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Using Models of the GARCH Family to Estimate the Level of Food and Non-Food Inflation in Ethiopia

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Abstract. An increase in inflation volatility implies higher uncertainty about future prices. As a result, producers and consumers can be affected by the increased inflation volatility, because it increases the uncertainty and the risk in the market. Thus, inflation volatility attracts the attention of researchers to find a suitable model which can predict the future conditions of the market. This study aims to fit appropriate ARMA-GARCH family models for food and non-food inflation rate of from the period January 1971 through June 2020. Since the main objective of the study is identifying an appropriate model for inflation series, the null and alternative hypotheses are defined in comparison of the two types of models. H_0: The symmetric GARCH models better capture inflation volatility of Ethiopia. H_1: The asymmetric GARCH models better capture inflation volatility of Ethiopia. The ARMA-GARCH family models were applied to capture the stylized facts of financial time series such us leptokurtic, volatility clustering and leverage effects. The mean model results show that, an ARMA (1, 2) and ARIMA (0, 1, 1) models are identified as the best fitted model for food and non-food inflation, respectively. From the estimation results of volatility model, an asymmetric TGARCH (1, 1) model with Student's t- distributional assumptions of the residual is the best model for non-food inflation. Thus, modeling of information, news of events is very significant determinants of volatility and GARCH family models are appropriate for the given series (monthly food-inflation volatility) of Ethiopia under the study period considered.

Key words: food inflation; non-food inflation; ARMA-GARCH family; Ethiopia.

JEL C10, C53

1. Introduction

Historically, Ethiopia inflationary experience was moderate and not considered as serious as the issue of economic growth. Since 2004, however, the country has experienced high and persistent inflation growth. Several macro-economic stabilization measures and policies were implemented over the past and seemed to be a complete failure. The booming economy has yet remained principally constrained by dual macroeconomic problems, i. e. price inflation and low international reserves [1].

A rising inflation has become one of the major economic challenges facing Ethiopian as the rate of inflation increase; people will lose confidence with state of the currency since the currency depreciates. The aforementioned creates a need of high wages in the economy and consequently the companies increase the prices of goods and services to overcome the wage increase and at the same time to continue making profits in offering their services [2].

Furthermore, an unanticipated inflation has a distributive effect from creditors to debtors, which increases uncertainty affecting consumption, savings, and borrowing and investment decisions. This raises the question of knowing the pattern of inflation rate by consumers, producers, government and economists to plan budgeting. Thus, modeling food inflation and non-food inflation were attracting the attention of macroeconomists and policy makers for many years both at the theoretical and at the empirical level.

The volatility of inflation has broad economic and financial implications, and this has motivated a vast literature on modeling such volatility. In this regard, Engle [3] first introduces the autoregressive conditional heteroscedasticity (ARCH) model to assess the validity of the conjecture of Friedman [4] that the unpredictability of inflation was a primary cause of business cycles since uncertainty due to this unpredictability would affect the investors' behavior. Pursuing this idea required a model in which this uncertainty could change over time [5]. Consequently, Bollerslev [6] proposed independently a more generalize ARCH (GARCH) model which is more parsimonious model of the conditional variance than a higher order ARCH model.

The GARCH model, however, cannot account for leverage effect, even though it accounts for volatility clustering and leptokurtosis in a series. This necessitated the development of new and extended models over GARCH that resulted into new models such as EGARCH, GJRGARCH, and TGARCH models because the behavior of inflation volatility is asymmetric rather than symmetric resulting in that the symmetric GARCH model provides misleading estimates of inflation uncertainty.

Moreover, Power GARCH (PGARCH) is a model introduced by Ding et al. [7]. It is able to capture and model the long memory property often observed in the series of volatility and with Engle and Lee [8] component GARCH model decomposing conditional variance into a short run and long run volatility, separately. In this regard, various researchers such as, Barimah [9], Okeyo et al. [10], Syed et al. [11], Asemota et al. [12] and among others tried to analyze inflation volatility using GARCH family models.

In the case of Ethiopia, few studies (Shiferaw [13], Anteneh et al. [14], Abebe et al. [15], Abebe [16], and among others) were carried out to evaluate the performance of GARCH models on explaining different agricultural product price volatility. However, to the best of my knowledge, not enough studies were performed separately to model food and food inflation volatility of Ethiopia using various GARCH family models.

The overall objective of this study is to fit an appropriate GARCH type models for food and non-inflation uncertainty (volatility) in Ethiopia over the period of January 1971 through June 2020. Unlike the existing literature where the inflation uncertainty is generally proxied by symmetric GARCH, in this study, the asymmetric GARCH and component GARCH (CGARCH) models were also used to compare the performance of various model in fitting inflation uncertainty of Ethiopia under the study period.

Since the main objective of the study is identifying an appropriate model for inflation series, the null and alternative hypotheses are defined in comparison of the two types of models as stated below:

H_0: The symmetric GARCH models better capturing inflation volatility of Ethiopia.

H_1: The asymmetric GARCH models better capture inflation volatility of Ethiopia.

2. Literature Review

2.1. Theoretical literature review

Theoretically, there are a number of literatures that describe a rise in inflation increases uncertainty about future inflation. Okun's [17] study was one of the first attempts to examine systematically the relationship between inflation and its variability. Consequently, Friedman [4] stated that rising inflation increases private agents' uncertainty about future monetary policy. He states that the more uncertain inflation is to extract the signal about relative prices from the absolute prices. When inflation is engrained in an economic system, it is difficult and costly to lower it because inflationary expectations become inertial and cannot be quickly and easily lowered to a sustainably low level.

Ball [18] added that, higher inflation rates generate greater uncertainty about the future policy so about future inflation rate. In a market economy, inflation uncertainty reduces the price system's efficiency in coordinating economic activity (Wilson [19]). Poon [20] also postulated that uncertainty (volatility) may disrupt the normal activity of day-to-day life of each individual and greatly affect economic performance.

Given that inflation uncertainty is an unobserved variable, many different measures have been proposed in the literature. Some studies rely on survey-based measures, others depend on volatility derived from time series models, and some use realized forecast errors. However, each measure is depending on the nature of the data and derived from different assumptions which are most likely not fulfilled completely.

Mostly, macroeconomic data are tending (time series), volatility derived from time series models are the interest of most studies. Even though, inflation uncertainty (volatility) measure captures the extent of fluctuations in inflation is clearly important for structural analysis, forecasting and policy purposes, the issue of finding suitable proxy for inflation volatility or uncertainty has been challenging. Although there could be several ways to estimate inflation volatility from the survey-based methods to empirical models, the most common used method is to estimate inflation volatility is the univariate autoregressive conditional heteroscedasticity (ARCH) models proposed by Engle [3] and Bollerslev [6] generalized ARCH (GARCH) model are the pioneer one.

It has been argued that the behavior of inflation volatility is asymmetric rather than symmetric. Fountas et al. [21] and Baunto et al. [22] are of the view that positive inflation shocks have a significantly greater impact on volatility compared to the negative's inflation shocks. Thus, given the nature of the data, the symmetric ARCH and GARCH models may provide misleading estimates of inflation uncertainty.

