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Department of Statistics

College of Natural and Computational Sciences

Multivariate Time Series Modeling and Forecasting Inflation Volatility in Ethiopia

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A Thesis Submitted to the Department of Statistics in Partial Fulfillment of the Requirement for Degree of Master of Science in Statistics (Applied Statistics)

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School of Graduate Studies

This is to certify that the thesis prepared by Meskerem Sama, entitled: Multivariate Time Series Modeling and Forecasting Inflation Volatility in Ethiopia and submitted in partial fulfillment of the requirements for the Degree Master of Science in Statistics (Applied statistics) compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Declaration

I, the undersigned, declare that the thesis is my original work, has not been presented for degrees in any other university and all sources of materials used for the thesis have been duly acknowledged.

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This thesis has been submitted for examination with my approval as a university advisor.

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Abstract

Multivariate Time Series Modeling and Forecasting Inflation Volatility in Ethiopia

By Meskerem Sema

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Inflation refers to a situation in which the economy's overall price level is rising and it becomes a major problem in Ethiopia. Additionally, when inflation Volatility rises; it exerts harmful effects on an economy not only through changes in the price level but also through increased price level uncertainty. This study aimed Multivariate Time Series Modeling and Forecasting Inflation Volatility in Ethiopia. To attain the proposed goal, monthly based observations from January 2010 to December 2020 with consumer price index (CPI), food price index (FPI), non-food price index (NFPI) and exchange rates (ER) taken from the National bank of Ethiopia (NBE). STATA 14 version and E-views 9 were used for the purpose of data analysis. *In this work, first we compare different Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) models, particularly comparing Baba, Engle, Kraft and Kroner (BEKK) - GARCH model with Dynamic Conditional Correlation model (DCC) – GARCH models based on* Akaike Information criterion (AIC), Schwartz Bayesian information criterion (SBIC) *and* Hannan-Quinn information criterion (HQIC). *The result of the study has shown that Unit root test reveals that all the series are non-stationary at level and stationary at the log return. The result of the study has also shown that the DCC-GARCH model outperforms in estimating parameters than BEKK-GARCH model. The result of forecasting revealed that high volatility prediction in FPI will increase a high rate, CPI will decrease a low rate, NFPI will decrease for the first twelve months and stable for the rest of twenty four months and ER increase for the first four months and stable for the rest of thirty two months. The DCC- GARCH algorithm is more efficient as compared with BEKK-GARCH algorithm based on time computational complexity. Thus, the moreover, government should attention to reduce inflation by taking action for further interventions.*

