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A Multivariate GARCH Model with Time-Varying Correlations: What Do Inflation Data Show in Ethiopia?

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Abstract

Inflation is a critical global issue and also a significant challenge in Ethiopia. Despite its profound impact on the economy, research on inflation volatility in Ethiopia remains limited and insufficient. This paper aims to address these gaps by employing BEKK (Baba, Engle, Kraft, and Kroner) and DCC (Dynamic Conditional Correlation) - GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models and analyze the characteristics of inflation trends, which supports informed economic decision making. We focus on four key inflation indicators: the Consumer Price Index (CPI), the Non-Food Price Index (NFPI), the Food Price Index (FPI), and the Exchange Rate (ER), which were compiled from the National Bank of Ethiopia (NBE) from January 2010 to December 2020. The study confirms inflation volatility, supported by the ARCH effect and Ljung-Box $Q(m)$ statistics, along with conditional heteroscedasticity tests. This study demonstrates that, unlike previous approaches that neglected dynamic correlations in inflation volatility, the DCC-GARCH model decisively outperforms the BEKK-GARCH model in both parameter estimation and forecasting accuracy, as evidenced by significantly better Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC), and Hannan-Quinn Information Criterion (HQIC) metrics. Our findings revealed that the DCC (1,1) model effectively captured volatility clustering without being persistent or explosive, as the sum of coefficients ($\theta = 0.1794, \beta = 0.7023$) is less than 1, confirming mean reversion. In contrast to previous studies, our approach provided a more robust understanding of inflation dynamics, identifying CPI and FPI as the most volatile indicators. The study reveals significant correlations among inflation indicators-CPI, FPI, NFPI, and ER indicating a cohesive inflationary pattern. The coefficients show that past volatility and shocks persistently influence current volatility, underscoring their interdependence. The forecast from the best model reveals substantial instability is observed in CPI and FPI returns. It suggests a sharp increase in FPI and a rise in ER. The better method captured inflation volatility more effectively than other competent models. The DCC-GARCH model offered deeper

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insights into volatility dynamics, revealing the shortcomings of earlier time series models in addressing inflation volatility.

Keywords Multivariate GARCH · DCC · BEKK · ARCH effect · Inflation

1 Introduction

In financial statistics, volatility, defined as variance, measures the dispersion of a random variable from its mean (Omotosho & Doguwa, 2012). Inflation volatility indicates instability in inflation rates (Samimi & Shahryar, 2009). This instability is critical due to its negative impacts on the economy, including increased uncertainty, lower output growth, and higher unemployment (Lucas, 2000). High inflation variability exacerbates uncertainty about future prices (Sisay et al., 2022) and harms economic stability (Fenira, 2014). Globally, the adverse effects of inflation volatility are recognized, contributing to economic instability and uncertainty (Ndiaye & Konte, 2017). It also raises the opportunity cost of holding money, discourages investment, and can lead to shortages due to consumer hoarding (Glick & Lozada, 2021). Thus, researching inflation volatility is essential for making informed decisions and implementing effective measures.

According to Garriga and Rodriguez (2020), external and global core price shocks largely account for inflation variation in low-income countries over recent decades, with multiple shocks identified (Emeru, 2020). The global impact of inflation volatility is well-documented (Ragan, 1993). For example, Avellaneda et al. (1997) attributes the detrimental effects of inflation on growth primarily to inflation volatility, a view supported by Huriso et al. (2023). This suggests that accurate estimation and understanding of inflation volatility are critical. Indicators such as the CPI reflect significant inflation volatility (Uwilingiyimana et al., 2015), which hampers optimal growth (Kahssay, 2017). Despite various stabilization efforts, it is recommended to focus on inflation indicators to describe the state of economic instability and uncertainty (Abebe et al., 2023). In Ethiopia, studies such as Alemu et al. (2016); Gotu and Tadesse (2023) often overlook the volatility of inflation (Emeru, 2020). Previous research on Ethiopian inflation, such as Geda and Tafere (2008), also did not consider its volatile nature (Emeru, 2020) and lacked advanced statistical tools for improved decision-making.

Two popular methods for modeling volatility are the GARCH models and stochastic volatility models. GARCH models capture time-varying volatility based on past data and parameters, and are commonly used in financial time series analysis (see, e.g., Nadarajah et al. (2021)). For example, Bildirici and Ersin (2009) applied GARCH to daily returns on the Istanbul Stock Exchange, Teresienė (2009) to the Lithuanian stock market, Chang and Su (2010) to the Vietnam stock market and its trading partners, Drakos et al. (2010) for the Athens stock exchange, Chang and Shen (2011) to study exchange-rate uncertainty's impact on unemployment in Asia, and Lee and Chiu (2011) to study the arbitrage in Taiwan and Japan's exchange rates.

ARCH and its GARCH extension (Feng & Shi, 2017) are popular in financial modeling, with further extensions (Entezarkheir, 2006). GARCH has also been used to analyze the volatility of inflation in commodities (Afuecheta et al., 2024) and stock markets (Alberg et al., 2008), although it sometimes fails to fully capture volatility issues. GARCH models have also been applied to the volatility of cryptocurrencies (Katsiampa, 2017) and analyzed the volatility of the exchange rate in the major African currencies (Afuecheta et al., 2024). The vector error correction model (VECM) for inflation volatility proposed by Asari et al. (2011) is assumption-dependent and prone to overfitting. Inflation trends have also been studied in other African countries (Kabundi, 2012; Barugahara, 2015; Kassouri, 2024; Jagero et al., 2022). However, the methods used in these studies lack robustness in handling skewed data. To address this limitation, Jagero et al. (2022) proposed the ARIMA model to forecast inflation rates in Kenya. Furthermore, Nsabimana and Ocran (2015) examined inflation prediction in East African countries, while Ibrahim and Kayongo (2022) conducted a comprehensive analysis of inflation trends. To better capture time-varying situations, the GARCH approach is highly recommended.

As an alternative, stochastic volatility models allow for changes in variance and provide a conventional regression framework for modeling volatility (Engle, 1982). Recent research has shifted to stochastic volatility models treating inflation uncertainty as a latent variable with an AR(1) process (Chan, 2017). While global evidence on ARCH effects in inflation is mixed (Özsoy & Doğan, 2022), high-inflation countries consistently show greater volatility, negatively impacting growth (Ullah et al., 2020).

This paper addresses the limitations of existing methods for a skewed data by analyzing key inflation indicators using GARCH-type approaches, specifically focusing on BEKK- and DCC-GARCH models. These methods are applied to capture time-varying inflation volatility based on Ethiopia's CPI, FPI, NFPI, and ER, aiming to overcome the shortcomings of traditional GARCH methods. Parameters for the BEKK-GARCH model were estimated using maximum likelihood estimation, while the DCC-GARCH model was estimated via a two-step approach. Model performance was evaluated using three information criteria, and the predictive capability of the best-performing model was assessed for the four inflation indicators.

The main contributions of this study include:

1) New data: This study applies the GARCH model using newly compiled data that incorporates recent advancements in time series methods to analyze inflation volatility in Ethiopia. This new data, which will be publicly available, is intended to supplement the development of other time series methods.

2) Time series model: Unlike existing time series methods, this method captures the correlation among these four inflation indicators and clearly indicates whether inflation is volatile or not.

3) Parameter estimation: Using advanced GARCH models improves parameter estimation. For the BEKK model, we utilized Maximum Likelihood Estimation (MLE). In the DCC model, we applied a two-step process with the first step to estimate variances in the GARCH models with the estimates from the maximum likelihood estimation, and the second step to use the MLE to estimate correlations.

4) Better performance evaluation: The results of the study revealed that the DCC (1,1) model outperforms the BEKK (1,1) model, making it the best option handling the inflation volatility data taken from the NBE. This is because the DCC model more effectively captures time-varying correlations, unlike the BEKK model.

5) Unlike previous works, this novel study employs the DCC-GARCH model by integrating a robust estimation framework to improve volatility and correlation estimation in high-dimensional settings. Additionally, we conducted a unit root test with structural breaks to account for potential regime shifts and improve the reliability of dynamic dependence modeling.

The structure of the rest of the paper is then organized as follows. The methods, focusing on multivariate GARCH models are described in Sect. 2. The data and data analysis results are given in Sect. 3. Finally, conclusions and discussions are given in Sect. 5.

2 Methods

In this section, we describe the models used to assess inflation volatility in Ethiopia. First, we define the notation of the terms used in this section for easier understanding, as shown in Table 1.

Table 1 Notations and their descriptions

Notations	Explanations
t	Time
y_t	The dependent variable at time t, which can be multivariate
T	Total number of observations
μ	The mean or average of a data set
σ	The standard deviation, a measure of data spread
K	The total number of components in multivariate y_t
β	A parameter to be estimated from the GARCH effect
H_t	The conditional covariance matrix
θ	The parameter to be estimated
Z_t	A vector of independently identically distributed random variables
π	Scalar or constant.
λ	Is scalar used for tuning the parameter
a, b	Are the scalars used in the BEKK parameter estimation
ω	Scalar
D_t	Diagonal matrix of conditional standard deviations
R_t	Time varying correlation matrix
σ_t^2	The conditional variance representing the volatility process
m	Lag order

2.1 Univariate GARCH Model

GARCH models are used to model time series data with volatility clustering, where periods of high volatility are followed by periods of low (Somarajan et al., 2019). The univariate GARCH model extends the ARCH model by including lagged conditional variances in the model. Specifically, the univariate GARCH model assumes that the conditional variance of the error term at time t depends on the lagged values of the squared errors and lagged conditional variances. It captures the idea that volatility is persistent over time. Given a time series y_t, the univariate GARCH model is given by:

$$\mathbf{y}_t = \mu_t + \epsilon_t, \quad \epsilon_t = \sigma_t Z_t, \quad Z_t \sim \text{i.i.d. } N(0,1) \tag{1}$$

where y_t is the observed financial data, μ_t is the expected value or mean of the observed returns or financial data, and σ_t^2 is the conditional variance representing the volatility process specified by

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \theta_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where $\omega > 0$ is a constant term, $\theta_i \geq 0$ represents the impact of past squared errors (ARCH term with order of p), $\beta_j \geq 0$ represents the impact of past conditional variances (GARCH term with order of q) and ϵ_t is the error term at time t.