Thus, modifications to the original GARCH model were necessarily to overcome these shortcomings of symmetric GARCH model in inflation series. The common asymmetric GARCH family models are an exponential GARCH (EGARCH) model introduced by Nelson [23], GJR-GARCH of Glosten et al. [24] and TGARCH model by Zakoian [25]. Subsequently, Engle and Lee [8] generalize introduced a component GARCH (CGARCH) model that decomposes the conditional variance into transitory and permanent components.

2.2. Empirical literature review

There are ample empirical studies conducted on modeling inflation volatility using the standard GARCH family models.

Barimah [9] examined the asymmetric effects of inflation-on-inflation uncertainty in Ghana for the period 1963:4 to 2014:2. He applied an EGARCH model on monthly inflation rates to estimate inflation uncertainty. From the result, the variance equation indicates that inflation uncertainty varies directly with the rate of inflation in highly inflationary periods.

Okeyo et al. [10] investigates inflation rate volatility in Kenya using ARCH type model on the data spanning from January 1985 to April 2016. The result of the study showed that the EGARCH (1, 1) with GED was the best in modeling and forecasting Kenya's monthly inflation rate. They recommended that governments, policy makers interested in modeling and forecasting monthly rates of inflation should take into consideration heteroscedasticity models since it captures the volatilities in the monthly rates of inflation.

Syed et al. [11] studied inflation volatility in 10 Asian economies using quarterly data from 1991 to 2012 by applying different GARCH family models. The result showed that the leverage parameter is statistically significant, indicating the existence of an asymmetric GARCH model in the model specifications. Thus, the GJR-GARCH model was an important model in estimating the existence of inflation stabilization of bidirectional causality running between inflation and inflation volatility.

Few empirical researches that were conducted to analyze inflation volatility using GARCH type models are discussed below.

Shiferaw [13] analyzed the log-returns price volatility of agricultural products under consideration using GARCH type models over the period from May 2001 to April 2011. From the result of model estimation, the GARCH (1, 1), GARCH (1, 2) and GARCH (2, 1) models are the most appropriate fitted models to evaluate the volatility of the log-returns of price of Cereal, pulse and oil crops respectively.

Anteneh et al. [14] model and identify determinants of monthly domestic price volatility of sugar in Ethiopia over the study period from December 2001 to December 2011 using GARCH family approach. From the results EGARCH model with Student-t distributional assumptions for residual was selected as the best fitted model for the series under the period considered.

Abebe et al. [15] applied multiplicative GARCH-MIDAS two component models for price return volatility of selected commodities traded at the Ethiopian commodity exchange (ECX). The component model helps to can capture the time-varying conditional as well as unconditional volatilities, and accommodates macroeconomic variables observed at different frequencies through mixed interval data sampling (MIDAS) specification. From the result it is observed that the fitted GARCH-MIDAS component models capture the stylized facts of financial time series.

Abebe [16] analyzed the average daily coffee price volatility of Ethiopia from 1 January 2010 to 30 June 2019 using GARCH-MIDAS component model which decomposes the conditional variance into short run component which follows a mean-reverting unit GARCH process and long-run component which consider different frequency macroeconomic indicators via mixed interval data sampling (MIDAS) specification. From the result of estimated model, all selected indicators are crucial in explaining price volatility. Moreover, the estimated GARCH-MIDAS model with money supply as a main driver is used for out-sample forecast. Based on, DM test statistic multiplicative GARCH-MIDAS model provides an explanation for stylized facts that cannot be captured by standard GARCH model.

Given the compatibility of the aforementioned GARCH family models for inflation series as discussed in both theoretical and empirical literature review, the researcher in the current study try to compare the performance of different GARCH type models, for monthly food and non-food inflation uncertainty of Ethiopia.

3. Data Source and Methodology

3.1. Data and Nature of the series

This study uses secondary data. The variables are monthly food and non-food inflation rate, which were compiled from the National Bank of Ethiopia. Theoretically, linear time series models such as ARIMA models are unable to explain a number of important features. Those common features are leptokurtosis, volatility clustering, leverage effects and long memory. Thus, GARCH family models proposed to analyze the stylized facts of the series under this study.

3.2. Stationary and Unit Root Test

The foundation of time series analysis is stationarity. Stationary series is characterized by a kind of statistical equilibrium around a constant mean level as well as a constant dispersion around that mean level (Box and Jenkins [26]). If a time series is not stationary, it is necessary to look for possible transformations that might induce stationarity.

Several statistical tests may be carried out to determine whether a series is stationary or non-stationary. In this study, the commonly used unit root test, the Augmented Dickey Fuller (ADF) test, which controls higher-order correlation, is used. In ADF test, if the null unit root (non-stationarity) is not rejected, apply differencing to make the series stationary.

3.3. ARMA Model Specification

The Box–Jenkins method (ARIMA) requires that the discrete time series data be equally spaced over time and that there be no missing values in the series. The ARMA model states that the current value of the series depends linearly on its own previous values plus a combination of current and previous values of a white noise error term.

The general stationary process yt under an ARMA (p, q) process is given by

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \beta_j \varepsilon_{t-i}, \quad (1)$$

where, y_t is inflation series, $\alpha_0, \alpha_1, \alpha_2, ..., \alpha_p$ are the coefficients of an AR model and $\beta_0, \beta_1, \beta_2, ..., \beta_p$ are MA coefficients, while p and q are integers indicating the lags of AR and MA model, respectively.

3.4. Model selection criteria

When we estimate the mean ARMA model, there are various model selection criteria, which are based on the likelihood function and the number of free parameters from the fitted ARMA model. This study used the Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Hannan Quin Information Criterion (HQIC).

3.5. Parameter Estimation ARMA Models

In order to estimate the parameters of an ARMA (p, q) model, the maximum likelihood estimation method that maximizes the joint probability density function of the innovation terms $\varepsilon_1, \varepsilon_2, ..., \varepsilon_T$ was applied.

3.6. Model Diagnostic Checking

After estimating the ARMA model and before interpreting its result, it is mandatory to check whether the model is appropriately specified or whether the model assumptions are satisfied.

1. *Breusch-Godfrey Lagrange Multiplier (LM) Test for Serial Correlation*. This test was developed by Breusch [27] and Godfrey [28] in 1978 and is used to test for serial correlation in the error terms. The Lagrange Multiplier (LM) test for serial correlation is computed first by estimating the sample residuals $\hat{\varepsilon}_t$ by ordinary least squares (OLS) and regress the current residual $\hat{\varepsilon}_t$ on the p lagged residuals.

The auxiliary regression model of residuals is given by:

$$\hat{\varepsilon}_t = \gamma\mu_t + \lambda_1\hat{\varepsilon}_{t-1} + \lambda_2\hat{\varepsilon}_{t-2} + \dots$$
$$\dots + \lambda_p\hat{\varepsilon}_{t-p} + \upsilon_t, \quad (2)$$

where μ_t is the original regressors in the ARMA model and υ_t is a white noise process. The null hypothesis of no serial correlation up to lag p is $H_0 : \lambda_1 = \lambda_2 = ... = \lambda_p = 0$.

