellent practice to test for the presence of the ARCH effect in the residuals of food and non-food return series before estimating a GARCH family model for those types of data. If the series' residuals do not exhibit any ARCH effects, the GARCH family model is superfluous and incorrectly provided. Below is a discussion of the available techniques to check for ARCH effects.

The study then employs a forecasting procedure and evaluation. The series of conditional correlation forecasts for the period of 2016m1 to 2020m10 is to be compared for both food and non-food return series. Starting with an initial estimation for the fifteen years of 2000m12 to 2015m12 for food and non-food return series, a forecast was made for the following monthly (T + 1). The estimation window was moved one month and another forecast was made for (T + 2). This procedure continues throughout the forecast period.

The forecasting evaluation also includes Root Mean Square Error (RMSE). The first measure of determining the goodness of the estimations and forecasts for food and non-food return series is calculating the Root Mean Square Error (RMSE), which is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{2}\sum_{t=1}^{n}(\sigma_t^2 - h_t^2)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

Where σ_t^2 is the proxy which is used as realized value for food and non-food return series and h_t^2 is the estimated conditional covariance for both series. We can determine the relatively best estimation model and make the best forecast depending upon the value of RMSE that is the minimum value of RMSE that makes the best model estimation for both return series.

Another way of determining the goodness of the estimations and forecasts for food and non-food return series is by calculating the Mean Absolute Error (MAE). This method measures how the received conditional covariance is close to their corresponding realized value for food and non-food return series. The formula is:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{n}|\sigma_t^2 - h_t^2| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

Where the proxy is used as realized value σ_t^2 for food and non-food return series and the estimated conditional covariance is used as h_t^2 for both series. By comparing the MAE between the estimated models, it can indicate which model makes the best estimations for both return series.

The third measure of determining the goodness of the estimations and forecasts for food and non-food return series is calculating the Mean absolute percentage error (MAPE). The formula is given by:

$$\mathrm{MAPE} = \frac{100}{T}\sum_{t=1}^{n}|\sigma_t^2 - h_t^2| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Comparing the MAPE between the estimated models for both food and non-food return series can indicate which model makes the best estimations.

Results and Discussion

Descriptive Analysis:

Three aggregate series were employed in the empirical analysis: the non-food price index (NFPI), the food price index (FPI), and the general consumer price index (CPI). The findings demonstrate that, except for standard deviation, which suggests a comparatively large dispersion for FPI, the values of the summary statistics are essentially equal.

Table 2:

Summary Statistics for CPI, Food and Non-food Price Inflation

	CPI	FPI	NFPI	RTSCPI	RTSFPI	RTSNFPI
Mean	74.36067	70.69895	71.83184	0.008700	0.009805	0.007197
Median	69.00000	68.20000	69.50000	0.008976	0.009385	0.007946
Maximum	180.8000	193.4000	166.4000	0.469027	0.161002	0.061539
Minimum	22.40000	17.30000	30.01000	-0.429141	-0.423174	-0.399235
Std. Dev.	42.04457	42.91577	36.63837	0.052660	0.037623	0.028767
Skewness	0.433108	0.675175	0.684701	-1.774009	-6.023506	-11.84968
Kurtosis	2.238052	2.903314	2.633565	63.22982	76.52073	168.9766
Jaque-Bera	13.25351	18.25154	20.01163	36098.85	55041.75	278756.6
Probability	0.001324	0.000109	0.000045	0.000000	0.000000	0.000000
Sum	17772.20	16897.05	17167.81	2.070632	2.333566	1.712864
Sum Sq. Dev.	420723.5	438339.7	319484.2	0.657231	0.335463	0.196121
Observations	239	239	239	238	238	238

Source: - Own Computation from CSA Report Data

As depicted in above Table 2, the average price index of food, non-food price, and Consumer price index were 70.69, 71.83, and 74.36 with a minimum index value of 17.30, 30.01, and 22.4, whereas the maximum prices index was 193.4, 166.4 and 180.8, respectively. The skewness coefficient for food, non-food inflation, and general CPI return series was 6.0235, -11.8496, and -1.774 with the kurtosis coefficient of food, non-food price inflation, and CPI return series being 76.52, 168.9766 and 63.2298 respectively, these coefficients of skewness and kurtosis of the monthly price return series showing the return series are highly leptokurtic or excess kurtosis.

Table 3

Trends of food price index, non-food price index, and general consumer price index

G.C	2000m12 - 2005m12	2006m1 - 2010m12	2011m1 - 2015m12	2016m1 - 2020m10
%Δ Food price index	0.34	0.57	0.28	0.51
%Δ Non-food price index	0.14	0.55	0.11	0.44
%Δ Consumer price index	0.27	0.56	0.22	0.48

Source: - Own Computation from CSA Report Data

As it was shown in the above table 3, the percentage change in food price was 0.34, the percentage change in non-food price was 0.14 and the percentage change in the general consumer price index was 0.27 from December 2000 up to December 2005, which shows the changes in prices for the five years. Secondly, the percentage change in food price was 0.57, the percentage change in non-food price was 0.55 and the percentage change in general consumer price index was 0.56 from January 2016 up to December 2010 which shows the changes in prices.