2.2 Multivariate GARCH Models

Univariate GARCH models only capture the volatility of a single time series, which can miss interdependence between assets. Multivariate GARCH (MGARCH) models, in addition to model volatility of each time series, capture correlations for better risk assessment. Among the numerous specifications of MGARCH models, the most popular are the VECM (Lütkepohl, 2004), the BEKK (Engle & Kroner, 1995), Constant Conditional Correlations (CCC) (Bollerslev, 1990) and the DCC (Engle, 2002). VECM-GARCH and BEKK-GARCH models are the models of conditional covariance matrix (Stelzer, 2008), whilst CCC-GARCH and DCC-GARCH are the models of conditional variances and correlations (Nelson, 1991).

2.2.1 BEKK-GARCH Model

BEKK-GARCH is a multivariate GARCH model that extends the univariate GARCH model to capture the dynamic correlation structure across multiple time series. The BEKK model is developed to model the conditional covariance matrix of multiple time series, ensuring that the covariance matrix remains positive-definite. It includes both direct and cross effects of past variances and covariances on current variances and covariances.

Let $\mathbf{y}_t$ be an $K \times 1$ vector of multivariate time series at a time t ($t = 1, 2, .., T$), where T is the total number of observations. For example, the multivariate $\mathbf{y}_t$ vector for the data considered in Section 3 with $K = 4$ at each time t can be written as:

$$\mathbf{y}_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{kt} \end{pmatrix} = \begin{pmatrix} \mathrm{CPI}_t \\ \mathrm{NFPI}_t \\ \mathrm{FPI}_t \\ \mathrm{ER}_t \end{pmatrix}, \quad t = 1, 2, \dots, T \tag{3}$$

where y_{1_t} is the value of CPI at time t, y_{2_t} is the value of the FPI at time t, y_{3_t} is the value of the NFPI at a time t, y_{4_t} is the value of the ER at time t.

Let H_t be the $K \times K$ conditional covariance matrix. The BEKK(1,1) model can be written as:

$$H_t = C'C + A'\epsilon_{t-1}\epsilon'_{t-1}A + B'H_{t-1}B \tag{4}$$

where C is an $K \times K$ lower triangular matrix that represents the impact of some external factors, A and B are $K \times K$ matrices that relates to the impact of the previous period's errors and describes the influence of the previous period's covariance matrix on the current covariance matrix respectively, ϵ_t is the $K \times 1$ vector of residuals. The BEKK model ensures that the covariance matrix H_t is positive-definite by construction. The most restricted version of the diagonal BEKK model is the scalar BEKK one with $\mathbf{A} = \mathbf{aI}$ and $\mathbf{B} = \mathbf{bI}$, where $\mathbf{a}$ and $\mathbf{b}$ are scalars. Estimation of a BEKK model still involves large computations due to several matrix transpositions. The number of parameters of the complete BEKK model is $(p+q)TK^2 + \frac{K(K+1)}{2}$, where p denotes the number of lagged terms of the conditional covariance matrix in the BEKK model, q denotes the number of lagged terms of the conditional variance matrix, K is denoting the number of assets that determines the generality of the process. Even in the diagonal one, the number of parameters soon reduces to $(p+q)T \times K + K\frac{K+1}{2}$. but it is still large. The BEKK model is not linear in parameters, which makes the convergence of the model difficult. However, the strong point lies in that the model structure automatically guarantees the positive definiteness of H_t. In essence, when $p = q = T = 1$, the BEKK model is applied to a univariate time series (Nelson, 1994).

2.2.2 CCC-GARCH Model

The CCC model, first proposed by Tsui and Yu (1999), estimates the conditional covariance matrix by focusing on the conditional correlation matrix, assuming it remains constant while conditional variances change over time. However, this assumption does not hold well for real financial time series, prompting further refinements to the model (Annastiina & Timo, 2008).

In financial returns, let $\mathbf{y}_t$ be a vector of variables with each T observations at a time t. The CCC-GARCH model specifies with the mean and residuals respectively:

$$\mathbf{y}_t = \mu_t + \boldsymbol{\epsilon}_t \tag{5}$$

where μ_t is the mean of returns of $\mathbf{y_t}$ and ϵ_t is the vector of residuals and ϵ_t is given by:

$$\boldsymbol{\epsilon}_t = H_t^{1/2} Z_t \tag{6}$$

where H_t is the conditional covariance matrix of ϵ_t and Z_t is a vector of i.i.d. random variables with zero mean and unit variance.

The CCC-GARCH model (Tsui & Yu, 1999) assumes constant correlations across time, which may overlook dynamic relationships between variables. The VEC-GARCH model (Cheng et al., 2019), while capturing long-term dependencies, may struggle with short-term dynamics. In contrast, the DCC and BEKK GARCH models allow for more flexibility, capturing time-varying correlations and providing a better fit for dynamic volatility structures.

2.2.3 DCC-GARCH Model

DCC-GARCH is another multivariate GARCH model that allows for time-varying correlations among multiple time series while maintaining the simplicity of the univariate GARCH model for each series. The DCC-GARCH model separates the modeling of conditional variances and correlations. It first models the conditional variances using univariate GARCH models and then models the dynamic correlations using a separate process.

Let $\mathbf{y}_t$ be an $k \times 1$ vector of time series, where $k = 1, 2, 3, ..., K$. The DCC-GARCH model can be expressed in two steps:

The first step is to model the conditional variances for the i^{th} time series, which is governed by a univariate GARCH model:

$$\sigma_{i,t}^2 = \omega_i + \sum_{j=1}^{p} \theta_{ij} \epsilon_{i,t-j}^2 + \sum_{k=1}^{q} \beta_{ik} \sigma_{i,t-k}^2 \tag{7}$$

where $\sigma_{i,t}^2$ is the conditional variance of the i^{th} time series, where p is denoting ARCH effects and q is denoting the GARCH parameters.

Then the second step is to model the dynamic correlations, where the conditional covariance matrix H_t is defined as follows:

$$H_t = D_t R_t D_t \tag{8}$$

where $D_t = \text{diag}(\sigma_{1,t}, \sigma_{2,t}, \dots, \sigma_{N,t})$ is the diagonal matrix of conditional standard deviations, and R_t is the time-varying correlation matrix. The correlation matrix R_t is updated as:

$$R_t = (1 - a - b)\bar{R} + a(\tilde{\epsilon}_{t-1} \tilde{\epsilon}_{t-1}') + bR_{t-1} \tag{9}$$

where $\tilde{\epsilon}_t = D_t^{-1} \epsilon_t$ is the standardized residual, $\bar{R}$ is the unconditional correlation matrix of $\tilde{\epsilon}_t$, and a and b are non-negative parameters that determine the impact of past shocks and correlations on current correlations.

The DCC model's limitation is that all conditional correlations share the same dynamic structure (Engle, 2002). It has $\frac{(K+1)\times(K+4)}{2}$ parameters, which is fewer than the complete BEKK model for small K. For large K, DCC reduces complexity by first estimating conditional variances using a univariate GARCH model, followed by estimating conditional correlations. It ensures the covariance matrix remains positive-definite, and its parameter count is independent of the number of returns. Adding new variables does not impact the volatility forecasts of existing ones.

The multivariate GARCH model assumes time-varying volatility based on past returns and variances the conditional mean as follows:

$$\mathbf{y}_t = \boldsymbol{\mu}_\mathbf{t} + \boldsymbol{\epsilon}_t \tag{10}$$

where $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{H}_t)$ and the conditional covariance matrix defined as follows:

$$\mathbf{H}_t = \mathbf{C} + \sum_{i=1}^{p} \mathbf{A}_i \boldsymbol{\epsilon}_{t-i} \boldsymbol{\epsilon}_{t-i}^\top + \sum_{j=1}^{q} \mathbf{B}_j \mathbf{H}_{t-j} \tag{11}$$

where $\mathbf{C}$ is a constant matrix, $\mathbf{A}_i$ terms capture past squared returns (ARCH effect) and $\mathbf{B}_j$ terms capture past variances (GARCH effect). The detail description of the DCC model (Acatrinei et al., 2013).

2.2.4 Basic Properties of MGARCH Family

Any MGARCH model should be unique and stationary satisfying

$$\sum_{i=1}^{p} \boldsymbol{\theta}_i + \sum_{j=1}^{q} \boldsymbol{\beta}_j < 1, \tag{12}$$

as the necessary and sufficient condition to have a unique and stationary solution, where β_j denotes the coefficients for lagged conditional variances, determining the effect of past volatilities on current volatility and θ_i is denoting coefficients for lagged squared residuals, determining the effect of past shocks on current volatility. We also employed the Zivot-Andrews test (Chidozie et al., 2024) to examine the presence of structural breaks in the stationarity of each inflation indicator based on the data.