The Obs*R-squared statistic is the Breusch-Godfrey LM test statistic. If the R2 statistic from the auxiliary regression is computed for this model, then the following asymptotic approximation can be used for the distribution of the test statistic, $TR^2 \sim X^2(p)$.

2. *Testing Normality of the Residual.* Normality tests are used to ascertain whether the residuals of the regression are normally distributed or not. The null hypothesis is that the residuals are normally distributed. Several tests for normality are available but the most commonly used test for normality of regression disturbances is due to Jarque and Bera [29]. The Jarque-Bera test statistic is given by

$$JB = T\left(\frac{\frac{\hat{\mu}_3}{(\hat{\sigma}^2)^{\frac{3}{2}}}}{6} + \frac{\left(\frac{\hat{\mu}_4}{(\hat{\sigma}^2)^2} - 3\right)^2}{24} \right), \quad (3)$$

where T is the sample size. Under the null hypothesis of normality, the test statistic is asymptotically distributed as $\chi^2(2)$. Thus, if JB test statistic is greater than $\chi^2(2)$, we reject the null hypothesis.

3. *Testing for ARCH Effect.* The Lagrange multiplier test of Engle (1982) is equivalent to the usual F test. To test the null hypothesis that there is no ARCH up to order p in the residuals, we run the regression of squared the residuals on my own lags to test for ARCH of order m as given by:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1\hat{\varepsilon}_{t-1}^2 + \gamma_2\hat{\varepsilon}_{t-2}^2 + ...$$
$$... + \gamma_m\hat{\varepsilon}_{t-m}^2 + \eta_t . \quad (4)$$

Then obtain R^2 from this auxiliary regression. The test statistic is defined as $LM = TR^2$ (the number of observations multiplied by the coefficient of multiple correlations) from the last regression, which is Engle's LM test statistic. The LM test statistic is asymptotically distributed as a χ^2(m) under quite general conditions. The null hypothesis given by $H_0 : \gamma_1 = \gamma_2 = ... = \gamma_m = 0$. The decision rule is to reject the null hypothesis.

3.7. Volatility Model Specification

One of the mean features of financial time series is time varying volatility which refers to a tendency of small values being followed by small values and large values being followed by large values (Torben et al. [5]).

1. *The ARCH Model.* As stated in Tsay [30] the basic idea of ARCH models is that: the shock ε_t is serially uncorrelated, but dependent and the dependence of ε_t can be described by a simple quadratic function of its lagged values.

Then the ARCH (q) process proposed by Engle [3] is given by

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 , \quad (5)$$

where σ_t^2 is the conditional variance of the error term in the mean model, ε_t is innovation or error term from the mean (ARMA) model. The positivity of σ_t^2 is assured by the following sufficient restrictions: $\omega > 0$ and $\alpha_i \geq 0$.

An ARCH (q) model is covariance stationary if and only if $\sum_{i=1}^{q}\alpha_i < 1$.

2. *Generalized ARCH (GARCH) models.* A Generalized ARCH (GARCH)

model introduced by Bollerslev [6] gives parsimonious way of estimating the parameters and successful in predicting conditional variances.

Thus, GARCH (p, q) (generalized ARCH due to Bollerslev [6] is given by:

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

where $\omega > 0$ is the constant term, $\alpha_i \geq 0$, for $i = 1, 2, \ldots, q$ is the effect of shocks (the ARCH effect), and $\beta_j \geq 0$, for $j = 1, 2, \ldots, p$ is the effect of the previous periods' variance (the GARCH effect). Bollerslev [6] shows that the necessary and sufficient condition for the second-order stationarity of model (6) is $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$. In this case, conditional variance forecasts converge upon the long-term average value of the variance (unconditional variance) as the prediction horizon increases.

3. *The EGARCH model.* Nelson [23] introduced the exponential GARCH (EGARCH) model. GARCH successfully captures thick-tailed returns, and volatility clustering. However, it is not well suited to capture the «leverage effect» since the conditional variance in GARCH model is only a function of the magnitude of the lagged residual and not their signs. However, in EGARCH model, σ_t^2 depends on both the size and the sign of lagged residuals and which accounts for such an asymmetric response to a shock (negative shocks).

The EGARCH (p, q) model specifies conditional variance in logarithmic form, which means that there is no need to impose an estimation constraint in order to avoid negative variance.

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - E \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{p} \beta_j \log\left(\sigma_{t-j}^2\right), \quad (7)$$

where α_i is magnitude effect, β_j is lagged log conditional variance, γ_k is the asymmetric response parameter or leverage parameter. We expect $\gamma_k < 0$, indicating that with appropriate conditioning of the parameters, this specification captures the stylized fact that a negative shock (bad news) leads to a higher conditional variance in the subsequent period than a positive shock (good news). The logarithmic formulation of the model guarantees positive conditional variance, without imposing restrictions on the parameters.

4. *The GJR GARCH model.* It is model developed by Glosten et al. [24] expressed the leverage effect in a quadratic form while EGARCH expressed in the exponential form.

The conditional variance is now given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k I_{t-k} \varepsilon_{t-k}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \quad (8)$$

where I_{t-k} is an indicator variable in which

$$I_t = \begin{cases} 1, \text{ if } \varepsilon_t < 0, \text{ represents the "bad news"} \\ 0, \text{ if } \varepsilon_t \geq 0, \text{ represents the "good news"} \end{cases}.$$

In this case, $\gamma_k > 0$ indicating negative shocks (bad news) have a deeper impact on future volatility than positive shocks.

5. *The Power TGARCH Model.* Zakoian [25] introduced threshold GARCH (TGARCH) model in 1994. The threshold GARCH is similar to the GJR model, different only because of the conditional standard deviation and absolute return instead of the conditional variance.

Threshold GARCH (p, r, q)) process is defined as:

$$\sigma_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{k=1}^{r} \gamma_k I_{t-k} \varepsilon_{t-k} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}. \quad (9)$$

The conditional volatility is positive when $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\alpha_i + \gamma_i \geq 0$.

In TGARCH we expect γ_i to be positive, so that bad news would have a more powerful effect on volatility than good news.

6. *The Power GARCH (PGARCH) Model.* Ding et al. [7] introduced the power GARCH model that has the advantage of being able to capture and model the long memory property often observed in volatility series. The primary feature of the power GARCH (p, q) model is the presence of a Box-Cox power trans- formation of the conditional variances.

The Power GARCH (PGARCH) is defined as:

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(\left|\varepsilon_{t-i}\right|\right)^\delta + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^\delta, \quad (10)$$

where δ is the power term parameter and should be greater than zero. The asymmetric effect presents if $\gamma_i \neq 0$, and $-1 < \gamma_i < 1$.

7. *The Component GARCH (CGARCH) Model.* Component GARCH model introduced by Engle and Lee [8] decompose conditional variance into a temporary or a permanent component. In this study, the component GARCH models are employed to decompose inflation uncertainty into short-run and long-run component by permitting transitory deviations of the conditional volatility around a time-varying trend.