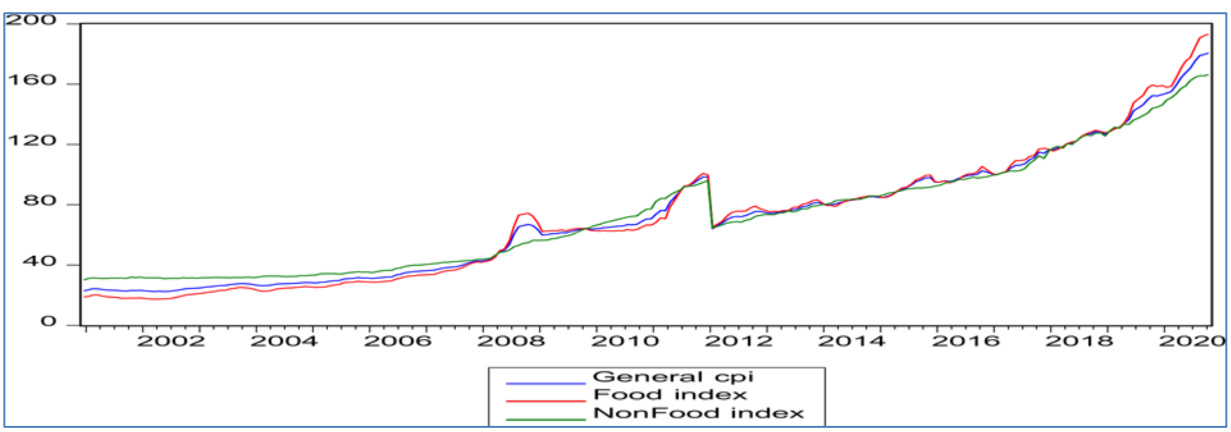
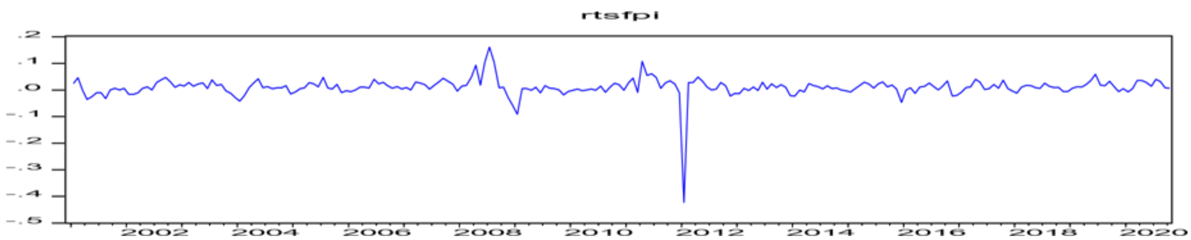


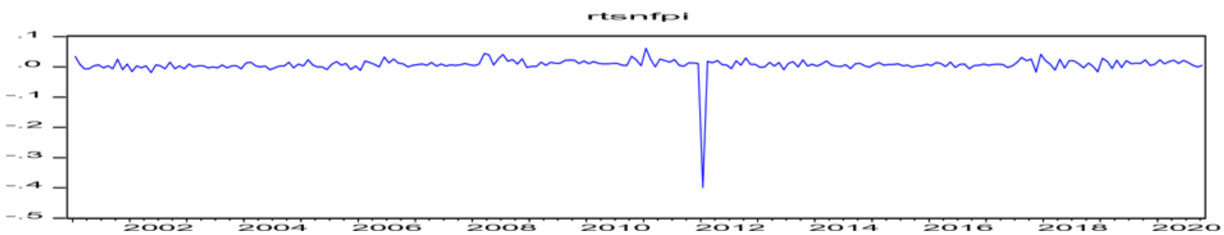
Figure 1: Time series plot for level series CPI, Food, and Non-food Price Inflation

The log return series was constructed for each of the prices to examine the presence of volatility in the series. As illustrated in Figure 1, periods of high volatility are observed for both of the series under consideration. The monthly return series displays volatility persistence properties, indicating that large changes tend to be followed by large changes and small changes tend to be followed by small changes and the return series suggests stationarity. The plots further show that the volatilities of food and non-food price inflations have a volatility clustering phenomenon and have a certain relation to their return volatility processes. That is, when the fluctuation volatility of the food price inflation grew, the volatility of non-food price inflation grew most of the time. This is the main intention for discussing the relationships between food and non-food price inflation.

Food return series



Non-food return series



General CPI

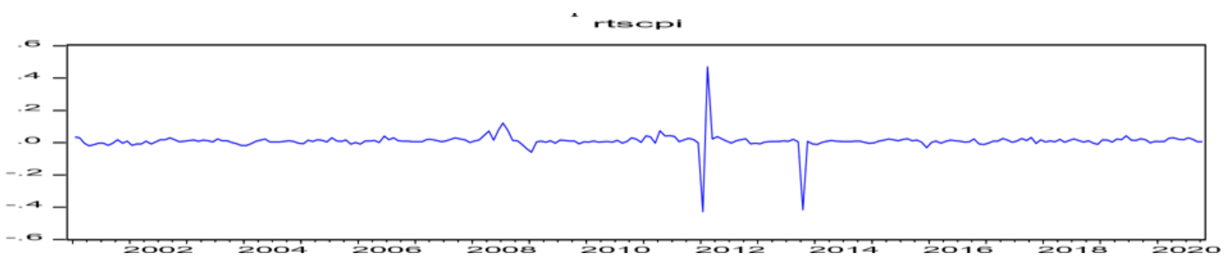


Figure 2: The monthly log return series for the price inflation of food and non-food

The plots of the monthly price log return series are shown in Figure 2. Both series seem to revolve around a fixed mean, that is, they seem to be stationary. Moreover, the CPI, FPI, and NFPI price return series exhibited volatility clustering (high-volatility events tend to cluster in time) which is one of the stylized facts of high-frequency financial time series.