2.3 Parameter Estimation

Before forecasting inflation volatility, we need to estimate the parameters in the GARCH model using Maximum Likelihood Estimation (MLE). As noted in Jayakumar and Sulthan (2013), MLE is typically used for VECM and BEKK-GARCH models, while CCC- and DCC-GARCH models often employ a two-step estimation approach. Handling the likelihood function can be complex, particularly given that financial time series exhibits volatility clustering and leptokurtosis, necessitating various residual distributions such as Gaussian and Student-t.

Suppose that $\mathbf{y}_t$ is a $k \times 1$ vector where (for $k = 1, \ldots, K$) is the vector of returns with conditional mean $\mu_t(\theta_0)$, and K is the total number of components in the multivariate time series with conditional variance matrix $\mathbf{H}_t(\theta_0)$, and conditional distribution $P(\mathbf{y}_t|\xi_0, \mathbf{\Omega}_{t-1})$ where Ω is the information set, or the historical data available up to time Ω_{t-1}, is the vector that contains the parameters of the distribution. Importantly, to justify the choice of the estimation procedure, the model to be estimated encompasses the true formulations of $\mu_t(\boldsymbol{\theta}_0)$ and $\mathbf{H}_t(\boldsymbol{\theta}_0)$. With this framework, θ_0 includes parameters for the conditional mean $\mu_t(\theta_0)$ and variance matrix $\mathbf{H}_t(\boldsymbol{\theta}_0)$ of the returns y_t defining how they evolve over time. $\boldsymbol{\eta}_0$ contains parameters for the distribution of the random variables $\mathbf{Z}_t$, such as those controlling the error distribution's shape. Proper estimation requires that the model accurately represents both the mean and the variance dynamics. The most widely usedibution in the literature is the multivariate normal, uniquely determined by its first two moments. In this case, the log-likelihood function is:

$$\mathbf{L_T}(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left[K\ln(2\pi) + \ln|\mathbf{H}_t| + (\mathbf{R}_t - \mu_t)'\mathbf{H}_t^{-1}(\mathbf{R}_t - \mu_t)\right] \tag{13}$$

where $\mathbf{T}$ is the number of observations, is the number variables, θ is the vector of parameters to be estimated. We employ the MLE to get the estimated optimal parameter in Eq.(13).

2.4 Model Selection and Diagnostics

As in Afuecheta et al. (2024), we use various information criteria to select the best model for fitting inflation volatility in Ethiopia. These criteria help identify the most suitable model among competing options. A key challenge is determining the ARCH order q and the GARCH order p for a given series. We employed the AIC (Wagenmakers & Farrell, 2004), the SBIC (Taiwo & Olatayo, 2021), and the HQIC (Jayakumar & Sulthan, 2013). The model with the lowest AIC, SBIC, or HQIC is considered the most representative of the true model.

After a GARCH family model has been fit to the data, the model diagnostics of the adequacy of the fit can be evaluated using a number of graphical and statistical diagnostics procedures. The standardized residuals are assumed to be independently identically distributed following standard normal distributions (Tsay, 2013). This was validated through the Jarque-Bera test. The Ljung-Box test is another widely used approach for assessing model fit, which tests for the appropriateness of the fitted model. It was developed by Box and Pierce (1970) and then later modified by Chen (2008).

A multivariate version of the Ljung-Box test statistic (Hassani & Yeganegi, 2019) is given by:

$$\mathbf{Q}_m = \mathbf{T}^2\sum_{j=1}^{m}(\mathbf{T} - j)^{-1}\mathrm{tr}\left[\mathbf{C}_{\mathbf{R}_t}^{-1}(0)\mathbf{C}_{\mathbf{R}_t}(j)\mathbf{C}_{\mathbf{R}_t}^{-1}(0)\mathbf{C}'_{\mathbf{R}_t}(j)\right] \tag{14}$$

where m is the number of lags included in the test, $\mathbf{R}_t$ is the vector of observed returns and $\mathbf{C}_{\mathbf{R}_t}(j)$ is the sample autocovariance matrix of order j. Under the null hypothesis of no serial correlation in $\mathbf{R}_t$, $\mathbf{Q}_m$ is asymptotically distributed as $\chi^2(\mathbf{K}^2 m)$. Li and McLeod Ashley and Patterson (2010) propose an alternative portmanteau statistic to detect misspecification in the conditional mean of an ARMA model. The modified version of their statistic is:

$$\mathbf{Q}^*_{(m)} = \mathbf{Q}_m + \frac{K^2 m(m+1)}{2T} \tag{15}$$

where $\mathbf{Q}^*_{(m)}$ is asymptotically distributed as $\chi^2(\mathbf{K}^2(m-s))$, where m is the lag order, and $s = p + q$. If the statistic $\mathbf{Q}_m$ at all lags is found to be non-significant, indicating the absence of autocorrelation in the residuals, then the selected model fits the data well.

2.5 Forecasting

In multivariate ARCH/GARCH models and their extensions, the covariance matrix varies over time. After estimating such a model, it is crucial to assess how future series are generated and whether they align with actual data. Forecasting with the BEKK-GARCH model relies on the conditional covariance equation:

$$\mathbf{H}_t = \mathbf{CC}' + \mathbf{A}'\epsilon_{(t-1)}\epsilon'_{(t-1)}\mathbf{A} + \mathbf{B}'\mathbf{H}_{(t-1)}\mathbf{B} \tag{16}$$

where $\mathbf{H}_t$ is a function of the past information that is in $\mathbf{H}_{(t-1)}$ and $\epsilon_{(t-1)}$. The estimated parameters from the MGARCH models can be used to predict the future covariance matrix.

Specifically, the forecast of the covariance matrix in the DCC model is implemented using a two-step procedure. The first step is to estimate GARCH models for variances and then obtain the maximum likelihood estimation for correlations. This involves separately forecasting the diagonal matrix of the time-varying standard deviation through univariate GARCH models Lundbergh and Teräsvirta (2002) and forecasting the conditional correlation matrix of the standardized residuals Tse (2002). Assuming that the volatility at time t is known, the forecast value at time $t + k$ can be derived. For a four-variable case, the forecast when $K = 1$ is given by:

$$\mathbf{h}_{ki,t+1} = \omega + \alpha\epsilon^2_{kt} + \beta\mathbf{h}_{ki,t} \quad \text{where} \quad k = 1, 2, 3, ..K \tag{17}$$

where $\mathbf{h}_{ki,t}$ is the conditional variance of the K^{th} asset or return series at time t. To attain the forecast $\mathbf{h}_{ki,t+1}$ at time $t + K$, one simply needs to repeat the substitution successively.

Under the assumption that $\hat{R} = \hat{Q}$ and $R_{(t+i)} = Q_{(t+i)}$ for $i = 1 \dots k$, a successive calculation as before can be performed to derive $\mathbf{R}_{(t+k)}$. The purpose of this assumption is for an accurate forecasting, consistency in the estimation and forecasting. MGARCH models can be used for forecasting. However, by analyzing the relative forecasting accuracy of the BEKK and DCC models, it can be deduced that the forecasting performance of MGARCH models is not always satisfactory. Many studies as discussed in Andersen et al. (2010) reveal that the apparent poor forecasting effect of the MGARCH models is due to using the squared shocks as an approximate value for the true conditional volatility.

3 Data and Analysis Results

The models discussed in Sect. 2 are applied to analyze the inflation volatility data. The parameters were estimated using maximum likelihood estimation and two step approach described in Sect. 2.2. We conducted a sequential analysis comparing two GARCH models considering two popular distributions to identify the most suitable for financial data. Our analysis, based on $T = 132$ observations from January 2010 to December 2020, utilized Stata 14 and E-Views 9 to generate and discuss descriptive and inferential results.

3.1 Data

The NBE is a cornerstone of the country's economic framework, playing a pivotal role in shaping monetary policy and providing crucial financial data. As the principal regulator of the banking system, the NBE is essential for monitoring inflation and maintaining economic stability. The dataset covering January 2010 to December 2020 includes four key indicators (that is, $K = 4$): CPI, FPI, NFPI, and ER. The CPI measures the cost of a standard basket of goods and services, reflecting general consumption patterns. The NFPI tracks inflation in non-food items, similar to the CPI but excluding food. The FPI focuses on food inflation, which is critical due to its significant impact on retail inflation, food expenditure, and wage adjustments. Lastly, the ER represents the value of one currency against another.

This dataset, comprising $T = 132$ monthly observations, is vital for accurate financial and economic analyses, underscoring the NBE's commitment to reliability and transparency. These indicators collectively represent global inflation trends, with each offering insights into different aspects of inflation and economic conditions.

3.2 Descriptive Analysis

Table 2 presents the mean of the four series, from which CPI, FPI, NFPI and ER respectively are approximately 97.66, 100.12, 95.57 and 22.11, with the standard deviations 36.80, 38.41, 34.03 and 6.07, the skewness are 0.59, 0.79, 0.49, and 0.69, respectively. This is an indication that the four returns in all indicators of inflation are slightly skewed to the right. It can be noted that the dispersion corresponding to FPI is high as compared with the other inflation indicators based on almost all statistical measures.

Figure 1 depicts the CPI, FPI, NFPI and ER for 132 observations reported on daily basis which indicates that the trend of inflation is increasing from 2010 to 2020 by days at the varying rates with ER the slowest.