The component GARCH (1, 1) model can be expressed as follows:

$$\sigma_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(\sigma_{t-1}^2 - q_{t-1}\right) (short-term)$$
$$q_t = \alpha_0 + \rho\left(q_{t-1} - \alpha_0\right) + \phi\left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2\right) \; (long-term), \quad (11)$$

where α and β indicates short run memory, while q_t is the time varying long-run volatility (long run memory). The first equation describes the transitory (short-term) component, which converges to zero with power(α+β). The second equation describes the long-run component, which converges to α_0 with powers of ρ.

3.8. Estimation of ARCH/GARCH models

The ARCH family models are estimated by maximum likelihood estimation method. It can be employed to find parameter values for both linear and non-linear models (see, Brooks [31]). However, the GARCH type model needs specification of the distribution assumption of the error term: normal (Gaussian), t-distribution and, Generalized Error Distribution (GED).

1. *Normal Distribution.* Engle [3] and Bollerslev [6] developed the distribution of the innovations z_t which has a standardized normal probability function.

$$f^*(z) = \frac{1}{\sqrt{2\pi\sigma_t^2}} e^{-\frac{\varepsilon_t^2}{2\sigma_t^2}} = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}},$$
$$-\infty < z < \infty, \quad (12)$$

where $f^*(z)$ the probability function or density is named standardized, marked by a star because $f^*(z)$ has zero mean and unit variance.

2. *Student-t-Distribution.* Bollerslev [32] proposed the standardized Student-t-distribution with $V>2$ degree of freedom, which better captures the observed kurtosis.

The Standardized Student-t-distribution density function $f^*(z/\nu)$ expressed as

$$f^*(z/\nu) = \frac{\Gamma[(V+1)/2]}{\sqrt{V\pi}\,\Gamma\left[\frac{V}{2}\right]\left(1+\frac{z^2}{V}\right)^{(\nu+1)/2}},$$
$$-\infty < z < \infty, \quad (13)$$

where Γ(.) is the usual gamma function, V is the degree of freedom which represents the parameter to be estimated. Like, the normal distribution, the t-distribution is symmetric around zero mean $\mu = 0$ *for* $V \geq 2$ and its variance, $\sigma_t^2 = \frac{V}{V-2}$ *for* $V \geq 3$ and kurtosis $K = \frac{6}{V-4}$ *for* $V \geq 5$, respectively.

However, for $V \to \infty$ the density of standardized student-t distribution converges to the density function of standardized student normal distribution.

3. *Generalized Error Distribution (GED)*. Nelson [23] suggested considering the family of Generalized Error Distributions, GED. The GED is a symmetric distribution that can be both leptokurtic and platykurtic depending on the degree of freedom $V(V>1)$.

When $f^*(z/\nu)$ assume a GED has the following density function:

$$f^*(z/\nu)=\frac{Ve^{-\frac{1}{2}\left|\frac{z}{\lambda}\right|^{V}}}{\Gamma\left(\frac{1}{V}\right)\lambda 2^{(V+1)/V}},$$

$$1<z<\infty,\quad 0<V\leq\infty, \tag{14}$$

where λ is tail -thickness parameter, $\lambda=\left[\frac{2^{-2/\nu}\Gamma\left[1/\nu\right]}{\Gamma\left(\frac{3}{V}\right)}\right]^{\frac{1}{2}}$.

For $V=2$, the GED is a standard normal distribution whereas the tails are thicker than in the normal case when $V<2$, and thinner when $V>2$. The GED becomes a uniform distribution on the interval $\left[-\sqrt{3},\sqrt{3}\right]$ when $V\to\infty$.

3.9. Model selection

An important practical problem is the determination of the ARCH order p and the GARCH order q for a particular series. Since GARCH models can be treated as ARMA models for squared residuals, traditional model selection criteria such as the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and Hannan-Quinn Criteria (HQC) may be used.

3.10. Model Adequacy Checking

After a GARCH model has been fitted to the data, the adequacy of the fit should be evaluated. In this study, we apply the ARCH-LM Test for standardized residuals of the fitted GARCH type models.

3.11. Volatility Forecasting

Tsay [30] stated again that the forecasts of the GARCH model are obtained similarly as the forecasts of an ARMA model. If we consider a GARCH (1, 1) model, which is one of the GARCH models under study at the forecast origin k, the 1-step ahead forecast of σ_{k+1}^2

$$\hat{\sigma}_k^2(1)=\alpha_0+\alpha_1\varepsilon_k^2+\beta_1\sigma_k^2.$$

For the general GARCH (1, 1) l-step head forecast of σ_{k+1}^2, at origin k, is $\hat{\sigma}_k^2(1)=\alpha_0+(\alpha_1+\beta_1)\sigma_k^2,\quad l>1.$

3.12. Measuring the Accuracy of Volatility Models forecasting

Evaluation of univariate volatility forecasts is relatively straightforward and relies on standard forecast evaluation techniques. Among the common statistical methods, which can be used to observe the prediction accuracy of a model, the root means square error (RMSE), the mean absolute error (MAE), the mean absolute percent error (MAPE), and the Theil inequality coefficient (TIC) are used in this study. The forecasting statistics are as follows:

$$RMSE=\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{\sigma}_t^2-\sigma_t^2\right)^2}, \tag{15}$$

where $\hat{\sigma}_t^2$ is one-step head volatility forecast, σ_t^2 is the actual volatility and T is the number of forecasts or the number of time or year in the out-of-sample period.

$$MAE=\frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2-\sigma_t^2\right|. \tag{16}$$

$$MAPE=\frac{1}{T}\sum_{t=1}^{T}\frac{\left|\hat{\sigma}_t^2-\sigma_t^2\right|}{\left|\sigma_t^2\right|}. \tag{17}$$

The Mean Absolute Deviation (MAD) is interesting since it is very robust to outliers and this criterion actually gives equal weighting to a large deviation of size z as to a sum of several deviations accumulating to z.

The Theil Inequality Coefficient (TIC) is a scale invariant measure that always lies between zero and one, where zero indicates a perfect fit.

$$TIC = \frac{\sum_{t=1}^{T} \frac{\left|\hat{\sigma}_t^2 - \sigma_t^2\right|}{T}}{\frac{1}{T}\sum_{t=1}^{T}\hat{\sigma}_t^2 + \sum_{t=1}^{T}\frac{\sigma_t^2}{T}}. \quad (18)$$

The smaller is the error in the first three forecast error statistics, the better the forecasting ability of that model according to that criterion.

4. Results and Discussions

4.1. Results of Descriptive Statistics

The data used in this study were monthly food and non-food inflation rate of Ethiopia from the period January 1971 through June 2020. To analyze the series, ARMA-GARCH family models were used.

The first step in time series analysis is time plot of the original series in level against time and observes its graphical properties. This help in understanding the trend as well as pattern of movement of the original series. Here we plot the original series of food & non-food inflation rate in Ethiopia as function of time. The time plots are depicted in Figure 1 & 2.