Unit root test for stationarity

Before trying to apply an appropriate model, the time series under consideration should be examined for stationarity. Testing for unit roots in the variables and determining the variables' integration order are requirements. Whether the time trend is stochastic or deterministic, a direct application of OLS to trended time series data usually shows a misleading correlation instead of the true one. As suggested by Enders (1995, referenced in Zelalem Mehari (2013), the most often used method for handling stochastic trends in time series data is to estimate the relationship in the first difference rather than at the level. The logarithm (ln) of each variable was obtained before the stationary or unit root tests because, as per (Gujarati, D. (2004)), log variables provide elasticity, lessen the effect of outliers, and smoothen out time series. The hypothesis to be tested is $H_o = 0$, the series is non-stationary against $H_1 \neq 0$, the series is stationary. In this study, Augmented Dickey-Fuller test (ADF) and Phillips Perron (PP) tests were used to check the stationary of the monthly series of food and non-food price inflation.

Table 4:

DF Unit Root Test of Stationarity for Level Prices, with Trend

Variable	Test statistic	Critical value			P-value
		1%	5 %	10 %	
CPI	-0.395	-3.997	-3.428	-3.137	0.9872
Food Index	-0.576	-3.997	-3.428	-3.137	0.9791
Non-Food	-0.467	-3.997	-3.428	-3.137	0.9845

Source: Stata Output

Table 5:

PP Unit Root Test of Stationarity for Level Prices, with Trend

Variable	Test statistic	Critical value			P-value
		1%	5 %	10 %	
CPI	-0.169	-3.997	-3.428	-3.137	0.9934
Food Index	-0.349	-3.997	-3.428	-3.137	0.9988
Non-Food	-0.438	-3.997	-3.428	-3.137	0.9857

Source: Stata Output

As can be observed from above Table 4 and Table 5 of the unit root test, the t-statistics are greater than the critical values at 1%, 5%, and 10% levels of significance and the p-value for both series are greater than 5% level of significance implying that the null hypothesis of the unit root would not be rejected that is, there is a unit root problem in each of the data.

If time series data is non-stationary, it is necessary to look for possible transformations that might bring stationarity. In practice, most econometricians usually transform financial prices into return forms. This is because often return series are found to be stationary in that the analysis is possible. The Logarithmic return series is obtained by:

$$r_t = 12\log(\frac{p_t}{pt-1}) \qquad (9)$$

Where rt is the Logarithmic return series of the price index multiplied by 12 which is simply a scaling factor to annualize such that in the study monthly data was used and each year contains 12 months and pt. is the series of the price index for food and non-food at time t and a log is a logarithm.

After transformation, as illustrated in Tables 6 and 7, all the t-statistics are less than the critical values at 1%, 5%, and 10% levels of significance and the p-value for both series are less than 5% level of significance indicating that the null hypothesis of unit root would be rejected in both cases. Therefore, the logarithmic return series are stationary for both food and non-food prices.

Table 6:

DF Unit Root Test of Stationarity for logarithmic form

Variable	Test statistic	Critical value			P-value
		1%	5 %	10 %	
CPI	-19.350	-3.997	-3.428	-3.137	0.000
Food Index	-11.923	-3.997	-3.428	-3.137	0.000
Non-Food	-15.606	-3.997	-3.428	-3.137	0.000

Source: Stata Output

Table 7:

PP Unit Root Test of Stationarity for logarithmic form

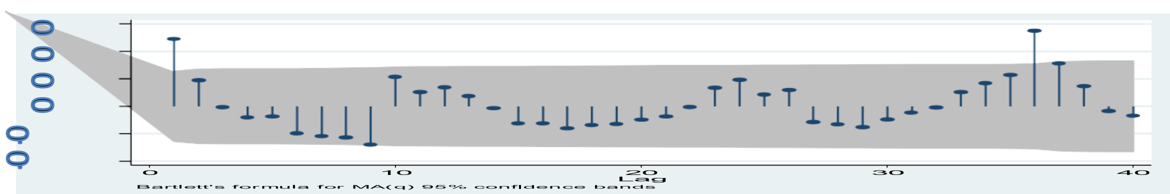
Variable	Test statistic	Critical value			P-value
		1%	5 %	10 %	
CPI	-19.360	-3.997	-3.428	-3.137	0.000
Food Index	-11.947	-3.997	-3.428	-3.137	0.000
Non-Food	-15.605	-3.997	-3.428	-3.137	0.000