Table 2 Summary of descriptive statistics

Series	Obs	Mean	Std. dev	Min	Max	Skewness	Kurtosis	CV
CPI	132	97.66	36.80	41.60	182.20	0.59	2.69	0.377
FPI	132	100.16	38.41	44.40	195.10	0.79	2.98	0.384
NFPI	132	95.57	34.03	42.90	171.00	0.49	2.39	0.36
ER	132	22.11	6.07	12.11	37.87	0.68	2.87	0.27

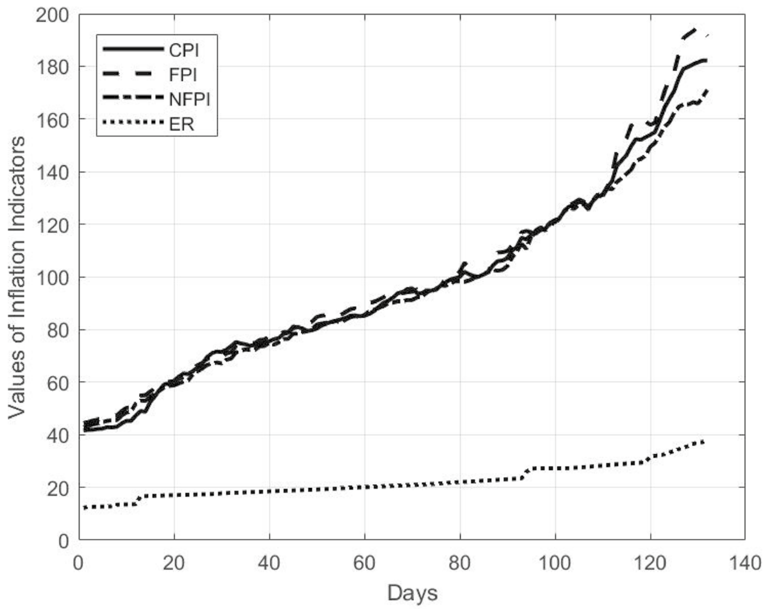

Fig. 1 Time series plot of CPI, FPI, NFPI, and ER values over Time (Days)

The results of this study suggest that the series of endogenous variables exhibit nonstationary behavior, indicating that they do not have a constant mean or variance, as illustrated in Fig. 1.

Throughout the period, the inflation trend exhibits phases of relative tranquillity followed by periods of high volatility. The inflation volatility in the four indicators is increasing on the four indicators of the inflation and its unconditional volatility have been higher with slighter increment, it appears that periods of higher average inflation correspond to periods of more volatile. This type of behaviour is called conditional heteroskedastic, since there are periods in which the variance is relatively high. Therefore, this stylized fact provides an interesting application of GARCH modeling in this study.

Based on the time series plot in Fig. 1, the quartile statistics for CPI, FPI, NFPI, and ER offer insight into the volatility of inflation between these variables. CPI and FPI, with their medians around 92.9 and 93.55 respectively, exhibit a relatively high level of central values and a broad interquartile range (IQR) of around 46.75 for CPI, indicating substantial variability in inflation rates. The NFPI, with a lower median of 90.4 and a somewhat smaller IQR, suggests less volatility compared to CPI and FPI but still reflects notable fluctuations. However, ER (exchange rate) shows the lowest median at 20.57 and the smallest IQR, indicating relatively stable exchange rates with less fluctuation compared to inflation indices. In general, CPI and FPI show higher volatility of inflation, while NFPI shows moderate volatility, and ER is the least volatile among the variables. The summary of this result is clearly addressed in Fig. 2.

The significant volatility observed in Figs. 1 and 2, particularly for the CPI and FPI, can be attributed to several economic factors. For the CPI, fluctuations in inflation can result from changes in demand, supply shocks, exchange rate movements, and government policies, such as adjustments in taxes or subsidies. These factors can cause rapid changes in the prices of goods and services consumed by households. Similarly, volatility in the FPI often reflects changes in production costs, including fluctuations in raw material prices, labor costs, and changes in industry-specific conditions. External factors such as global commodity price changes, geopolitical tensions, or supply chain disruptions can further exacerbate volatility in both indices. Understanding these drivers is crucial for interpreting trends in inflation and formulating appropriate policy responses. In this study, we first examined the presence of potential outliers in the inflation indicators using a boxplot, which revealed the existence of outliers in the FPI. We then applied a log transformation to mitigate their effect.

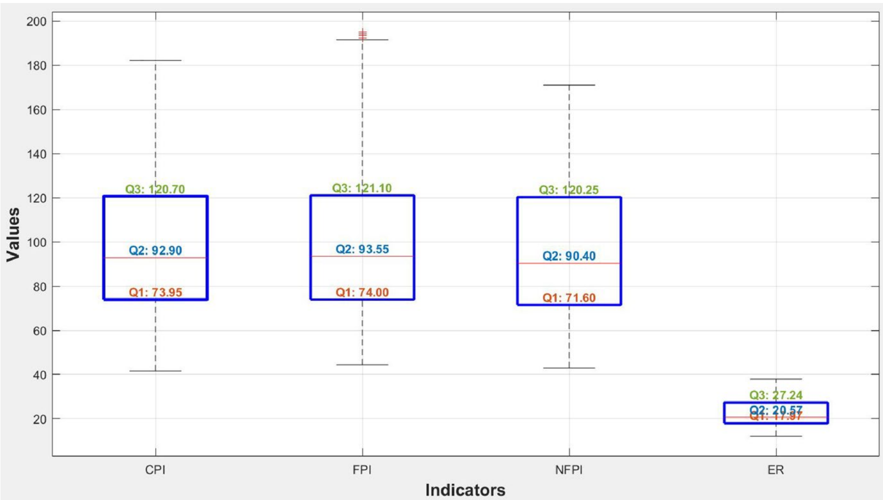

Fig. 2 Box plot of inflation indicators showing the variability of CPI, FPI, NFPI, and ER

3.3 Unit-Root Tests

The Ethiopian economy has experienced some major shocks and government interventions in recent decades. Possible famine outbreaks include food price shock in 1976 Gebre-Medhin and Vahlquist (1976), the revolution in 1991 Tiruneh (1991), the global COVID-19 pandemic Anagaw (2023) and bold government reform Regassa (2022). The time series under consideration should be checked for stationary before one can attempt to fit a suitable model, from which we noted that the series of the endogenous variables display a non-stationary behavior. The structural breaks of the four key indicators of the inflation were examined. The evidence shows that there is a break in the slope of the CPI, NFPI, FPI and ER, after 2010 as given in Fig. 1 indicating that the four inflation variables have no stationary behaviour, which needs to be justified using the statistical tests. To assess the existence of structural breaks, we also conducted the Zivot-Andrews unit root test for structural breaks.

3.4 Zivot-Andrews Unit Root Test for Structural Breaks

We applied the Zivot-Andrews unit root test to examine the stationarity behavior of four key inflation variables, accounting for structural breaks. The results presented in Table 3 indicate that, at the 5% significance level, the test statistics range from 5.411 to 6.017. These values exceed the critical value of 5.08, leading to the rejection of the null hypothesis of no structural break. This provides sufficient evidence to conclude that structural breaks exist at the identified break points, which aligns with the findings shown in Fig. 1.

The stationarity of the series can be tested by ADF and PP tests. Table 4 presents the results of ADF and PP unit-root tests, both with an intercept and a deterministic linear trend. The tests evaluate the null hypothesis H_0: the series is non-stationary, against the alternative hypothesis H_1: the series is stationary. The critical values used for these tests are referenced from Wang et al. (2001), and the results in Table 4 indicate that the null hypothesis, which states that the series in levels contain a unit root, could not be rejected for all three series. In other words, the respective p-values are greater than the conventional significance level of $\alpha = 0.05$. The results for both tests, at the level and first differences, are presented in Table 4.

The results indicate that the null hypothesis of non-stationarity could not be rejected for all four series, as p-values exceed the conventional significance level $\alpha = 0.05$. Testing the series at level refers to examining the original time

Table 3 Zivot-Andrews test results with critical values, break point positions, and variables

Variables	Test statistic	Critical values	Break point position
CPI	−5.4635	−5.08	32
FPI	−6.4117	−5.08	49
NFPI	−5.4112	−5.08	44
ER	−6.0174	−5.08	13

Table 4 Unit root test results (At Level)

Series	Level with intercept				Level with intercept and trend			
	Test statistic		Probability		Test statistic		Probability	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
CPI	3.824	1.459	1.00	1.00	1.409	2.214	1.00	1.00
FPI	3.495	1.740	1.00	1.00	1.062	1.856	1.00	1.00
NFPI	3.310	1.244	1.00	1.00	1.028	1.959	1.00	1.00
ER	2.448	1.849	0.999	0.999	1.000	2.643	1.00	1.00

Critical value 5%: −2.888 (Intercept), −3.446 (Intercept and trend)

series for stationarity. If the series contains unit roots, it is non-stationary. To ensure that the data meets the assumptions of stationarity, and given that the null hypothesis could not be rejected, tests were applied to the first differences of the non-stationary time series, as shown in Fig. 3. The subsequent testing of these first differences confirms the order of integration needed for the series to achieve stationarity.

Fig. 3 indicates that the pattern of each inflation indicator remains constant after differencing. PP test for the test statistic in Table 4 showed that, we do not reject the null hypothesis by both ADF and PPT test. However, the same tests were applied to the first differences and we reject the null hypothesis since the variables appear to be stationary at the first difference as given in Table 5.