On Figure 1, food inflation rate looks like white noise series and varying about zero, i. e. close to stationary, while non-food inflation rate on Figure 2 shows somehow non-stationary since the fluctuation rate is relatively high. However, the plot of series by itself is not an end, rather we use as a clue.

Table 1 shows the summary statistics of food and non-food inflation rate. The table reveals the positive mean food and non-food inflation rate of 10.77 and 8.03, respectively. It also shows that monthly food inflation falls to lowest level (–52.6) on July 2001 and reaches its maximum level (91.7) on July 2008.

Moreover, a very high Jarque Berra (J-B) value 343.3 for food inflation and 42.7 for non-food inflation rate and a very small corresponding p-value, therefore, the null hypothesis of normality was rejected for the data. To support the inference on normality, the skewness (0.99) and (0.65) for food and non-food inflation, respectively are greater than 0 (skewness of a normal distribution is 0) and the kurtosis (6.14) and (3.03) are higher than 3 (kurtosis of a normal distribution is 3). The positive skewness is an indication that the upper tail of the distribution is thicker than the lower tail which implies that it rises more often than it drops, reflecting the renewed confidence in the market.

4.2. Unit root test results

The time series should be checked for stationarity before we fit a suitable model. In this study, an Augmented Dickey-Fuller test (ADF) test is used to check the

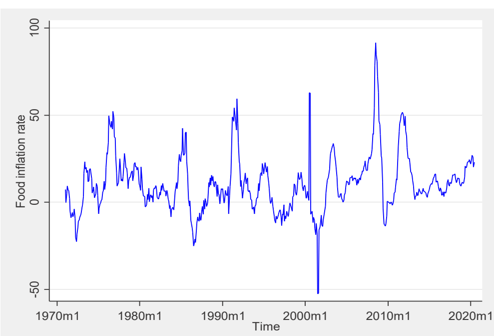

Fig. 1. The time plot of food-inflation rate

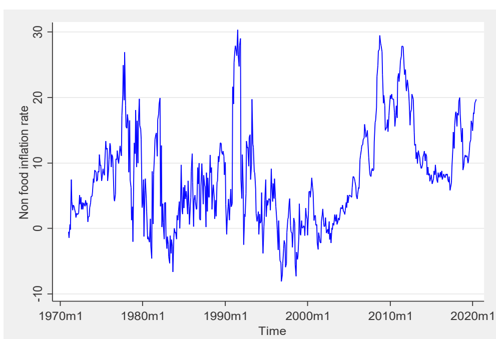

Fig. 2. Time plot of non-food inflation rate

Table 1. **Descriptive statistics of food and non-food inflation rate**

Statistics	Food inflation rate	Non-food inflation rate
Mean	10.77712	8.034845
Std. Dev.	16.7424	7.645212
Min	-52.64756	-8.082834
Max	91.73248	30.2925
Skewness	0.993686	0.656414
Kurtosis	6.149851	3.037737
Jarque-Bera	343.3124	42.69227
Probability	0.000000	0.000000
Obs	594	594

Source: Author's Computation

stationarity of the monthly inflation series. In the case of Dickey-Fuller test, there may be autocorrelation problems. To tackle such autocorrelation problem, Dickey-Fuller has developed a test called Augmented Dickey Fuller (ADF) test. In ADF test, the null hypothesis stated that the variable is not stationary or have a unit root test.

The results of the ADF test statistic for food and non-food inflation series are depicted in Table 2. Normally we use 5% critical value to evaluate the stationarity condition of the series. For example, the test statistic for food inflation rate with constant term and constant & linear trend are 4.7067 and 4.7756 in absolute value, which is greater than 5% critical value (2.86 & 3.4175), respectively, indicating rejection of the null hypothesis of non-stationarity. However, the non-food inflation rate is non-stationary at level since the test statistic with constant (2.47) and constant & linear trend (2.6456) in absolute value is less than 5% critical value (2.86 & 3.41), respectively, indicating failure to reject the null hypothesis of non-stationarity. Thus, we need to apply first difference to make it stationary as indicated in the Table 2.

Table 2. **Unit root tests for the series at level and difference**

Variables		ADF Test Critical values				
		t-statistic	1%	5%	10%	*P*-value
Food inflation rate (level)	With constant	-4.7067	-3.441	-2.866	-2.5693	0.0001
	Constant & linear trend	-4.7756	-3.973	-3.4175	-3.1312	0.0005
Non-Food inflation rate (level)	Constant	-2.4757	-3.4413	-2.8662	-2.5693	0.1220
	Constant & linear trend	-2.6456	-3.9739	-3.4175	-3.1312	0.2601
Non-Food inflation rate(first difference)	Constant	-12.374	-3.4413	-2.8662	-2.569	0.0000
	Constant & linear trend	-12.363	-3.9739	-3.4175	-3.131	0.0000

Source: Author's Computation

From the results, the first difference of non- food inflation rate is stationary since the test statistic with constant (12.37) and constant & linear trend (12.36) in absolute value is greater than 5 % critical value (2.86 & 3.13), respectively.

4.3. ARIMA type model estimation results

Before we specify volatility model for the given series, we should specify a mean equation. In this study, an Autoregressive Moving Average model (ARMA) type models specify the conditional mean equations for the food and non-food inflation rate.

Given the significance of the coefficients and absence of serial correlation in the residuals and smallest value of information criteria, the following models are determined. From the results on Table 3, ARMA (1, 2) model was identified as the best mean model for estimating the coefficients of food inflation rate.

From the results of Table 4, ARIMA (0, 1, 1) model was identified as the best mean model for estimating the coefficients of non-food inflation rate using the AIC, BIC and HQIC.

4.4. Model adequacy checking

Before we consider the fitted model as the best fit and interpret its results, it is mandatory to check whether the model assumptions are satisfied. If the basic model assumptions are violated, then a new model should be specified until it provides an adequate fit to the data.

Test of serial correlation in the residuals. In this case, serial correlation in the residuals was tested using the Breusch-Godfrey Serial Correlation LM Test for each of the tentatively selected ARMA models: ARMA (1, 2) and ARIMA (0, 1, 1)

Table 3. **Estimation Results of ARMA Models for food inflation with Information Criteria**

Model	Parameter	Coefficients	Std. error	*t*-statistic	*P*-value	Information criteria		
						AIC	BIC	HQIC
ARMA (1, 0)	μ	10.8766	3.6322	2.9944	0.0029	6.543	6.565	6.551
	α_1	-0.9244	0.0099	92.6001	0.0000			
ARMA (2, 0)	μ	10.860	3.2048	3.3887	0.0007	6.531	6.560	6.542
	α_1	1.0395	0.0357	29.06785	0.0000			
	α_2	-0.1242	0.03691	-3.36549	0.0008			
ARMA (1, 1))	μ	10.8624	3.1966	3.39806	0.0007	6.524	6.554	6.536
	α_1	0.8965	0.0119	75.0989	0.0000			
	β_1	0.1942	0.0266	7.2963	0.0000			
ARMA (1, 2)	μ	10.896	3.6709	2.9683	0.0031	6.512	6.549	6.526
	α_1	0.9198	0.0170	53.9630	0.0000			
	β_1	0.1647	0.0404	4.0706	0.0001			
	β_2	-0.1217	0.0256	-4.7477	0.0000			

Source: Author's Computation

Note: Models with no serial correlation in the residuals are considered.