Source: Stata Output

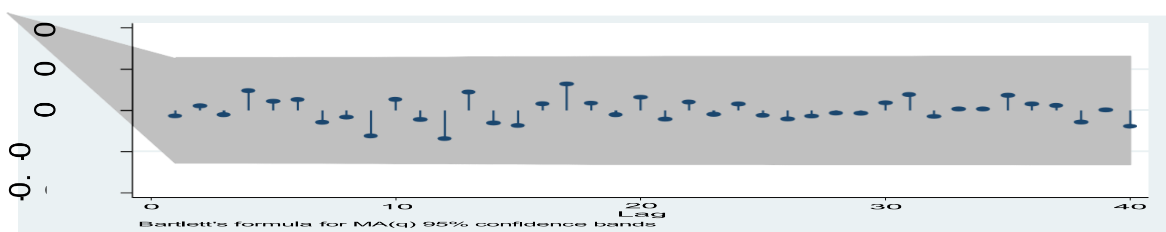
Another important feature of the return series is that usually, the return series shows no or little autocorrelation. Figure 4.3 shows the plots of the sample autocorrelation functions (ACFs) of the three return series. A sample ACF has approximate upper and lower confidence bounds. The two sample ACFs suggest that the serial correlations of monthly price returns series are very small except at a few lags. Most of the sample ACFs were within or near their confidence limits indicating that autocorrelations that fall inside the limits were not significantly different from zero. The null hypothesis of zero autocorrelation was rejected if the sample autocorrelation lies outside the interval $*{-1.96X}\frac{1}{\sqrt{T}}, 1.96X\frac{1}{\sqrt{T}}+$.

The autocorrelation and partial autocorrelation of food and non-food price inflation return series implies that the null hypothesis of no autocorrelation was rejected since all p-values for both return series are less than 5% level of significance.

AC function of food price inflation log return



AC function of non-food price inflation log return



AC function of General Consumer price inflation log return

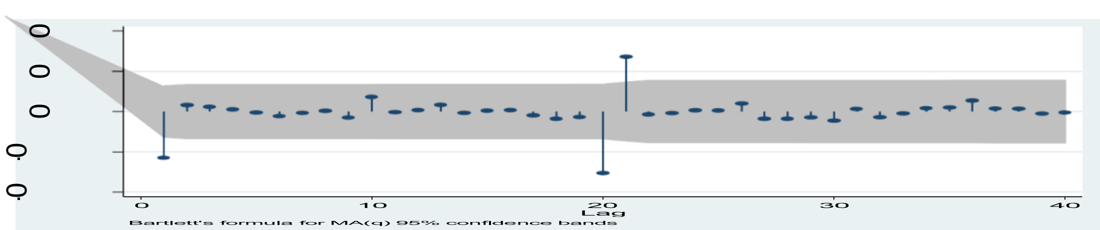


Figure 3: Sample autocorrelation functions of monthly return series

In economic time series, several autocorrelations of the return series to be tested are jointly zero. Therefore, first plot the autocorrelation function for the series. The plot is an indication of serial correlation but does not apply to a complete decision. Instead, it can be used in the Portmanteau white noise test or general statistics of linear dependency Q(m), where m is the lag length. Under the null hypothesis that H0: ρ1= ρ 2=………= ρ m=0, Q (m) is distributed as a chi-squared distribution with m degree of freedom. From Table 7, looking at the p-values at a 5% level of significance, we can agree that the returns are not auto-correlated, but the squared returns are highly auto-correlated.

Table:7

Portmanteau test for white noise

Return Series	Q(12)	Prob>Chi(2)
CPI return series	13.0109	0.1265
Food return series	16.6163	0.0726
Non-food return series	35.4302	0.1820
CPI return squared	85.8865	0.0000
Food return squared	78.9917	0.0000
Non-food return squared	89.0410	0.0000

Source: Stata Output

Volatility Modeling:

To build a volatility model for the log return series, the first step is specifying the mean equation. Once the mean equation was specified, the ARCH effects should be tested using the residuals of the mean equation and checking whether significant or not/specifying a volatility model. Based on two statistics, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), it has chosen the mean equation to estimate the joint mean and variance parameters. In most applications, lower-order ARMA models, say, ARMA (1, 0), ARMA (0, 1), ARMA (1, 1), ARMA (1, 2), ARMA (2, 1) and ARMA (2, 2) were used. The table below gives the alternative ARMA models together with their corresponding AIC and BIC.

Table 8:

AIC & BIC conditional mean equation

		Return Series			
Lag length		Food Price		Non-food Price	
P	Q	AIC	BIC	AIC	BIC
0	1	-893.7982	-883.3814	-1008.736	-998.3189
0	2	-894.1893	-880.3002	-1006.762	-992.8734
1	0	-893.8366	-879.9475	-849.367	-842.7113
1	1	-895.5892	-885.1724	-1008.737	-998.3198
1	2	-892.2109	-874.8495	-842.3397	-832.3706
2	0	-893.924	-880.0349	-1006.766	-992.8772
2	1	-893.1331	-875.7718	-1005.048	-987.687
2	2	-891.1874	-870.3538	-1004.508	-983.6747