Both tests indicate that all variables included in the model are not stationary at their levels but become stationary after taking the first difference, meaning the series are integrated of order 1. Table 5 shows that the null hypothesis is rejected

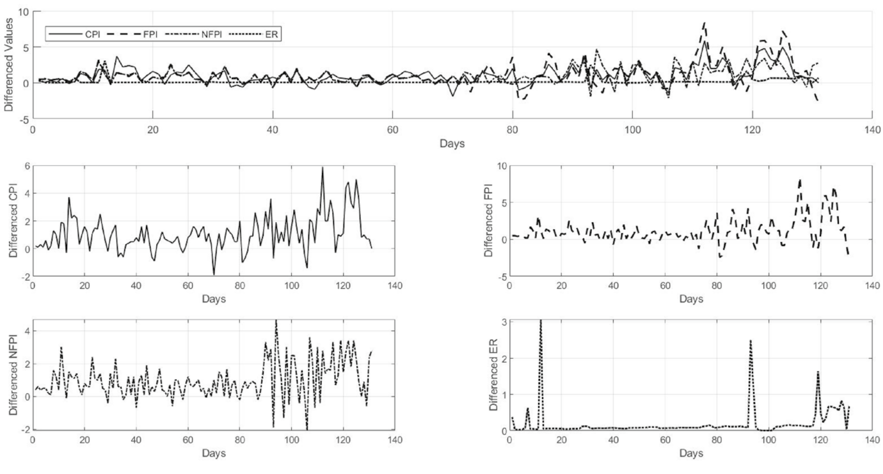

Fig. 3 Time series plot for indicators of inflation after differencing: Solid line denotes the CPI; Dashed line denotes the FPI; Dashed dot line NFPI and Dotted line is ER

Table 5 Unit root test results (Difference of the return series)

Series	Level with intercept				Level with intercept and trend			
	Test statistic		Probability		Test statistic		Probability	
	ADF	PP	ADF	PP	ADF	PP	ADF	PP
D(CPI)	−7.30	−76.74	0.000	0.00	−7.72	−84.30	0.00	0.00
D(FPI)	−6.50	−67.19	0.00	0.00	−6.76	−73.21	0.00	0.00
D(NFPI)	−11.62	−134.59	0.00	0.00	−12.51	−144.24	0.00	0.00
D(ER)	−8.954	−100.78	0.00	0.00	−9.250	−104.75	0.00	0.00
Critical value	−2.888				−3.446			

for the returns of all four series, as the p-values in both the PP and ADF tests are below 5%.

3.5 Modeling Volatility

To address inflation volatility in Ethiopia effectively, it is crucial to test for the presence of an ARCH effect. The analysis involves plotting observations on the y-axis and time (Days) on the x-axis. As illustrated in Fig. 3, the y-axis limits are consistent across all plots, facilitating direct comparisons of volatility among different series. The results indicate that the FPI, CPI, NFPI, and ER are volatile, with FPI being the most volatile, followed by CPI and NFPI, respectively. Notably, ER exhibits the least volatility.

This observation aligns with the individual plots in Fig. 3,

which show the volatility of inflation indicator separately.

Figure 3 shows that variances are not constant, indicating the presence of volatility clustering in Ethiopia's inflation indicators. This suggests that periods of high volatility are often followed by further high-volatility periods, while periods of low volatility tend to follow more low-volatility periods. Such clustering implies that volatility is not randomly distributed but occurs in waves, a pattern that can be more accurately analyzed using GARCH models. The Lagrange Multiple (LM) test results in Table 6 show that the null hypothesis of no serial autocorrelation (i.e., no ARCH effect) is rejected at a 5% significance level, indicating the presence of serial correlation in the time series and confirming the existence of ARCH effects.

Heteroskedasticity test was used to identify the presence of ARCH effect with the null hypothesis of no ARCH effects (that is, homoskedasticity) in the residuals. Table 6 shows that, the value of LM test for ARCH for overall series are significant at 5% level. This implies the rejection of null hypothesis and we conclude that there is an ARCH

Table 6 Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH)

Lags (p)	χ^2	Df	P
1	90.109	1	0.000

H_0: No ARCH effect vs. H_1: has ARCH effect

effect. The test equation for ARCH effect also signifies the presence of ARCH effect. Both tests based on serial correlation LM and heteroskedasticity signify the existence of volatility clustering (ARCH) effect. Therefore, MGARCH was employed for volatility modeling. ARCH or GARCH model is fitted to the squared residuals of the model to avoid the heteroskedasticity from the residuals.

The result corresponding to this effect is given Table 6. The result corresponding to χ^2-statistic reveals that the presence of ARCH effects at 5% significance level for all inflation indicators. It can be noted that there is volatility clustering in financial time series, where periods of high volatility tend to be followed by more high volatility, and periods of low volatility are followed by more low volatility. This pattern suggests that volatility is not constant over time but tends to cluster, reflecting the impact of market shocks or economic events. Volatility clustering is often observed in stock returns, exchange rates, and other financial metrics, and it plays a crucial role in risk management and forecasting models. Such behavior can be effectively modeled using techniques like GARCH, which capture the time-varying nature of volatility, from which it is possible to use MGARCH family models in estimating the optimal parameters.

3.6 MGARCH Models

3.6.1 Parameter Estimation of Volatility

The LM, Engle and Sheppard tests can be employed for testing the constant correlation hypothesis versus the smoothly changing dynamic correlations as shown in several previous works (Stock & Watson, 2016). Both the LM, Engle, and Sheppard tests indicate the rejection of the null hypothesis, providing evidence of an ARCH effect and suggesting the presence of time-varying correlation in the returns, thereby implying that the use of a CCC-GARCH model is not necessary.

3.6.2 Lag-Length Selection

To select the most appropriate lag, we fit the models with different lags to obtain their information criterion values, where the best model for the data is the model with minimum information criterion values. Because; too many lags result in loss of degree of freedom, insignificant coefficients and multicollinearity, and too few lags result in model misspecification errors. The result is summarized in Table 7.

As shown in Table 7, the values of information criteria for diagonal BEKK(1, 1) was the smallest compared to the other lags. Therefore, BEKK(1, 1) was selected for diagonal BEKK model. Also, the result from DCC showed that, the values of information criteria for DCC(1, 1) was the smallest compared to the other lags. Further by comparing the information criteria for DCC(1, 1) and BEKK(1, 1), the information criteria for BEKK(1, 1) was larger than that of DCC(1, 1) from which we noted that DCC(1, 1) can be selected as the best MGARCH model for this study to test, estimate and measure the extent of sectorial volatility.

Table 7 Model selection for DCC- and BEKK-GARCH models

Lags	lag	log-likelihood	SBIC	HQIC	AIC
Lag selection for DCC					
0	0	131408.80	−16.2	−16.4	−16.5
0	1	131799.24	−17.9	−18.1	−18.3
0	2	131799.24	−18.3	−18.5	−18.7
1	1	131841.39	−18.61*	−19.05*	−19.02*
1	2	131837.26	−18.5	−18.75	−19.03
2	1	131837.67	−18.5	−18.76	−19.04
2	2	131837.75	−18.45	−18.73	−19.02
Lag selection for BEKK					
0	0	131604.03	−14.58	−14.74	−15.01
0	1	131688.66	−16.02	−16.16	−16.30
0	2	131704.01	−16.04	−16.32	−16.51
1	1	131723.04	−16.28*	−16.56*	−16.74*
1	2	131713.08	−16.04	−16.37	−16.60
2	1	131715.62	−16.08	−16.42	−16.64
2	2	131716.01	−16.02	−16.42	−16.58

(*) indicates the lag selected by the criterion and *lag* is indicating the order of the lags

In the Ethiopian context, understanding sectoral volatility is crucial for assessing economic stability and investment risks. Ethiopia's economy, which is largely dependent on agriculture, manufacturing, and services, experiences fluctuations due to factors such as inflation, currency depreciation, and global commodity price changes (Ketema & Diriba, 2021). The MGARCH framework, particularly the DCC(1,1) model, helps capture the dynamic correlations between different economic sectors. This is essential for policymakers, investors, and financial institutions to develop risk management strategies, enhance economic forecasting, and support sustainable economic growth. This study offers a significant advantage over traditional univariate methods by capturing the interdependencies and dynamic volatility relationships between economic sectors using the MGARCH framework. Unlike univariate approaches, which analyze each sector in isolation, MGARCH models-particularly DCC(1,1)-account for volatility spillovers and correlations over time. Additionally, the study focuses on four key indicators of inflation, providing a more comprehensive understanding of inflation dynamics. This is especially valuable in the Ethiopian context, where economic sectors are highly interconnected, and fluctuations in one sector can impact others. By incorporating these relationships, the study provides a more accurate risk assessment, enhances forecasting capabilities, and equips policymakers with a more robust tool for economic planning and financial stability analysis.

Finally, in the Ethiopian context, the DCC model is useful for tracking real-time inflation volatility due to its efficiency in capturing time-varying correlations. However, it assumes stationarity, which may not always hold in Ethiopia's fluctuating economy, and it oversimplifies volatility spillovers. On the other hand, the BEKK

Table 8 Estimated parameters of the DCC-GARCH Model

Component	Parameter	Coefficient	Std. error	t-value	*p*-value
Conditional variance parameters					
CPI	ARCH (θ)	0.78	0.13	5.92	<0.001***
	GARCH (β)	0.09	0.02	5.41	<0.001***
	Constant (V)	0.70	0.03	23.43	<0.001***
FPI	ARCH (θ)	0.01	0.03	4.00	<0.001***
	GARCH (β)	0.09	0.01	9.56	<0.001***
	Constant (V)	0.69	0.19	3.55	0.038*
NFPI	ARCH (θ)	0.49	0.22	2.25	0.005**
	GARCH (β)	0.49	0.18	2.69	0.019*
	Constant (V)	0.04	0.01	0.44	0.280
ER	ARCH (θ)	0.08	0.09	0.89	0.270
	GARCH (β)	0.17	0.04	4.46	0.010**
DCC correlation estimates					
	ρ_{12}	0.69	0.10	6.85	<0.001***
	ρ_{13}	0.63	0.07	8.72	<0.001***
	ρ_{14}	0.50	0.09	5.33	<0.001***
	ρ_{23}	0.70	0.08	8.57	<0.001***
	ρ_{24}	0.55	0.08	6.65	<0.001***
	ρ_{34}	0.51	0.07	6.93	<0.001***
DCC model parameters					
	θ	0.18	0.01	12.41	<0.001***
	β	0.70	0.02	47.36	<0.001***

CPI: Consumer Price Index, FPI: Food Price Index, NFPI: Non-Food Price Index, ER: Exchange Rate. ARCH (θ) and GARCH (β) are model parameters for conditional variance. ρ_{ij} represents dynamic conditional correlations between indices

model provides a richer analysis by capturing volatility transmission and structural shocks, making it more suitable for understanding how inflation affects different economic sectors. However, it is computationally demanding and prone to overfitting. While DCC is preferable for quick insights, BEKK is better for detailed risk assessments and policy decisions.