Table 4. **Estimation Results of ARIMA Models for non-food inflation with Information Criteria**

Model	Parameter	Coefficients	Std. error	*t*-statistic	*P*-value	Information criteria		
						AIC	BIC	HQIC
ARIMA (1, 1, 0)	μ	0.0343	0.1023	0.3354	0.7374	5.111	5.133	5.119
	α_1	-0.2616	0.0275	-9.5036	0.0000			
ARIMA (2, 1, 0)	μ	0.0342	0.0970	0.3523	0.7247	5.111	5.140	5.122
	α_1	-0.2771	0.0299	-9.2520	0.0000			
	α_2	-0.0592	0.0299	-1.9768	0.0485			
ARIMA (0, 1, 1)	μ	0.0340	0.0956	0.3563	0.7217	5.110	5.132	5.119
	β_1	-0.2605	0.0301	-8.6345	0.0000			

Source: Author's Computation

Note: Models with no serial correlation in the residuals are considered.

models for the conditional mean of food inflation and non-food inflation rate, respectively. The null hypothesis asserts that there is no serial correlation in the residual series. As we observe from Table 5, the serial correlation LM test results for this equation with 1 lag in the test equation strongly reject the null of no serial correlation.

Normality test of residuals from the mean equation. To investigate whether the residuals of the fitted model (mean equation) are normally distributed, the Jarque-Bera test was applied. The residuals normality from ARMA (1, 2) for food inflation and ARIMA (0, 1, 1) for non-food inflation rate were conducted and reported in Table 6. We can see from Table 6 that the Jarque-Bera statistic is not significant, and hence, there is no significant evidence to reject the null hypothesis of normality. This indicates that the residuals of the fitted models are normally distributed for both of the series under consideration.

Test of ARCH Effect Results. Before we estimate ARCH type models, there should be volatility clustering and ARCH effect in the residuals of the estimated ARMA (1, 2) for food inflation and ARIMA (0, 1, 1) for non-food inflation rate.

From the Table 7, we observed that the p-value for food inflation rate is greater than 5 % which indicates fail to reject the null of homoscedastic variance in the error

Table 5. **Results of Breusch-Godfrey Serial Correlation LM Test of the fitted model**

Test statistic	Food inflation rate	Non-food inflation rate
F-statistic	2.247	0.9405
	(0.106)	(0.391)
Obs**R*-squared	14.571	1.897
	(0.104)	(0.387)

Source: Author's Computation

Note: Values inside the bracket are p-values

Table 6. **Normality test of the residuals from the fitted mean model**

Variables	Skweness	Kurtosis	Jarque-Bera Statistic	*P*-value
Food inflation rate	-0.035	3.528	2.711	0.257
Non-food inflation rate	-0.1085	3.722	4.008	0.134

Source: Author's Computation

Table 7. **Result for ARCH LM Test for the fitted models**

Test statistic	Food inflation rate	Non-food inflation rate
F-statistic	0.2627	6.183054
	(0.6084)	(0.01325)
Obs**R*-squared	0.2635	6.139671
	(0.6077)	(0.0132)

Source: Author's Computation

Note: Values inside parenthesis are p-values.

term of ARMA (1, 2) model. However, the p-value on ARMA (0, 1, 1) model of non-food inflation rate is less than 5% indicating to reject the null of homoscedastic variance. Therefore, food inflation rate has a constant variance while non-food inflation rate has a non-constant variance (heteroscedasticity), which requires an application of GARCH type model for non-food inflation rate.

4.5. Estimation result of ARMA model for food inflation rate

In order to identify the appropriate ARMA model, the minimum information criteria, absence of serial correlation on the residual, and the most significant coefficients were used. The AR slope coefficients of the model are statistically significant at the 1% marginal significant levels. Thus, the first and second lags of non-food inflation rate have positively predicted the future value of non-food inflation rate. That is the past realization of non-food inflation rate will influence non-food inflation rate at a 1% level. The moving average coefficient is negative and statistically significant at the 1% level, which means the residuals of the first lag will negatively predict non-food inflation rate at the 1% level. Table 8 summarizes the results as below.

4.6. Forecasting

Before we use the fitted model to forecast the value of the of food inflation rate, we should compare the forecasting performance of the candidate model using different error criteria, such as RMSE, MAE, MAPE and Theil's inequality coefficient. From the results in Table 9, the fitted ARMA (1, 2) model has minimum error as compared to other fitted ARMA models which are determined based on minimum information criteria and absence of serial correlation on the residuals. Forecasting the food inflation rate using ARMA (1, 2) model are shown in Fig. 3.

4.7. Estimation Results of GARCH type models

Once the presence of ARCH effects on the residuals of the fitted mean model is confirmed, then we need to estimate

Table 8. **Interpretation of ARMA (1, 2) model for food inflation rate**

Fitted Model	Parameters	Coefficients	Std. error	*t*-statistic	*P*-value
ARMA (1, 2)	μ	10.89654	3.670936	2.968327	0.0031
	α_1	0.919852	0.017046	53.96304	0.0000
	β_1	0.164757	0.040475	4.070606	0.0001
	β_2	-0.121749	0.025643	-4.747798	0.0000

Source: Author's Computation

Note: Models with no serial correlation in the residuals are considered.

Table 9. **Forecasting evaluation of different ARMA type model for food inflation rate**

Model	Forecasting accuracy Measure			
	RMSE MAE MAPE Theil			
ARMA (1, 0)	16.697	11.8568	9.577	0.5441
ARMA (2, 0)	16.651	11.8207	9.742	0.5439
ARMA (1, 1)	16.7104	11.8663	8.995	0.5445
ARMA (1, 2)	16.6380	11.8120	6.244	0.5433

Source: Author's Computation

Note: Models with no serial correlation in the residuals are considered.

the series using GARCH type models. However, before we define the final model, the optimal lag for GARCH family models has to be determined. In this case, the parameters of the models are estimated using maximum likelihood method under the assumption of different error distributions.