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ACRONYMS

ACF: -Autocorrelation

ADF:-Augmented Dickey Fuller Test

AIC: - Akaike Information Criterion

AR: -Autoregressive

ARCH: -Autoregressive Conditional Heteroskedasticity

ARDL:-Autoregresssive Distributed Lag Model

ARIMA: -Autoregressive Integrated Moving Average

BEKK: - Baba, Engle, Kraft and Kroner

COVID: -Corona Virus Disease

CSA: -Central Statistical Agency

CCC: -Constant Conditional Correlation

CPI: -Consumer Price Index

DCC:-Dynamic Conditional Correlation

DVEC:-Diagonal Vector Error Correction

ECM:-Error Correction Modeling

EGARCH;-Exponential Generalized Autoregressive Conditional Heteroskedasticity

GARCH: - Generalized Autoregressive Conditional Heteroskedasticity

GDP: -Gross Domestic Products

GMM:-Generalized Method of Moment

HQIC: - Hannan-Quinn Information Criterion

IID:-Identically Independently Distributed

LM: - Lagrange Multiplier

MAE: - Mean Absolute Error

MAPE: - Mean Absolute Percentage Error

MGARCH: - Multivariate Generalized Autoregressive Conditional Heteroskedasticity

MLE:-Maximum Likelihood Estimation

NBE: - National Bank of Ethiopia

PP: - Phillips Perron Test

RMSE: - Root Mean Squared Error

SARIMA:-Seasonal Autoregressive Integrated Moving Average

SBIC: - Schwartz Bayesian Information Criterion

S.E:- Standard Error

TAR:-Threshold Autoregressive Model

VAR: - Vector Autoregressive

VEC:-Vector Error Correction

VECH:-Vector Error Correction Hetroscedastic

VECM:-Vector Error Correction Multivariate

XCF: -Cross Correlation Functions

1. INTRODUCTION

1.1. BACKGROUND OF THE STUDY

Inflation is the decline of purchasing power of a given currency over time and a sustained increase in general level of prices and services over time. In economics points of view, inflation is defined a crucial role in the healthy functioning of an economic performance of a given country. An alarm increase of inflation uncertainty constitutes a potential risk (Ediger, al el, 2018). High variability of inflation over time makes expectations over the future price level more uncertain (Kahssay. T, 2017).Therefore, now a days, an inflation aims to measure the overall impact of price changes for a diversified set of products and services, which allows for a single value representation of the increase in the price level of goods and services in an economy over a period of time (Ediger, al el, 2018).

When a lack of price stability rises, it exerts harmful effects on an economy not only through changes in the price level but also through increased price level of uncertainty. Among the harmful effects of inflation, the negative consequences of inflation volatility are of particular concern. The negative effects of inflation are widely recognized (Fenira. M, 2014). The macroeconomic performance of developing countries, mainly sub-Saharan Africa, is highly influenced by volatility and uncertainty in inflation. The transmission of these effects into the economy leads to a significant slowdown in an economic activity (Ndiaye.C, 2017 and Konte. M,2017). The negative effects of inflation include an increase in the opportunity cost of holding money, uncertainty over future inflation which may discourage investment and savings, and if inflation were rapid enough, shortages of goods as consumers begin hoarding out of concern that prices will increase in the future (Jason.F, 2020).

There are many major indicators which measures inflation, because there are many different price indices relating to different sectors of the economy. Inflation is a continuous increment in the general price level, or continuous decrement in the value of money and it is a continuous decrement in the value of money. Thus, if the rise is decreased continuously, it is regarded as deflation (Seifu. N, 2011).

According to the report by (World Bank, 2019) most of variation of inflation among low-income countries over the past decades across the worldwide is accounted by an external shocks and global core price shocks. It was also estimated Global food and energy price shocks account for another 13 percent of core inflation variation in low-income countries half more than in advanced economies and one-fifth more than in emerging markets and developing economies.

In Ethiopia raw inflation figures are reported monthly using the Consumer Price Index (CPI) by the (CSA, 2019). This inflation is becoming a problem, affecting the growth optimally (Kahssay. T, 2017). Ethiopian economy had been continually facing unprecedented and double digit inflation growth however; the country has experienced high and persistent inflation growth. Thus, determining the indicators of inflation and forecasting is essential to tackle the impact of inflation on the economy of Ethiopia. Even though, several macro-economic stabilization measures and policies were implemented by the government, however still focusing in the areas of number of indicators of inflation is required (Fufa. G, 2020) and (Alemayehu.G, 2011).Thereby, considering a number of major indicators of inflation helps to better understand the status of Ethiopian economy, and then tackle the major causes of the current rampant inflation in Ethiopia.

A number of approaches were suggested to model and examine the Volatility of inflation using time series algorithms (Ezekiel. N. et.al, 2015). However, these approaches still lack performing well. For instance, one approach, which considers only the time series being forecast, is known as univariate forecasting, where an Autoregressive integrated moving average (ARIMA) modeling is a specific subset of univariate modeling. Another alternative approach is a multivariate model which can be expressed in only one equation including exogenous predictor variables. To tackle this setback, in this work, we propose comparing multivariate GARCH methods first through incorporating more indicators of inflation such as Consumer Price Index (CPI), Food price index, Nonfood price index and Exchange rate. The most well-known indicator of inflation is the Consumer Price Index (CPI), which measures the percentage change in the price of a basket of goods and services consumed by households (Seifu, N. 2011). In particular, to forecast inflation volatility in Ethiopia, we propose the BEKK and DCC GARCH algorithms via incorporating a number of indicators of inflation.