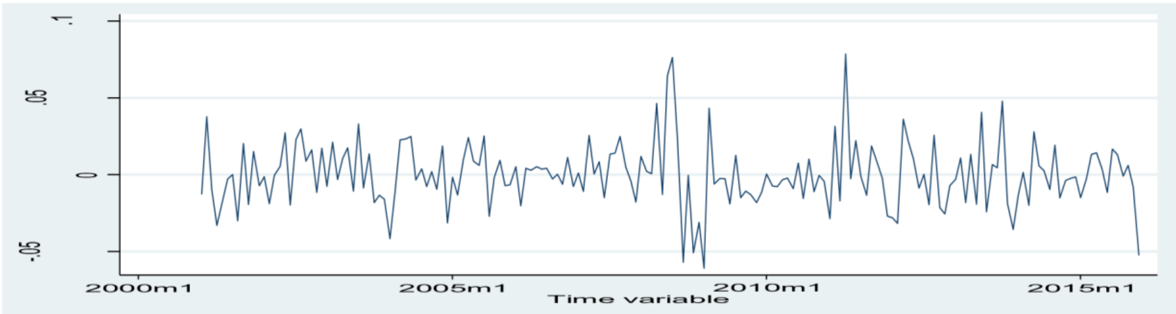
Source: Stata Output

As can be seen in Table 8 above, the best in-sample results are achieved by ARMA (1, 1) for both inflation log return series. Therefore, ARMA (1, 1) is the best having minimum AIC & BIC conditional mean equation for both of the two cases.

Test for ARCH Effects

Considering the chosen mean model, that is, ARMA (1, 1), and on fitting this model, if there is no volatility clustering in each of the returns, the random disturbance term Ɛt should be a white noise process. The standardized residual plot from ARMA (1, 1) can be an initial insight to judge the heteroskedastic characteristics of the error term. The standardized residual plot for food and non-food returns series is given in Figure 4.4 below. As can be seen from Figure 4.4that for both of the series there was an elongated period of low volatility and an elongated period of high volatility. In other words, periods of high volatility are followed by periods of high volatility and periods of low volatility tend to be followed by periods of low volatility, which is known as volatility clustering. This suggests that the residuals or error terms are conditionally heteroskedastic and can be represented by GARCH models.

Residual plot of FPI from ARMA model



Residual plot of NFPI from ARMA model

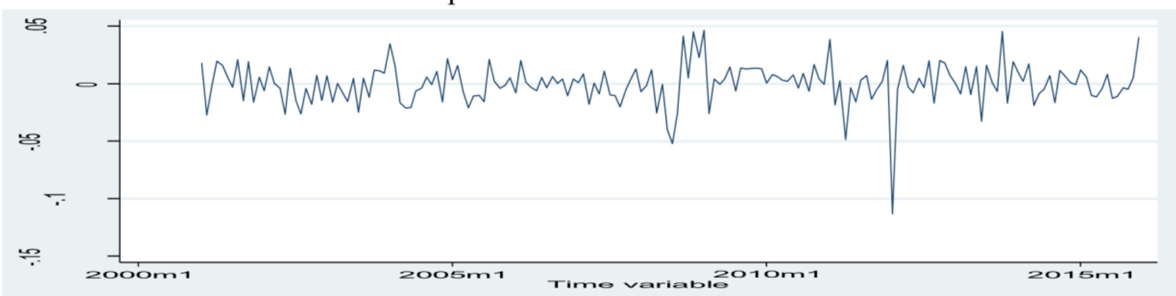


Figure 4: Residual plots of the food and non-food return series from the mean model

Table 9 below shows the results of the ARCH-LM test for the food and non-food return series. The last column of the table includes the p-values that indicate rejection of the null hypothesis that "there is no ARCH effect" up to the fourth lag at a 5% level of significance. The results indicate that both return series are volatile and need to be modeled using GARCH models.

Table 9:

ARCH LM Test Summary Statistics

Series	Obs*R2	χ^2(12)	Lag(12)	p-value
Food price	19.524	9.49	2	0.0006
Non-food price	19.003	9.49	2	0.0293

Source: Stata Output

GARCH Model Identification:

If an ARCH effect is found to be significant, we determine the order of an ARCH model. In practice, for ARCH modeling a long lag is often needed and this requires estimating a large number of parameters. To reduce the computational problem, a GARCH model with low lags can be helpful. This results in a more parsimonious representation of the conditional variance process. To estimate and evaluate the forecasts of the competing GARCH models, different p and q values for the standard symmetric GARCH models are tested using different statistics such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to choose the best model based on the in-sample data. The appropriate specification is chosen and then for this specific p and q, the alternative GARCH models are estimated, and tested, and finally one GARCH model is chosen based on forecasting ability. For this GARCH (p, q) model different distributions are evaluated namely, normal distribution, student's t-distribution, and generalized error distribution (GED). Finally, the parameters for the chosen GARCH model are presented. Table 10 below summarizes these two statistics computed from different GARCH models. Note that the AIC and BIC of the GARCH models are obtained by estimating the mean return and variance equations simultaneously.

Table 10:

ARMA (1, 1)-GARCH model selection based on AIC and BIC Food return series, in sample

Statistics	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
AIC	-21.31 (2)	-19.51 (3)	-22.73 (1)	-17.49 (4)
BIC	-105.69 (1)	-103.99 (2)	-100.77 (3)	-95.63 (4)
Rank Sum	3	5	4	8

ARMA (1, 1)-GARCH model selection based on AIC and BIC Nonfood return series, in sample

Statistics	GARCH(1,1)	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
AIC	-323.48 (1)	-322.20 (2)	-321.73 (4)	-321.76 (3)
BIC	-304.73 (1)	-300.33 (2)	-299.87 (3)	-296.77 (4)
Rank Sum	2	4	7	7

Source: Stata Output

As can be seen from Table 10 above, the row ranks indicate the ranking of the various GARCH models based on the two statistics. As a result, the lower the rank sum is the better the model. The best models for the food and non-food return series are GARCH (1, 1).