3.6.3 DCC-ARCH Model

The estimation of GARCH models is typically performed using the conditional maximum likelihood approach to estimate the model parameters.

The estimated parameters are shown in Table 8. As we know that the summation of ARCH and GARCH effects measures the existence of volatility. As seen from Table 8, the sum of all the coefficients are less than 1 (i.e., $\left(\sum \theta_j + \sum \beta_i < 1\right)$ for all 4 time series. This shows that, volatility is not permanent, not explosive and the previous volatility prediction is not as much important (Sinha et al., 2017).

Note: CPI is considered as variable 1, FPI is considered as variable 2, NFPI is considered as variable 3, and EX-Ret is considered as variable 4.

Based on the results given in Table 8, we can write DCC-GARCH models as follows:

$$\hat{\delta}^2_{\mathrm{CPI},t} = 3.372 + 0.092 \times \hat{\delta}^2_{\mathrm{CPI},t-1} + 0.782 \times \epsilon_{\mathrm{CPI},t-1} \tag{18}$$

$$\hat{\delta}^2_{\mathrm{FPI},t} = 0.70 + 0.09 \times \hat{\delta}^2_{\mathrm{FPI},t-1} + 0.010 \times \epsilon_{\mathrm{FPI},t-1} \tag{19}$$

$$\hat{\delta}^2_{\mathrm{NFPI},t} = 0.69 + 0.49 \times \hat{\delta}^2_{\mathrm{NFPI},t-1} + 0.49 \times \epsilon_{\mathrm{NFPI},t-1} \tag{20}$$

$$\hat{\delta}^2_{\mathrm{ER},t} = 0.04 + 0.17\hat{\delta}^2_{\mathrm{ER},t-1} + 0.08\epsilon^2_{\mathrm{ER},t-1} \tag{21}$$

where δ indicates the difference of the time series.

In the given equations, $\hat{\sigma}^2$ represents the variance of the respective time series at time t, while the constant term 3.372 denotes the baseline level of volatility. The higher coefficients such as 0.49 and 0.49 signify a stronger persistence of past volatility and shocks, respectively, on current volatility based on the NFPI inflation indicator. These coefficients reveal how historical volatility and shocks persist and shape the current volatility levels of inflation indicators. Additionally, they provide insight into the correlation between different inflation indicators, highlighting the interconnectedness of these economic variables. The above equation is given by:

$$\begin{aligned}
\hat{\delta}_{(\mathrm{FPI,CPI}),t} &= \rho_{(\mathrm{FPI,CPI})}\hat{\sigma}_{\mathrm{FPI},t}\hat{\sigma}_{\mathrm{CPI},t} \quad \text{where} \quad \rho_{(\mathrm{FPI,CPI})} = 0.692\\
\hat{\delta}_{(\mathrm{NFPI,CPI}),t} &= \rho_{(\mathrm{NFPI,CPI})}\hat{\sigma}_{\mathrm{NFPI},t}\hat{\sigma}_{\mathrm{CPI},t} \quad \text{where} \quad \rho_{(\mathrm{NFPI,CPI})} = 0.628\\
\hat{\delta}_{(\mathrm{ER,CPI}),t} &= \rho_{(\mathrm{ER,CPI})}\hat{\sigma}_{\mathrm{ER},t}\hat{\sigma}_{\mathrm{CPI},t} \quad \text{where} \quad \rho_{(\mathrm{ER,CPI})} = 0.504\\
\hat{\delta}_{(\mathrm{NFPI,FPI}),t} &= \rho_{(\mathrm{NFPI,FPI})}\hat{\sigma}_{\mathrm{NFPI},t}\hat{\sigma}_{\mathrm{FPI},t} \quad \text{where} \quad \rho_{(\mathrm{NFPI,FPI})} = 0.703\\
\hat{\delta}_{(\mathrm{ER,FPI}),t} &= \rho_{(\mathrm{ER,FPI})}\hat{\sigma}_{\mathrm{ER},t}\hat{\sigma}_{\mathrm{FPI},t} \quad \text{where} \quad \rho_{(\mathrm{ER,FPI})} = 0.552\\
\hat{\delta}_{(\mathrm{ER,NFPI}),t} &= \rho_{(\mathrm{ER,NFPI})}\hat{\sigma}_{\mathrm{ER},t}\hat{\sigma}_{\mathrm{NFPI},t} \quad \text{where} \quad \rho_{(\mathrm{ER,NFPI})} = 0.513
\end{aligned}$$

where $\rho(\mathrm{FPI, CPI}) = 0.692$ indicates a strong positive linear relationship between the FPI and the CPI. This suggests that as the FPI increases, the CPI tends to increase as well, and vice versa. A correlation value of 0.692 is fairly high, meaning that the movements in food prices are significantly associated with movements in general consumer prices. This correlation highlights the interdependence between these two inflation indicators, implying that changes in food prices can have a notable impact on overall consumer price levels. The strong 0.692 correlation between the food price index and consumer price index highlights the significant impact of food price fluctuations on overall inflation. This finding is crucial for informing policies aimed at stabilizing food prices, adjusting subsidies, and protecting vulnerable populations from economic shocks. Similarly, the correlation coefficient $\rho(\mathrm{ER, CPI}) = 0.504$ indicates a moderate positive relationship between the EX-Ret and the CPI. This suggests that there is a tendency for the CPI to move in the same direction as changes in exchange rate returns, though the association is less pronounced compared to the correlation between FPI and CPI. A correlation value of 0.504 reflects a moderate degree of interdependence, meaning that while exchange rate fluctuations do influence consumer price levels, the relationship is not as strong as with food prices. This implies that changes in exchange rates have a moderate impact on the overall consumer price levels but are less influential compared to food prices. The correlation coefficient of 0.504 between EX-Ret and CPI indicates a moderate positive relationship, suggesting that changes in exchange rates have a moderate impact on inflation. This finding can help guide policy decisions related to exchange rate management and inflation control. The correlation coefficient $\rho(\text{NFPI}, \text{FPI}) = 0.703$ indicates a strong positive relationship between the NFPI and FPI. This means that as changes occur in the NFPI, there is a significant tendency for corresponding changes in the FPI, with the two indices moving in the same direction. The value of 0.703 suggests that the movements in these two indices are closely related, showing a substantial level of co-movement or synchronization between them. The correlation coefficient of 0.703 between NFPI and FPI indicates a strong positive relationship, meaning that changes in the National Food Price Index (NFPI) are closely linked to fluctuations in the Food Price Index (FPI). This suggests that trends in national food prices significantly influence overall food price changes. The correlation coefficient $\rho(\text{ER}, \text{FPI}) = 0.552$ indicates a moderate positive relationship between the ER and the FPI. This suggests that changes in exchange rate returns are moderately associated with changes in the food price index. Specifically, a positive correlation of 0.552 means that when the exchange rate returns increase, there is a tendency for the food price index to increase as well, and vice versa. The moderate strength of this correlation implies a noticeable, though not extremely strong, relationship between these two variables. The correlation coefficient of 0.552 between ER and FPI indicates a moderate positive relationship, suggesting that fluctuations in the exchange rate (ER) are somewhat linked to changes in the Food Price Index (FPI). This implies that variations in exchange rates can have a moderate impact on food price trends. Finally, the correlation coefficient $\rho(\text{ER}, \text{NFPI}) = 0.513$ indicates a moderate positive relationship between the EX-Ret and the NFPI. This means that as the values of the NFPI increase, there tends to be a moderate increase in the exchange rate returns, and vice versa. A coefficient of 0.513 suggests a significant but not overly strong association, implying that while there is some degree of linkage between these two variables, other factors may also influence their behavior. The correlation coefficient of 0.513 between EX-Ret and NFPI indicates a moderate positive relationship, suggesting that changes in the exchange rate (EX-Ret) are moderately associated with fluctuations in the Non-Food Price Index (NFPI). This implies that variations in exchange rates can influence the trends in non-food prices to some extent.