Model Selection of GARCH Family Model. In order to determine the order of GARCH type models, the Akaikian

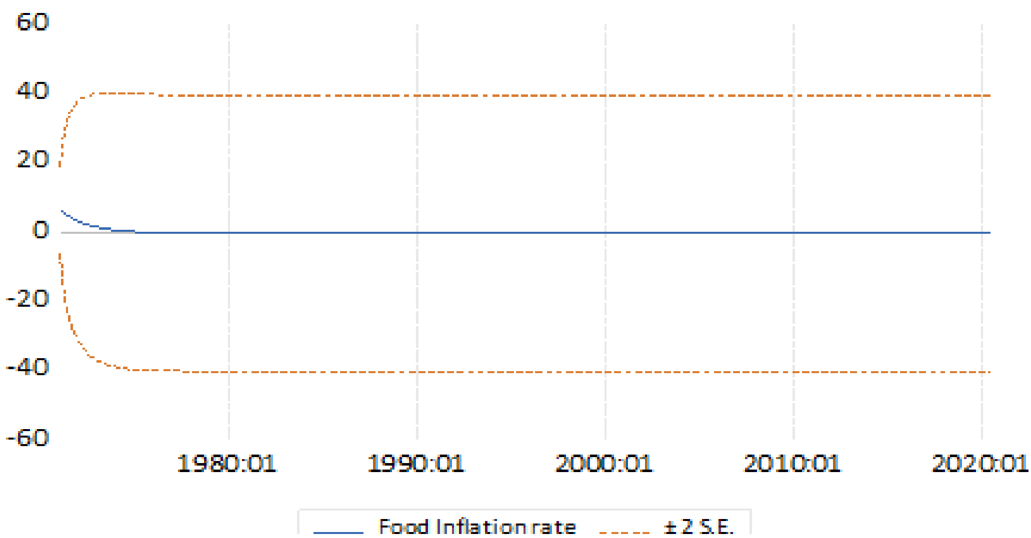

Fig. 3. Forecasting the food inflation rate using ARMA (1, 2) model

information criterion (AIC), Bayesian information criterion (BIC) and Hannan-Quinn Information Criteria (HQIC) are used for selecting the symmetric, asymmetric, and component fitted GARCH models. From Table 10, we observed that TGARCH (1, 1) and PGARCH (1,1) models under normal distribution, EGARCH (1, 1), TGARCH (1, 1), PGARCH (1, 1) and CGARCH (1, 1) models under Student's t-distribution, and GARCH (1, 1), EGARCH (1, 1), TGARCH (1, 1) and PGARCH (1, 1) models under Generalized error distributional assumption of the residuals were selected as candidate models using minimum AIC, BIC and HQIC. Thus, based on the minimum information criteria, TGARCH (1, 1) with student's t-distributional assumption for residuals identified as the best performing model selected candidate model.

In addition to information criteria, forecasting performance of the candidate GARCH type models are used to identify an appropriate conditional volatility model. The basic accuracy statistics are RMSE, MAE, MAPE and Theil inequality coefficient as shown in Table 11. The models with the smallest statistics are used as the best fit for modeling the conditional volatility of non-food inflation rate.

From the results on Table 11, TGARCH (1, 1) with Student's t-distributional assumption for residuals perform better to describe inflation volatility since they possess the smallest forecast error measures in the majority of the statistics considered for non-food inflation rate. Therefore, the null hypothesis that inflation should be better captured by the symmetric GARCH model is rejected and the alternative which states that the asymmetric GARCH model better capture inflation series of Ethiopia under the period of investigation is accepted.

Parameter Estimation Results. Once the TGARCH (1, 1) model with student's t-distributional assumption for residuals is selected as the better fit based on

Table 10. **Optimal lag selection-based AIC, BIC and HQIC under different error distribution**

Model	Error distribution	AIC	BIC	HQIC	Asymmetric effect
GARCH (1, 1)	Generalized error distribution	4.6513	4.6956	4.6686	*
EGARCH (1, 1)	Student's t-distribution	4.6354	4.6871	4.6555	Significant
EGARCH (1, 1)	Generalized error distribution (GED)	4.6488	4.7006	4.6690	Significant
TGARCH (1, 1)	Normal distribution	4.7120	4.7564	4.7293	Significant
TGARCH (1, 1)	Student's t distribution	4.6293	4.6811	4.6495	Significant
TGARCH (1, 1)	Generalized error distribution (GED)	4.6437	4.6954	4.6638	Significant
PGARCH (1, 1)	Normal distribution	4.7161	4.7604	4.7333	Significant
PGARCH (1, 1)	Student's t-distribution	4.6357	4.6875	4.6559	Significant
PGARCH (1, 1)	Generalized error distribution	4.6498	4.7016	4.6700	Significant
CGARCH (1, 1)	Student's t distribution	4.6386	4.6977	4.6616	*

Source: Author's Computation

Table 11. **Forecast accuracy statistics for GARCH type model for non-food inflation**

Model	Error distribution	Forecasting accuracy Measure			
		RMSE	MAE	MAPE	Theil
GARCH (1, 1)	Generalized error distribution	3.2130	2.1538	104.696	*0.9802
EGARCH (1, 1)	Student's t-distribution	3.2141	2.1550	112.481	0.9637
EGARCH (1, 1)	Generalized error distribution (GED)	3.2135	2.1543	109.192	0.9702
TGARCH (1, 1)	Student's t distribution	3.2131	2.1542	111.165	0.9662
TGARCH (1, 1)	Generalized error distribution (GED)	3.2134	2.1542	108.461	0.9717
PGARCH (1, 1)	Student's t-distribution	3.2138	2.1547	111.035	0.9664
PGARCH (1, 1)	Generalized error distribution	3.2134	2.1542	108.289	0.9721
CGARCH (1, 1)	Student's t distribution	3.2133	2.1541	107.833	0.9730

Source: Author's Computation

information criteria and forecast accuracy measures, then the next step is to interpret the result and forecasting future value of the series. The parameters in the TGARCH (1, 1) model are estimated using the maximum likelihood (ML) method, which are presented on Table 12.

The result on Table 12 indicates that a one month lagged shocks (i. e. ARCH (–1)) of the monthly non-food inflation rate is statistically significant at the 1 % level. This indicates that the current month non-food inflation volatility is affected by its 1-month lagged shocks. This may be an indication that current non-food inflation volatility is sensitive to past inflation movements. Similarly, GARCH (–1) terms are which indicates volatility persistence is statistically significant at the 1 % level. This indicates that current month inflation volatility affected by its 1-month lagged inflation volatility.

Moreover, the coefficient of the asymmetric term is positive (0.1376) and statistically significant at the 1 % level, indicates that bad news (unexpected increase in monthly non-food inflation) has larger impact on the non-food inflation volatility than good news (unexpected decrease in monthly food-inflation volatility). Thus, modeling of information, news of events is very significant determinants of volatility.

Table 12. **Estimation results of TGARCH (1, 1) model for non-food inflation rate**

Variables	Coefficients	Std. error	*t*-statistic	*P*-value
c	0.0304	0.0259	1.1755	0.2398
β_1	0.1590	0.0450	3.5329	0.0004
γ	0.1376	0.0489	2.8101	0.005
β_2	0.9199	0.0210	43.7219	0.0000

Source: Author's Computation

4.8. Model Checking

In order to check whether the fitted models are good fit to the data ARCH-LM Test for standardized residuals of the fitted TGARCH (1, 1) model was performed. As can be seen in Table 13, the ARCH-LM test indicates that the standardized residuals of the fitted model did not exhibit any additional ARCH effect. Therefore, the selection of TGARCH (1, 1) model with student's t distributional assumption of residuals to investigate non-food inflation rate volatility was well justified.