Checking the Adequacy of ARMA-GARCH Models:

In the Tables above, the appropriate lag lengths for both inflation series were chosen, that is, ARMA (1, 1)-GARCH (1, 1) for the food and non-food return series, and now it is necessary to check the adequacy of each of the model under the proposed distributions. To check the adequacy of the variance equation, test whether the square of the standardized residuals is serially correlated or not. If it is serially correlated, this would suggest that the conditional variance equation is not valid. This fact must be confirmed by a statistical test which is a portmanteau test of white noise and is given in Table 12. All p-values in the table are greater than 5% level of significance. So, it failed to reject the null hypothesis of white noise of the error term. Hence all GARCH models under the three distribution assumptions are adequate.

Table 12:

Portmanteau test for white noise, ARMA-GARCH model

N-GARCH			T-GARCH		GED-GARCH	
Residuals	Food	Non-food	Food	Non-food	Food	Non-food
Standardized	64.5045 (0.1224)	43.6672 (0.0847)	49.7586 (0.0948)	49.7986 (0.0954)	46.6748 (0.1915)	64.4889 (0.1211)
Squared stand. Residuals.	43.6692 (0.08524)	25.0568 (0.0747)	49.7786 (0.0958)	26.5507 (0.0754)	46.6648 (0.0815)	30.8472 (0.0911)

N.B: Values in the brackets are p-values

Source: Stata Output

Checking for Normally Distributed Standardized Errors

Once the selected model is adequate in modeling the volatility of a financial time series variable it is necessary to check the normality of the residuals. The histogram of normality test of the standardized residuals from each ARMA-GARCH model. In all of the graphs, it appears that we have approximately normally distributed standardized errors, except for deviations at the end tails. This indicates the residuals are normality distributed.

Volatility forecasting

One of the fundamental applications of time series analysis or developing a time series model is forecasting. The previous discussion confirms that ARMA (1,1)-GARCH (1,1) is a good model to describe the series. In this section, we examine the forecasting accuracy of the fitted model and then make a volatility forecast for out-of-sample data. To assess the out-of-sample forecasting ability of the model it is advisable to retain some observations at the end of the sample period which are not used to estimate the model. Therefore, using the data from 2000m12–2015m12 the estimates are derived, and then the volatility of food and nonfood prices using variance as volatility measures were forecasted using the out-sample observations from the period 2016m1–2010m10 under static forecasting. The results are displayed as we can see from the figure below.

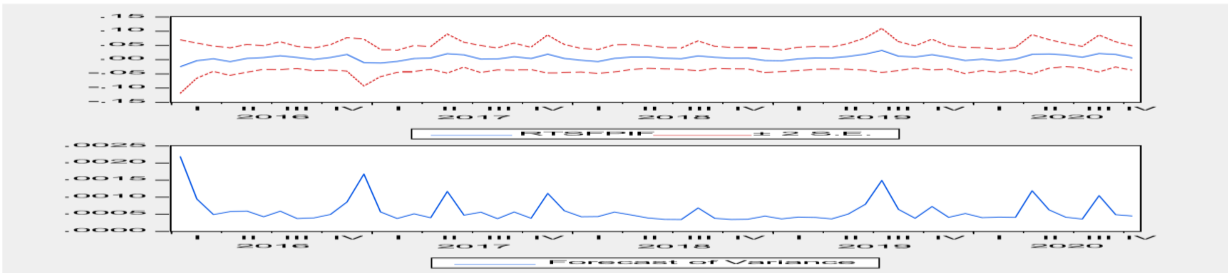


Figure 5: out-sample forecast of monthly price volatility of food return series

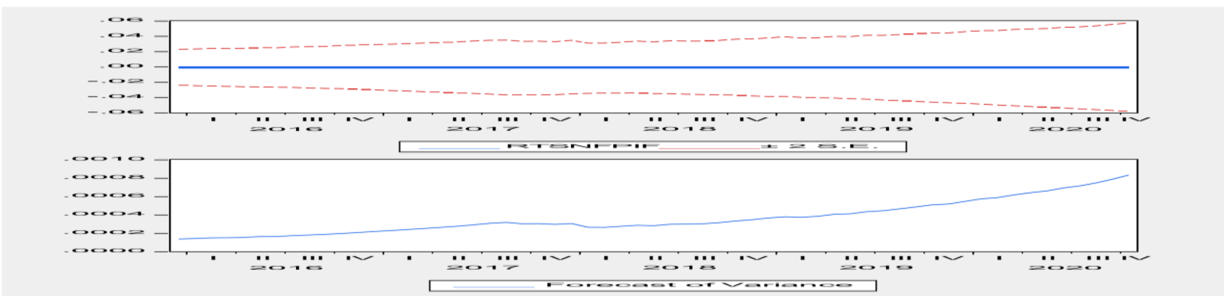


Figure 6: out-sample forecast of monthly price volatility of nonfood return series

As we can see from the Figure above, the price volatility of food shows an increasing and decreasing pattern over the forecasting periods under consideration and this shows the price of food commodities changes conditionally and for nonfood price volatility there is a continuously increasing pattern and steadily with increasing rate from the years December 2018 till the final observation considered under study. Moreover, high domestic price volatility was observed around the year January 2011.

Forecasting Measure:

Based on Tables 13 and 14, different forecast measures were presented. Compare the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) measures for estimation by taking the monthly return series.