All coefficients of the conditional variance specification meet the necessary and stability condition of

$$0 < \theta_i < 1, \quad 0 < \beta_j < 1, \quad \text{and} \quad \theta_i + \beta_j < 1 \tag{22}$$

where $k = 1, 2, 3, 4$ is denoting the number of indicators of inflation factors. This indicates that the volatility of inflation is neither permanent nor explosive, which means that a shock to volatility in one period will not lead to even greater volatility in the next period, and past volatility prediction is not as such important (Osman et al., 2023). This result clearly entails the presence of time-varying conditional volatility of returns and implies that the effect of today's shock remains in the forecasts of variance for many periods in the future. As we can see from the values of the models presented in Table 8, the ARCH coefficients are lower than the coefficients of the GARCH term coefficients, revealing further evidence of a high rate of change in conditional volatility and significant time dependence. The DCC-GARCH estimates are $\theta = 0.1794$ and $\beta = 0.7023$, and both estimators are statistically significant at the 5% level of significance, satisfying the condition of

$$\theta + \beta < 1 \tag{23}$$

and suggesting that the conditional variance is mean reverting toward its equilibrium level.

In Table 8, the coefficient of the series in FPI has a large coefficient of DCC-β, indicating that NFPI has a large impact on today's volatility. In CPI and NFPI, there is a greater coefficient of DCC-θ, so we expect today's correlation to be explained by or associated with yesterday's correlation. Moreover, there is a positive association among CPI, FPI, NFPI, and ER.

3.6.4 DCC-GARCH Model Diagnostics

After fitting the DCC-GARCH model, we assessed its adequacy using the Ljung-Box statistics (Q-test) and Li-McLeod (Q*-test) for residuals to test any serial correlation. The results, detailed in Table 9, support the null hypothesis of no serial correlation, as indicated by the statistically insignificant p-values. This finding underscores the model's robust statistical performance. Specifically, the non-significant Q-test statistics affirm the absence of autocorrelation in the residuals, affirming the suitability of the selected model for accurately fitting the data.

3.6.5 Volatility Forecasting

To further validate the forecasting results, Figures 4 and 5 are used. Figure 4 shows the in-sample volatility forecasts, which are derived from data spanning January 2010 to December 2020. This figure helps us understand how well the forecasting model performs with historical data that it was trained on. This result shows in-sample volatility forecasts using data from January 2010 to December 2020. This in-sample forecasting

Table 9 DCC-GARCH model adequacy Checking

Model	Q-Test		Q*-Test	
	Value	Prob	Value	Prob
DCC-GARCH	17.2548	0.1924	17.2106	0.1903

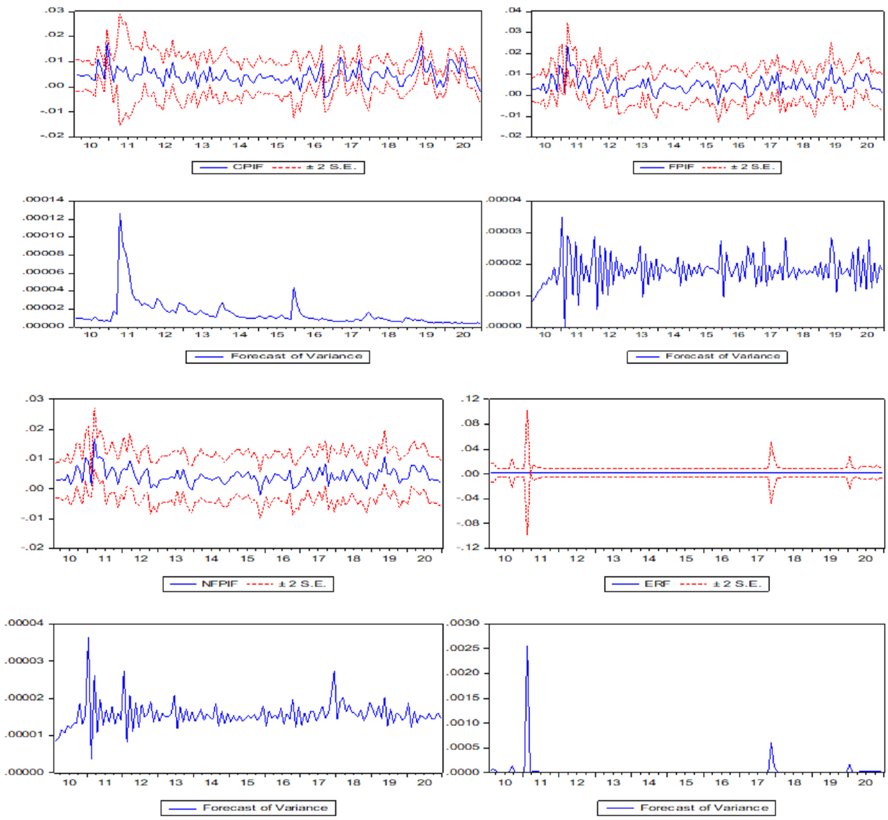

Fig. 4 In-sample forecasted volatility

uses historical data to develop and validate the model, allowing us to assess its performance and accuracy within the time period.

In contrast, Fig. 5 presents out-of-sample volatility forecasts for the period from January 2021 to December 2023. This allows us to assess the model's ability to predict future volatility based on new data not included in the training set. By comparing these figures, we can evaluate both the accuracy of the model with historical data and its effectiveness in forecasting future trends. This period is outside the range of the historical data used for model development. Out-of-sample forecasting evaluates the model's ability to predict future volatility based on new, unseen data, offering insights into its predictive accuracy and generalizability.

Both Figs. 4 and 5 illustrate that the forecasts fall within ±2 standard error bands, with a 95% confidence interval. So, it can be concluded that the model is satisfactory. The forecast indicates that there is likely to be instability in the returns of CPI and FPI, and stability in the return series of NFPI and ER for the next thirty six months. This implies that FPI is expected to increase very fast, CPI will decrease, NFPI will decrease for the first twelve months and remains

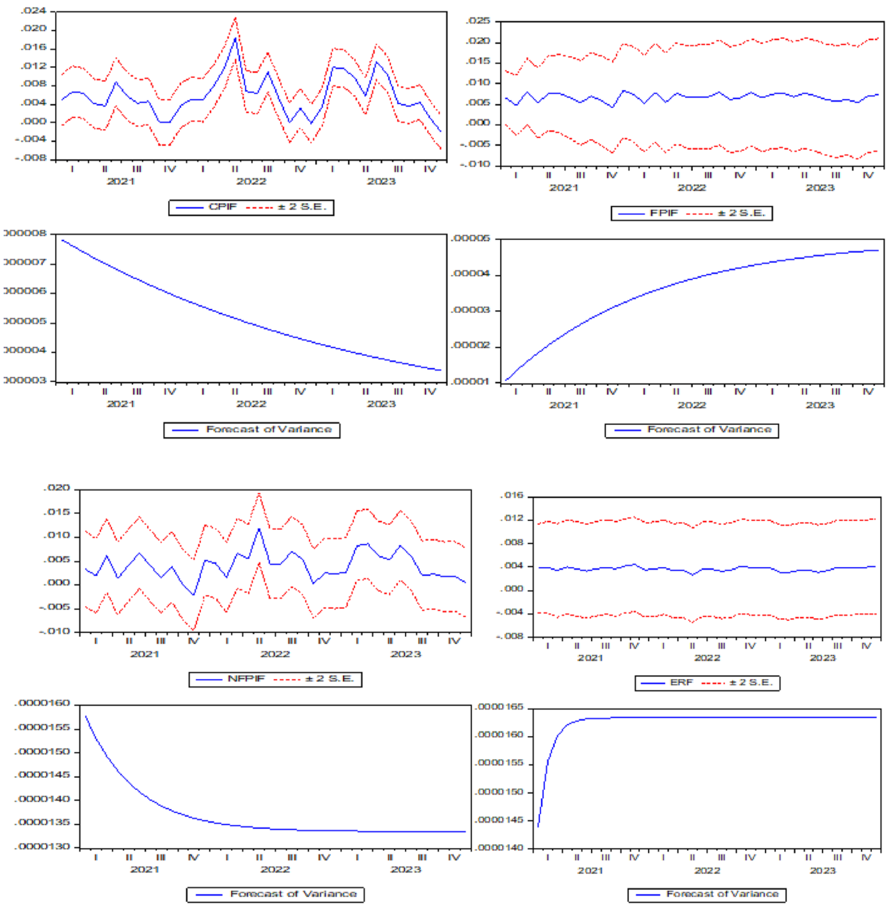

Fig. 5 Out-samples forecasted volatility

stable for the rest of twenty four months and ER will increase for the first four months and remains stable for the rest of thirty two months. Therefore, analyzing and forecasting volatility is helpful as it informs investors the measures of risk involved in holding an asset. Finally, we assessed the prediction accuracy and verified that the DCC GARCH model outperforms other models in forecasting inflation volatility, offering more reliable overall predictions despite some challenges with relative volatility accuracy. The DCC GARCH model performs well in terms of forecast accuracy, as demonstrated by several evaluation metrics. The low Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) suggest that the model's predictions are closely aligned with the actual values, with minimal systematic bias, as indicated by the small Mean Error (ME). These results underscore the effectiveness of the DCC GARCH model in forecasting inflation volatility. One of the fundamental applications of time series analysis, particularly in developing time series models, is forecasting

Table 10 Volatility forecast evaluation measures

Forecast evaluation measures	Variance
Mean squared error (MSE)	6.187×10^{-6}
Mean error (ME)	−0.002271
Mean absolute error (MAE)	0.002271
Root mean squared error (RMSE)	0.002487

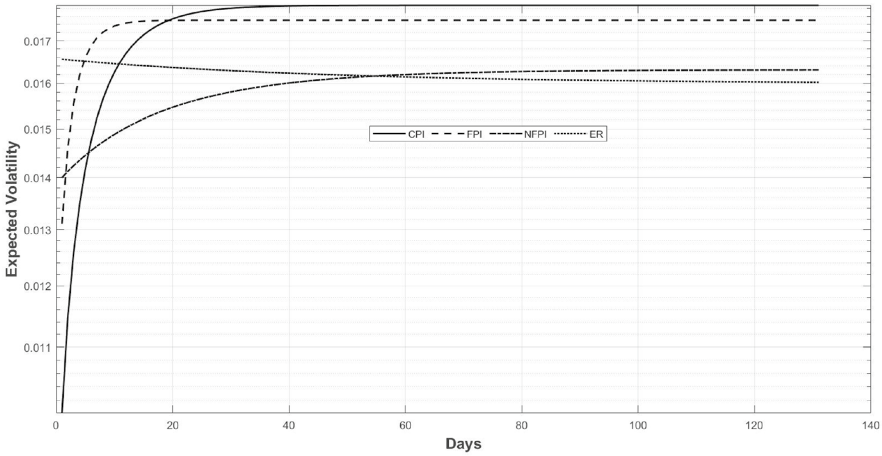

Fig. 6 Expected volatility versus time in days: Solid line denotes the CPI; Dashed line denotes the FPI; Dashed dot line NFPI and Dotted line is ER

inflation volatility using the DCC model. To assess forecasting accuracy, we used several evaluation metrics, including MSE, ME, MAE, and RMSE, with the summary results provided in Table 10.