Overview of Inflation in Ethiopia

Ethiopia is one of top registering an estimated population of 114 million people in Africa (CSA, 2019); however the current increase of inflation is one of the major challenges. Pressures on prices and the balance of payment heightened as a result of the global food and economic crisis, which causes seriously economy of a country. Thus, an increase of inflation, particularly through higher food price, could worsen the economic inequality. High inflation would also increase uncertainty about future inflation. According to the Ethiopian government data, about 38 percent of the population lived below the official poverty line in 2005, but it is likely that a larger proportion experiences extended periods of poverty due to shocks. Some evidences related to the welfare impacts of high food inflation on the rural population are somewhat inconclusive, however cogently it is noted that as it has a significant negative impact on the urban population (Loening. J, and Oseni. G, 2008).

To mitigate an alarm increasing of an inflation and the rising cost of living, the government has been taking various measures (Atnafu .G, 2020). However, the measures taken by the government are not still promising to address the major causes of inflation. Additionally, (Atnafu .G, 2020) mentioned that any measure to control inflation should be around structural economic problems cogently addressing the major indicators of inflation. Moreover, National Bank of Ethiopia, (2012) lowered reserve requirement after the banking sector faced severe liquidity problem. However, this measure was not accompanied by an appropriate sterilization mechanism and contributed to a sharp increase in money supply from 32 percent in December 2011 to 35 percent at the end of January 2012 (World Bank, 2019). Therefore, to tackle some of the problem related inflation in Ethiopia, Multivariate Time Series Modeling and Forecasting Inflation volatility is important to pinpoint directions to the decision makers to take an action for further intervention.

1.2 STATEMENT OF THE PROBLEM

Global estimates of inflation indicate a substantial room for improvement (Leshoro, Temitope LA, 2012 and Phiri, Andrew, 2018), due to inflation affects the life of people adversely through reducing the real income of people and investment. Inflation volatility is a major problem impacting the social aspects and economy of a country discouraging investment and saving in the world (Tadesse.W, 2020). Today, inflation is as a major problem impacting the economy across the globe. As a result of high inflation, shortages of goods happen where the consumers are suffering. Moreover, the issue of Inflation volatility is another major economic concern, due to its impending risks to the concerned economic agents, when inflation is unpredictable, the risk adverse economic agents will incur losses (Ahiakpor, J. 2019).Thus, today across the globe, inflation is getting an attention.

Approximately, in the developing country particularly in Africa the degree of severity of inflation is becoming anguish. For instance, Africa's inflation is projected to increase slightly from 3.2 percent in 2018 to 3.4 percent in 2019 and 3.7 percent in 2020.As a result of high impact of inflation, the currencies of South Sudan, Ethiopia and Eritrea, might record stronger depreciations due to the larger macroeconomic imbalances. Ethiopia is expected to have large deficits due to the impact of inflation. It is noted that countries with high inflation tends to have a lower rates of investment and economic growth (Kahasay, T. 2017). Therefore, conducting a research to forecast inflation volatility in Ethiopia both timely and indispensible to mitigate the major indicators of inflation.

Even though high inflation volatility problem has multiple causes on economy, it is widely agreed that studying it's forecasting, and identifying the indicators of inflation is one of the most immediate determinants (Seifu.N, 2011 and Girma. M, 2020). Currently, a high rate of inflation observed in Ethiopia, which in turn makes Ethiopian products and business activities less competitive in the global market. Moreover, inflation adversely affects domestic industries and impacts the living standard of dwellers in urban is mostly influenced by inflation in Ethiopia (Atnafu, G. 2020). (Barimah, H. 2014, Ismail, O. and Oluwasegun. B, 2017) studied to forecast inflation in Ghana but, they didn't consider the issue of inflation volatility.