Table 13:

Forecast error measures, ARMA (1, 1)-GARCH (1, 1) models for Food return series

Statistics	N-GARCH	T-GARCH	GED-GARCH
RMSE	52.17435	51.28552	54.60178
MAE	37.87145	36.86054	40.69742
MAPE	51.53030	49.46214	57.90196

Source: Stata Output

Table 14: Forecast error measures, ARMA (1, 1)-GARCH (1, 1) models for Non-food return series

Statistics	N-GARCH	T-GARCH	GED-GARCH
RMSE	31.72562	30.20811	36.36234
MAE	20.41014	19.44141	23.41740
MAPE	23.00918	21.55105	26.47470

Source: Stata Output

Estimations of the GARCH

The values of the coefficients of the two series are shown below in Table 15. The estimation was done assuming that the error term comes from the student’s t-distribution. From the table, it can be seen that some of the coefficients in both of the returns are not significant at a 5% level of significance; for instance, the constant term is not significant in both cases. Looking at the parameter estimates of ARCH and GARCH terms from the table below they satisfy the non-negativity rule for both return series price inflation.

Table 15:

Parameter estimates from ARMA GARCH models, with student's t distribution

Returns	Food price	Non-food price
Mean equation		
c	-5.72e-06 (0.990)	-0 .0000286 (0.372)
AR (1)	-0.3067005 (0.000)	-0.0404124 (0.649)
MA (1)	0.4856 (0.000)	-0.9043047 (0.000)
Variance equation		
c	0.0000165 (0.105)	3.25e-06 (0.180)
RESID (-1) ^2	0.333451 (0.017)	0 .140688 (0.091)
GARCH (-1)	0.5312124 (0.002)	0.6924103 (0.000)
RESID (-1) ^2+ GARCH (-1)	0.8646634	0.8330983

Source: Stata Output

From the table output, the volatility equation gives $\alpha 0$ = 0.0000165, $\alpha 1$ =0.333451 and $\beta 1$ =0.5312124 for food price and $\alpha 0$ = 3.25 e-06, $\alpha 1$ =0 .140688 and $\beta 1$ =0.6924103 for Non-food price volatility. A high value of β1 means that volatility is persistent and it takes a long time to change. A high value of α1 means that volatility is spiky and quick to react to market movements. For Both food and Nonfood price volatility, the equation becomes as follows:

$\sigma 2t$ =0.0000165 +0.333451s$2t - 1$ +0.5312124 $\sigma 2t$ – 1, For food price.
$\sigma 2t$ =0.00000325 +0.140688s$2t - 1$ +0.0.6924103$\sigma 2t$ – 1, For Non Food price.

Generally, the variance equations indicated volatility effects in the returns series through the sample period considered. Concerning the estimated conditional correlation (food, non−food), the correlation was found to be positive and significant for all models. This indicates that positive relationship between the conditional volatility series of the food and nonfood price inflation series. This implies that if the volatility of food price inflation increases, the volatility of non-food price inflation also increases and vice versa.

For more, the study investigates the subgroup commodities that determine the food and nonfood price volatility and out of 22 commodities variables their ARCH effects should be tested using the residuals of the mean equation and checking whether significant or not/specifying a volatility model. Consequently from food subcategories, Cereals (wheat, maize, sorghum, teff, burley, etc), Bread and other prepared food, oil and fats, Meat, Fish and Seafood, Vegetable and fruits and coffee, (been, whole) and Tea leaves are significant whereas the left Pulses, Milk, Cheese and egg, Spices, Potatoes, other Tubers and stems and Other Foods Items are not significant at 5% and has no ARCH effect. From the non-food categories cigarettes and tobacco, Clothing and Footwear, House Rent, Water, Fuel and electricity, Medical Care and Health, Transport, Communication, and Education are significant at 5% and have an ARCH effect, whereas the Beverages, Furniture Furnishing, Household Equipment and Operation, Personal Care and Effects, Miscellaneous Good has no ARCH effect and not significant at 5% level. Therefore, the study considers those subgroup commodities that are significant and excludes from the estimates those that are not significant at a 5% level of significance.

Table 16:

Non-food price subgroup commodities Parameter estimates from ARMA-GARCH models, with student's t distribution

Commodity Returns	Mean equation			Variance equation		
	c	AR (1)	MA (1)	c	Resid	GARCH (-1)
Beverages and tobacco	-0.0154 (0.9407)	-0.0572 (0.9442)	-0.0495 (0.9926)	0.05272 (0.4416)	0.6114 (0.6060)	0.0731 (0.0010)
Clothing and Footwear	-0.0269 (0.4767)	-0.1910 (0.9905)	0.0602 (0.9969)	0.05063 (0.4558)	1.0610 (0.5927)	0.5798 (0.3226)
House Rent, Water, Fuel and electricity	4.1678 (0.0020)	0.7965 (0.0068)	0.5857 (0.0092)	0.0294 (0.0089)	0.0015 (0.0048)	0.2560 (0.0435)
Medical Care and Health	0.0080 (0.0000)	0.326 (0.0871)	0.0253 (0.9451)	0.00741 (0.0082)	0.01500 (0.0093)	0.6000 (0.0059)
Transport	0.2457 (0.0023)	0.8504 (0.000)	0.6016 (0.9629)	0.0026 (0.0185)	0.0005 (0.0056)	0.00009 (0.0036)
Communication	4.1990 0.0000	0.0429 0.0256	0.1348 0.6586	0.0004 0.0848	0.0259 0.0850	0.0058 0.3921
Education	-0.0139 (0.9447)	0.0017 (0.0000)	0.020124 (0.0589)	0.01181 (0.0976)	0.04259 (0.9090)	0.80484 (0.0000)