4.9. Forecasting

One of the fundamental uses of developing GARCH model is forecasting. In this section, we examine the forecasting accuracy of the fitted models and then we make in-sample forecasts. As we observe from Figure 4, a continuous rise in the volatility of non-food inflation rate is observed.

5. Conclusion

An increase in inflation volatility implies higher uncertainty about future prices. As a result, producers and consumers can be affected by the increased inflation volatility, because it increases the uncertainty and the risk in the market. Thus, inflation volatility attracts the attention of researchers to find a suitable model, which can predict the future conditions of the market. This study aims to fit appropriate ARMA-GARCH family models for food

Table 13. **ARCH-LM Test for Standardized Residuals of the Fitted TGARCH (1, 1) model**

Test statistic	Estimates
F-statistic	0.3756
	(0.5501)
Obs**R*-squared	0.3585
	(0.5493)

Source: Author's Computation

Note: Values in parenthesis are p-values.

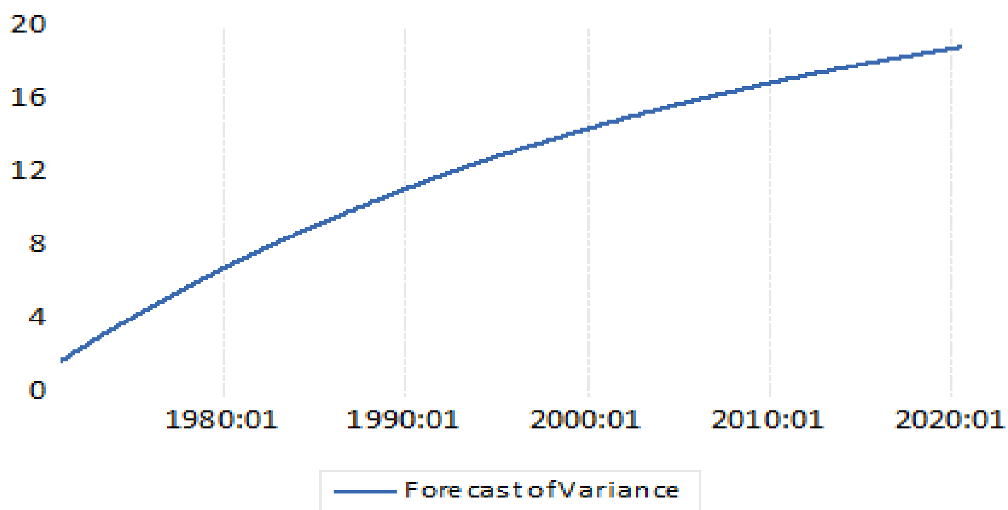

Fig. 4. In-sample forecast of non-food inflation volatility using TGARCH (1, 1) model

and non-food inflation rate of from the period January 1971 through June 2020.

In the preliminary analysis, food inflation rate shows a white noise property, while non-food inflation rate has somehow fluctuation having the characteristics of financial time series such as leptokurtic distributions, which leads to an adequate ground to apply GARCH family models. The result of unit root test shows that food inflation is stationary at level, while non-food inflation rate is stationary at first difference.

On the estimation results of the mean equation, an ARMA type model is appropriate for food inflation rate since ARCH-LM test on the squared residuals of the best fitted ARMA (1, 2) model confirmed the absence of remaining ARC H effect. Thus, we apply an ARMA (1, 2) model for food inflation rate to estimate the coefficients and forecast the future series. However, the ARCH–LM test on the residual of ARIMA (0, 1, 1) model on non-food inflation rate shows the existence of remaining ARCH effect which needs to require the application of GARCH family models.

In the estimation of volatility family models for non-food inflation rate, TGARCH (1, 1) model with Student's t-distributional assumption of residual was selected as the best fitted model among different kind of candidate models using information criteria (AIC, BIC & HQIC) and forecast error criteria (such us: MAE, MAPE, RMSE and Theil inequality coefficient).

The result of TGARCH (1, 1) model shows that one month lagged shocks (i. e. ARCH (–1)) of the monthly non-food inflation rate that are statistically significant at the 1 % level indicate that the current month non-food inflation volatility was affected by its 1-month lagged shocks. This may be an indication that current non-food inflation volatility is sensitive to past inflation movements. Similarly, GARCH (–1) terms are which indicates volatility persistence is statistically significant at the 1 % level. This indicates that current month inflation volatility is affected by its 1-month lagged inflation volatility. Moreover, the coefficient of the asymmetric term is positive and statistically significant at the 1 % level, indicating that bad news (an unexpected increase in monthly non-food inflation) has larger impact on the non-food inflation volatility than good news (an unexpected decrease in monthly food-inflation volatility). Thus, modeling of information, news of events are very significant determinants of volatility and GARCH family models are appropriate for the given series (monthly food-inflation volatility) of Ethiopia under the study period considered.

Therefore, inflation volatility brings risks to consumers, especially fixed income earners as compared to producer. Then the concerned stakeholders, particularly the government pays careful attention because attempting to avoid such volatility costs the economy far more than its direct costs and leads to inefficiencies and benefits to only some parts of society. This is due to direct government interventions to curb inflation volatility, which can distort markets and lead to resource misallocation if markets are not regulated properly.

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Использование моделей семейства GARCH для оценки уровня продовольственной и непродовольственной инфляции в Эфиопии

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Аннотация. Повышение волатильности инфляции подразумевает более высокую неопределенность относительно будущих цен. В результате производители и потребители могут пострадать от повышенной волатильности инфляции, поскольку это увеличивает неопределенность и риски на рынке. Таким образом, волатильность инфляции привлекает внимание исследователей к поиску подходящей модели, которая может предсказывать будущие условия рынка. Это исследование направлено на то, чтобы соответствовать подходящим моделям семейства ARMA-GARCH для продовольственных и непродовольственных темпов инфляции за период с января 1971 г. по июнь 2020 г. Поскольку основной целью исследования является определение подходящей модели для рядов инфляции, определены две гипотезы исследования в сравнении двух типов моделей. Первая гипотеза – симметричные модели GARCH лучше отражают волатильность инфляции в Эфиопии. Вторая гипотеза – асимметричные модели GARCH лучше отражают волатильность инфляции в Эфиопии. Модели семейства ARMA-GARCH были применены для фиксации стилизованных фактов финансовых временных рядов, таких как лептокуртические распределения, кластеризации волатильности инфляции и эффектов левериджа. Усредненные результаты показывают, что модели ARMA (1, 2) и ARIMA (0, 1, 1) определены как наиболее подходящие для продовольственной и непродовольственной инфляции, соответственно. По результатам оценок волатильности, асимметричная модель TGARCH (1, 1) с допущениями Стьюдента о *t*-распределении остатка является лучшей моделью для непродовольственной инфляции. Моделирование информации, новостей о событиях является весьма значимым детерминантом волатильности и модели семейства GARCH подходят для данного ряда (ежемесячная волатильность продовольственной инфляции) Эфиопии в рассматриваемом исследуемом периоде.

Ключевые слова: продовольственная инфляция; непродовольственная инфляция; семейство моделей ARMA-GARCH; Эфиопия.

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