Seifu N (2011) and Girma. M, (2020) addressed VAR model with a limited number of indicators of an inflation in Ethiopia. To tackle this dilemma, first we incorporated additional indicators of inflation, and secondly we compere two models to examine inflation volatility in Ethiopia. Therefore, the main goal of the study is Multivariate Time Series Modeling and Forecasting Inflation volatility in Ethiopia.

1.3 OBJECTIVE OF THE STUDY

The main objective of study is Multivariate Time Series Modeling and Forecasting Inflation Volatility in Ethiopia.

1.3.2 SPECIFIC OBJECTIVES

The specific objectives are:

- To compare the two popular MGARGH model.
- Modeling and forecasting inflation volatility in Ethiopia.

1.4 SIGNIFICANCE OF THE STUDY

Forecasting inflation in Ethiopia is indispensible to tackle the major causes of inflation. Thereby, modeling and forecasting inflation volatility is necessary, as the recommendation attained through modeling can be used an input for decision makers for poverty alleviation. Additionally, this work is important for policy-makers to better understand the nature of its uncertainty. This research work is useful to monitor, analyze and forecast of headline inflation volatility. This work can be used as a benchmark for other scholars as well. Generally,

- Increase understanding of inflation volatility in Ethiopia
- Helps to entail to other scholars to use relatively the best model that fits inflation volatility in Ethiopia.
- Helps the government and policy makers to take an action for further intervention.

1.5 LIMITATION OF THE STUDY

The main drawback of this study is that food and non- food prices are used as the determinant of inflation; however, other variables like money supply, wages and GDP are not taken into account. The reason for excluding these variables from the study is difficult, of getting the data in monthly bases.

1.6 MOTIVATIONS AND CONTRIBUTIONS OF THE WORK

Inflation affects everyone from ordinary people to businesses and the stock market. Invoked by the lack of the research works done in the areas of Multivariate GARCH algorithms, we considered two models to forecast inflation volatility in Ethiopia. Thus, the major contributions of this work are:

- Comparing BEKK and DCC GARCH models to forecast inflation volatility in Ethiopia to identify relatively better model that forecast inflation volatility, then the government will put attention to take an action for further intervention Ethiopia.
- Compared to (Seifu N, 2010) which only considers trend of inflation in Ethiopia, however, in our work, we tried to forecast inflation volatility considering more indicators of inflation.

1.7 ORGANIZATION OF THE PAPER/THESIS

This thesis is structured into five chapters. The first chapter describes the introduction of the work. The second chapter highlights the related works. Chapter three mainly focuses on data and methodology. Chapter Four addresses the results and discussion while the last chapter, chapter five indicates the concluding remarks, recommendations and future works. Finally, lists of references and appendices mentioned at the end.

2. LITERATURE REVIEW

2.1 THE THEORETICAL LITERATURE REVIEW

This section describes related works in modeling inflation volatility, nature of data and variables, and approaches taken into account.

Definition and measures of Inflation

Inflation is a controversial term which has undergone modification since it was first defined by the Neo-classical economists. The Neo-classical defined inflation as a galloping rise in prices caused by excessive increase in the quantity of money while the Keynesians true inflation happens when money supply increases beyond full employment level (Wahb, S. 1997). Even though different *economists* defined inflation in different ways there is an agreement that inflation is a sustained increase in the general price level of prices for goods and services. There is evidence that when inflation increases, there is usually a decline in the purchasing power of money. The most commonly used variable to measures inflation was consumer price index, which measures the overall of inflation (Ferreira, R. 2016). The definitions of inflation were also given in Chapter 1.

Measures of Inflation

The main measures of inflation are not clearly addressed. The widely used definition of inflation states that inflation is a sustained rise in general price level. This definition is supported by mathematically as:

$$\pi = \frac{P_t - P_{t-1}}{P_{t-1}} * 100$$

Where π inflation in percentageP_t denotes the present price level and P_{t-1} refers to the past price level and t denotes the time. (Dornbusch. R, et al 2001) addressed the major measures of inflation.