Source: Stata Output

Table 17:

Food price subgroup commodities Parameter estimates from ARMA GARCH models, with student's t distribution

Commodity Returns	Mean equation			Variance equation		
	c	AR (1)	MA (1)	c	Resid	GARCH
Cereals	4.447 (0.9899)	0.0994 (0.0475)	0.03312 (0.9860)	0.3128 (0.04646)	0.1500 (0.009)	0.6000 (0.00075)
Bread and prepared food	8.4078 (0.1284)	0.9976 (0.000)	0.2747 (0.0000)	0.00018 (0.0050)	1.06410 (0.000)	0.4153 (0.0000)
oil and fats	2.0010 (0.0960)	0.9999 (0.0000)	0.07832 (0.2195)	0.0003 (0.000)	0.07632 (0.0000)	0.0560 (0.0213)
Meat	8.5067 (0.000)	0.9926 (0.0000)	-0.5454 (0.0000)	0.00014 (0.0082)	0.31150 (0.0000)	0.0985 (0.0000)
Fish and Seafood	4.5093 (0.000)	0.0477 (0.000)	-0.7081 (0.000)	0.000105 (0.0445)	0.14572 (0.0000)	0.1787 (0.0000)
Vegetable and fruits	9.9590 (0.0674)	0.9987 (0.000)	0.2448 (0.0077)	0.000094 0.06104	0.19157 0.0009	0.8727 0.0000
coffee, (been, whole) and Tea leaves	4.5257 (0.000)	0.9942 (0.0000)	0.00843 (0.9276)	0.001220 (0.6116)	0.009612 (0.5913)	0.17162 (0.9162)

Source: Stata Output

The GARCH results are presented in two tables 16 and 17. For all return series, the estimated coefficients satisfy the non-negativity condition. In summary, Education, Medical Care and Health, House Rent, Water, Fuel, Electricity, Clothing, and Footwear, appear to show higher volatility, whereas Transport, communication, Beverages, and tobacco show lower volatility in the nonfood price return series.

Conclusion and Implications

The objective of this study was to model and forecast the volatility of food and non-food prices in the Ethiopian market over the period from December 2000 to September 2020. From the preliminary analysis over the period considered, both of the price series show an increasing trend pattern. But the return series shows the stationary for both food and non-food prices. Additionally, the price return series of food and non-food show the characteristics of financial time series such as leptokurtic distributions. This provides an adequate ground for the use of GARCH family models. The squared return series were highly correlated for both food and non-food prices.

The lag length selection was the next work because unless true lag length is selected the precision of the parameters may be biased. The lag length selection criteria were conducted using both the usual test and the result showed the lag length would be lag two. This paper used the Johansen co-integration test to test the long-run relationship between CPI and FPI in Ethiopia as the variables are co-integrated of order one. Both trace and max-eigen value statistics show there was a long-run relationship between CPI and FPI. The result shows that FPI hurts CPI in the short run and long run. The one long-run equation obtained from the normalization equation states that other variables held constant, in the long run, as FPI is increased by 1%, it is associated with the increase of CPI by 42.8431%. This shows that there is a positive relationship between CPI and FPI. In the two inflation returns it appears that the ARCH term coefficients were significant at a 5% level of significance. The result is an implication of the existence of volatility clustering, that is, large changes followed by large changes and small changes followed by small changes. In the case of food prices, the result is linked with the Hansen (2010) findings. They conclude that the GARCH (1, 1) model is enough to capture the volatility of exchange rates return volatility, but in the case of non-food prices the finding is something different.

This study suggests using accurate forecast evaluation values in GARCH models. In our analysis to evaluate the forecasts we utilize the Root Mean square error, mean absolute error, and mean absolute percentage error of predictive power, comparing forecasting performance based on the three values obtained. Overall, the positive relationship between these price inflation returns is reliable with previous researchers on energy and commodity co-volatility (Choi and Hammoudeh (2010); Du et al. (2011); Mensi et al. (2013).

From the empirical findings of this study, the following recommendations are drawn future researchers should be motivated in modeling the volatility using GARCH models to pay certain consideration to the measure of forecasting performance whenever viable.

- Public policymakers should be interested in foreseeing the price volatility of these two major prices in the context of the Ethiopian economy and consider using the information documented in this study as input in their considerations given that it is based on some powerful econometric work and highly appropriate data.

- The Minister of Trade should play an active role in identifying current and appropriate information related to food and non-food items by effectively using market volatility of food and non-food prices and providing a report for policymakers to manage risks.

- The scope of the analysis in this study has been limited to the volatility of the food and non-food prices. To overcome this limitation and provide a more nuanced analysis, it might be profitable for future researchers to consider other determinants that affect the price volatilities like interest rate, and money supply into the analysis.

- The Ethiopian government should focus on stabilization policies to dampen the high volatilities of commodities and a prudent fiscal policy as a means of avoiding sources of subgroup commodities imbalance is quite apparent to reduce the rapidly rising food prices and nonfood prices in the country.

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