Figure 6 presents a detailed depiction of the volatility trends for various inflation indicators across different time periods. The result highlights that the CPI and the FPI display considerable fluctuations, suggesting that these indicators experience significant variability over time. This high volatility may reflect the impact of sudden economic shifts, changes in consumer behavior, or supply chain disruptions affecting prices. In contrast, the NFPI and ER show comparatively lower volatility, indicating more stable trends in these areas. The reduced volatility of NFPI and ER suggests that these indicators are less prone to abrupt changes, possibly due to more consistent underlying factors or effective stabilization mechanisms in place. This contrast underscores the varying degrees of price stability and economic dynamics represented by each indicator.

The DCC-GARCH model provides a significant advantage over traditional univariate methods by capturing the time-varying correlations among key economic indicators such as the CPI, FPI, NFPI, and EX. Unlike univariate models that analyze each index separately, DCC-GARCH dynamically models the evolving relationships between these variables, offering a more comprehensive understanding of inflationary trends and market fluctuations. This adaptability is particularly useful for policymakers and investors, as it enhances forecasting accuracy, improves risk management, and provides deeper insights into the interdependencies between food prices, exchange rates, and overall inflation. Furthermore, we compare the efficiency of the two models in parameter estimation. The DCC-GARCH model proves to be more efficient than the BEKK-GARCH model, as shown in Table 10. This efficiency is reflected in the faster convergence and lower computational cost of the DCC-GARCH model compared to its counterpart as given in Table 11. This is due to the BEKK-GARCH model can become computationally expensive as the number of variables increases due to its full covariance matrix structure, DCC-GARCH simplifies this by modeling the correlations separately from the variances, making it more computationally efficient.

4 Limitations of the Work

The current study provides a good foundation for understanding Ethiopian inflation but is limited by focusing on only four key indicators, which may not capture the full complexity of inflation. We will also incorporate control variables to assess the robustness of the DCC-GARCH model in future work. Important economic variables, such as GDP and income, as well as the impact of conflicts, were excluded from the analysis, which are crucial for a comprehensive understanding of inflation dynamics. Omitting these factors may result in an incomplete model, potentially missing significant influences on inflation. Future research should expand the analysis to include these variables, which would enhance the robustness and predictive power of the model, offering more accurate insights into inflation trends and informing better policy decisions.

5 Discussions and Conclusions

This study utilized the multivariate GARCH model to estimate inflation volatility in Ethiopia, using data obtained from the NBE. Inflation represents a significant global economic challenge, and Ethiopia is no exception. The analysis incorporated 132 observations across four inflation indicators to achieve the study's objectives. A central research question addressed was whether inflation characteristics exhibit volatility.

A key finding of this study is the detection of volatility clustering, or ARCH effects, which result from serial correlation and time-varying variance (heteroskedasticity) in the inflation series. This finding aligns with the observations

Table 11 Time complexity

Model	Time in seconds
DCC-model	0.11
BEKK-model	0.43

in Mohammed (2019). The study applied BEKK-GARCH and DCC-GARCH models to evaluate inflation volatility and forecasting in Ethiopia. Our results demonstrated that the DCC(1,1) model offered a superior fit compared to the BEKK(1,1) model and other models, as evidenced by AIC, SBIC, and HQIC information criteria. This conclusion is consistent with the findings of Ezekiel et al. (2022), which also reported that the DCC-GARCH method outperformed the BEKK-GARCH method in forecasting inflation volatility. Furthermore, the cumulative error from each parameter in the BEKK-GARCH models is notably higher than that observed in the DCC-GARCH models (Huang et al., 2010). Our study builds on Mashamba and Magweva (2022), which analyzed Zimbabwe's monthly volatility from July 2009 to July 2018, by adding more inflation indicators. Unlike Mashamba and Magweva (2022), which used an AR(1)-GARCH(1,1) model, we confirm its suitability for our analysis. Our study builds on the work presented in Mashamba and Magweva (2022), which analyzed monthly volatility data from Zimbabwe for the period of July 2009 to July 2018, by including additional inflation indicators in our analysis. Unlike the approach in Mashamba and Magweva (2022), which utilized an AR(1)-GARCH(1,1) model, our study affirmed the use of the AR(1)-GARCH(1,1) process for several reasons. This model effectively captured both the autoregressive behavior (how past values influence current ones) and the volatility clustering (periods of high and low volatility grouping together), which are important for accurately modeling inflation trends. By affirming this model, we demonstrated its reliability in forecasting and understanding the dynamics of inflation with the additional indicators we have incorporated.

Our research work mainly focused on modeling and forecasting inflation volatility, while Girma (2012) addressed the relationship between inflation and economic growth in Ethiopia, through an empirical analysis, 1980-2011 via using the VEC (vector error correction). Moreover, Anguyo et al. (2020) studied inflation dynamics in Uganda using quartile regression with only two variables. A limitation of this approach is that it may overlook other important factors influencing inflation, which could lead to biased or incomplete results.

Our research finding went beyond Girma (2012) in the aspect of considering inflation volatility through comparing two popular MGARCH models, we also examined key aspects of inflation volatility, such as structural breaks, and evaluated the computational load.

In Gofere (2013), a VAR model examined the link between inflation and foreign prices, finding that monetary and fiscal factors significantly influence short-term price dynamics. Our study, however, focused on forecasting inflation volatility using four indicators, aligning more closely with the approach in Geda and Tafere (2008). Future work should consider additional structural indicators of inflation.

The study by Legass et al. (2021) employed a VECM to model Ethiopian inflation and its dynamics from 1980 to 2012, highlighting the significant roles of supply-side, monetary, and external factors in explaining long-term price inflation through their co-integrating relationships. In contrast, our work focused on forecasting inflation volatility using a broader range of indicators.

The study by Legass et al. (2021) modeled Ethiopian inflation growth from 1980 to 2012 using VECM, highlighting significant effects of supply, monetary, and external factors on long-term inflation. Our research, however, forecasted inflation volatility with additional indicators. Many studies, such as Neda (2010), used CPI and NFPI variables but overlooked inflation volatility. Zaman and Khan (2018) found that food inflation significantly impacts non-food inflation, especially in developing economies. Our study better captured inflation volatility by using more indicators, unlike Gathingi (2014), which modeled inflation from 2005-2013 using ARIMA and VAR models.

In conclusion, this study forecasted inflation volatility using monthly data from the NBE for the period January 2010 to December 2020, encompassing 132 observations. The data was differences to facilitate analysis. Unit root tests (Augmented Dickey-Fuller and Phillips-Perron) confirmed that all series were non-stationary, necessitating log-transformation to achieve stationarity. We applied two widely-used multivariate GARCH models-DCC and BEKK-to forecast inflation volatility in Ethiopia.

Key findings include evidence of volatility clustering identified through the ARCH Lagrange Multiplier test, and the DCC-GARCH model's parameter estimation reflects high volatility and significant time dependence. Specifically, the ARCH coefficients are lower than the GARCH coefficients for FPI, indicating substantial changes in conditional volatility. Our analysis revealed that the DCC-GARCH model outperformed BEKK-GARCH in forecasting accuracy based on various tests and information criteria. For NFPI and CPI, the GARCH coefficients are lower than the ARCH coefficients, while the ARCH coefficient for ER was found to be insignificant.

Forecasts from the model showed that FPI volatility would rise sharply, CPI would decrease slightly, NFPI would decline initially over twelve months before stabilizing, and the ER would increase for the first four months before stabilizing for the next thirty-two months. The DCC-GARCH model also demonstrated superior computational efficiency compared to BEKK-GARCH.

Given these findings, it is imperative for the government and policymakers to reduce the influence of inflation in the future in Ethiopia. The statistical results suggest that inflation dynamics in Ethiopia are significantly influenced by food prices and exchange rates. Policymakers can use this information to design targeted monetary policies, such as adjusting interest rates or controlling inflation through strategic interventions in the food and exchange rate sectors. These findings can help stabilize prices and protect vulnerable populations from economic shocks. Strategic actions are crucial to effectively curb inflationary pressures and stabilize the economy. It is also essential to conduct research that incorporates all key indicators of inflation in Ethiopia.

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Data Availability The datasets used during the current study are available from the corresponding author upon reasonable request. The dataset was taken from NBE. There are no restrictions on the availability, and the investigators are willing to provide the data.

Declarations

Competing interests The authors declare that they have no Conflict of interest.

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