Consumer Price Index (CPI)

CPI is one of a predominant measure of inflation. It measures the cost of buying a fixed basket of goods and services representative of the purchase of consumers. Inflation is measured by measuring the percentage change in the prices of a given basket goods over time as compared to the price in the base year: In Ethiopia the central statistical authority computes the CPI. The authority makes house hold expenditure survey every five years (Seifu, N. 2011).

The general formula of a CPI is given by:

$$CPI = \frac{Cost\ of\ basket\ in\ current\ year}{Cost\ of\ basket\ in\ base\ year} * 100$$

Characteristics of Inflation

The characteristic of any financial asset is its return, which is typically considered to be a random variable. The spread of outcomes of this variable, known as asset volatility, plays an important role in numerous financial applications. Volatility is a measure of the dispersion in a probability density. The variance is a measure of the dispersion of the density function around its mean. The standard deviation δ which is the square root of the variance is the most common measure of dispersion for a random variable (Alexander, C. 2001).

Volatility refers to the spread of all outcomes of an uncertain variable. In finance, are interested in the outcomes of asset returns. Volatility is associated with the sample standard deviation of returns over some period of time. It is a quantified measure of market risk. Volatility is related to risk, but it is not exactly the same. Risk is the uncertainty of a negative outcome of some event. (Francq, C and Zakoian, J. 2010) noted as modeling financial time series is a complex problem due to the variety of the series in use, significance of the frequency of observation and availability of very large data sets.

2.2. EMPIRICAL LITERATURE REVIEW

There are several related works done in forecasting inflation across the globe. For instance, (Nguyen, H et al 2012) proposed Co-integration and Error Correction Modeling (ECM) to identify the determinants of inflation in Swaziland based on the data taken in the period of 1974 to 2000. The results show that the exchange and wage rates have been found to have significant long run influence on the level of prices in Swaziland.

A study conducted in Ghana by (Iddrisu, A.K et al, 2019) on volatility of Ghana's inflation rates for the period of 2000 to 2018 via Auto-regressive Conditionally Heteroskedasticity (ARCH), Generalized ARCH (GARCH), and Exponential GARCH (EGARCH) models. The proposed methods were used to model the projections of inflation volatility from 2000 to 2018. The findings of the study have shown that higher order mode ls are required to properly explain Ghana's inflation volatility and the EGARCH (12, 1) is the best fitting model for the data. The EGARCH (12, 1) model is robust and forecast volatility of inflation rates based on the Akaike Information Criterion (AIC).

A study conducted by (Hossain, M.S, et.al 2016) to identify the relationship between money supply and inflation in Bangladesh using Johansen co-integration method. The findings of the study have shown that the existence of long run co-integrating relationship between money supply and inflation. The result of the Granger causality test has revealed that a unidirectional causal relationship running from money supply to inflation which provides evidence in support for quantity theorist's view.

A study conducted by (Rana. E, 2018) was to examine a new transmission mechanism of inflation that is effect of food prices on non-food prices using the panel generalized method of moment (GMM) based on the data-set covers the time period of 2000 to 2014. The panel Granger causality tests like error correction model, panel Stacked and Dumitrescu Hurlin test of causality are also employed to see the direction of causality between food prices and non-food prices. The results of panel GMM estimation indicate that food prices positively affect non-food prices in all the income groups of economies. The causality direction is also found from food prices to non-food prices in these groups of economies. It concludes that inflation transmission mechanism of food prices to non-food prices exists in developing countries. For policy making, it is suggested that any attempt to control inflation in developing economies, one component of anti-inflationary policy should be to control the food prices.

Several empirical researches have been conducted to forecast inflation rate using the popular Autoregressive Integrated Moving Average (ARIMA) model, popularized by (Box and Jenkins, 1976), mainly (Junttila. G, 2001), Box and Jenkins, 1976)) approached to model and forecast Inflation. Additionally, (Pufnik and Kunovac, 2006) studied forecasting an inflation in Croatia However, modeling and forecasting inflation rate is better done by the approach described by (Engle and Bollerslev, 1982 and 1986) respectively because of its ability to tackle the dynamic nature of the data.

The study conducted by (Alan. K, 2016) to proposed the SARIMA model which considers the component of seasonality in the series, the VECM model which is multivariate model with three variables; the Uganda inflation rates, Uganda exchange rates and the world coffee prices based on the monthly data from April 1998 to September 2015. The research results imply that Uganda's inflation rate has an aspect of seasonality since the SARIMA model performed better than the ARIMA model when it comes to both out-of-sample and in-sample forecast performance based on the RMSE and MAE respectively. VECM model performed worse than the ARIMA and SARIMA models under both the in-sample and out-of-sample performance since it had the maximum RMSE and MAE.

The study conducted by (Segay. H, 2014) is aimed to understand the short run and the long run price dynamics and identify the Determinants of recent Inflation in Ethiopia using vector autoregressive (VAR) models using the 2001/02 and 2011/12 datasets. The findings of the study suggest that the determinants of inflation differ between sectors (food and non-food inflation) and the time horizons under consideration. The result also entails that most important forces behind food inflation in the long run are exchange rate, broad money supply, narrow money supply, food consumption price index, non-food consumption price index, interest rate, real GDP and nominal GDP.

The study conducted by (Fitsum .S et al, 2016) to determine the causal relationship among the indicators of the inflation (CPI and money supply, and CPI and GDP) in Ethiopia for the period 1970/71-2010/11 data using the Johansen co-integration test. The result of the study has shown that co-integrating vector and the Granger causality analysis demonstrate that the long run bidirectional causality between CPI and money supply, and unidirectional causality from GDP to CPI. In the short run, one way of causality was found from money supply and GDP to CPI. Therefore, the key findings of the study indicates inflation is a monetary phenomenon in Ethiopia, and is negatively and significantly affected by GDP.

The study conducted by (AbdelkreemYouse and Sisay Debebe, 2021) which aimed to analysis the Dynamics of inflation and its impact on economic growth in East African Countries: Ethiopia, Sudan and Kenya using Autoregressive Distributed Lag (ARDL) model. The findings reveals that the exchange rate and the supply of the long-run economic growth rate influence Ethiopia's money supply. However, the issue of forecasting inflation volatility is not taken into account.

A study conducted by (Seifu. N, 2011) proposed VAR model for CPI and its components to forecast the rate of inflation in Ethiopia. The data used were monthly observations from January 2000 to December 2010. The final result shows that a Vector Error Correction (VEC) model of lag two with one co integration equations best fits the data. The forecasting accuracy of the model was checked using the Root Mea Squared Error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil-U statistics. Finally, using the fitted model out-of-sample forecasts were produced for Ethiopian inflation rate.

3. DATA and Methodology

3.1 DATA SOURCE

The data set considered in this study obtained from National Bank of Ethiopia (NBE). We were considering the secondary data for the trend analysis of inflation. The data was carried out from January 2010 to December 2020, where the variables such as Consumer Price Index (CPI), Food Price Index (FPI), Non-food price index (NFPI) and Exchange rate (ER) taken into account.

3.2 VARIABLES OF THE STUDY

The variables included in the study were CPI, NFPI, FPI and ER. In this subsection we briefly go through thoroughly in describing each variable taken into consideration.

a. Consumer Price Index (CPI)

The consumer price index measures the cost of buying a standard basket of goods and services at different points of time. The standard basket is constituted to represent as closely as possible the consumption pattern of the population group in which case the inflation rate calculated is specific to the group and may include food and clothing, housing, fuel, entertainment and other common items of consumption in day to day life (Seifu, N. 2011).

The formula for calculating price index is;

$$\text{CPI} = \frac{\text{Cost of basket in current year}}{\text{Cost of basket in base year}} \times 100 \qquad (1)$$

b. Non-food Price Index

Non-food price index (NFPI) used to measures the inflation of non-food.

c. Food Price Index

Food price index (FPI) used to measures the inflation of food. The issue of food inflation has attracted rising concern in the national media and among policy makers, academics and of course the public at large, as well as among development partners. Food inflation has become a major cause of concern for not only the common-man, but also for the policy makers. Unlike in many advanced economies, food inflation has had a non-trivial impact on aggregate retail inflation in the world. In Ethiopia, Food inflation reflecting several causes, like: - High share of food expenditure in total household expenditure and correspondingly high weight in the CPI; Inflation expectations which are anchored by food inflation; and wage indexation to consumer priceinflation and thereby indirectly to food inflation (Ferreira, R. 2016).

d. Exchange Rate

An exchange rate is the value of one nation's currency versus the currency of another nation or economic zone (Fitsum, S. 2016).

3.3. Methodology

Univariate time series analysis is a methodology for the analysis of time series data with complex structure of the data. Autoregressive Integrated Moving Average (ARIMA) modeling is a specific subset of Univariate modeling, with time series is expressed in terms of past values of itself plus current and lagged values of a white noise error terms. While, multivariate time series analysis looks at variables which involves more than one time series data sets, and explain the interactions and co movements among a group of time series variables (Alemayehu, G. 2011).

3.3.1 TEST OF STATIONARY/UNIT ROOT TEST

The foundation of time series analysis is stationary. A time series Y_t is said to be strictly stationary if and only if the joint distribution of $Y_{t1}, \ldots, Y_{tk}$ is identical to that of $Y_{t1+k}, \ldots, Y_{tk+k}$ for all t ,where t is time, k is an arbitrary positive integer and $t_1,\ t_2 \ldots, t_k$ is the collection of k positive integers. A weaker version of stationary is often assumed. A time series Y_t is weakly stationary if both the mean of Y_t and the covariance between Y_t and Y_{t-k} are time-invariant. More specifically, $Y_t$is weakly stationary if

(a) E (Y_t) = μ which is constant for all t and

(b) Cov ($Y_t, Y_{t-j} = \mathrm{r}_t$) for all t and j= 0, 1, 2 …

In applications, weak stationary enables one to make inferences concerning future observations (Thomas, S. 2014).

Aditionally Y_t is strictly stationary if its first two moments are finite, then Y_t is also weakly stationary. The converse is not true in general. However, if the time series Y_t is normally distributed, then weak stationarity is equivalent to strict stationary. Before applying any statistical tests and model, it is advisable to plot the time series plot of the data to know the nature of the series. A unit root test is a test for stationary and many unit root tests are exist. To examine this we apply the following two popular tests.

Augmented Dickey-Fuller (ADF) Test

In time series modeling, ADF tests the null hypothesis that a unit root is present in a series (Dickey and Fuller, 1979). Thus, the ADF test is applied to following model.

$$Y_t = \mu + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \ldots + \emptyset_p Y_{t-p} + \varepsilon_t \qquad (2)$$

$$\Delta Y_t = \mu + \beta_t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t$$

Where μ and β denotes a constant and coefficient on a time trend respectively. $\gamma = \left(\sum_{i=1}^{p} \emptyset_i\right) - 1, \delta_i = -\sum_{k=i+1}^{p} \delta_k$, Δ is the first difference operator and p the lag order of the AR process Assuming $\mu = \beta = 0$.

Thus under the ADF test, we are going to test the hypothesis:

$$H_0: \gamma = 0 \quad Vs \quad H_1: \gamma > 0.$$

The test statistic is

$$ADF = \frac{\hat{\gamma}}{S.E(\hat{\gamma})} \qquad (3)$$

Where DFT is the ADF test statistic at t degree of freedom, is compared with the relevant critical value. The ADF statistic is always negative for stationary series. The more negative it is, the stronger the rejection of null hypothesis that there is a unit roots at some level of confidence.

Phillips Perron (PP) Test

The PP test (Peter Phillips and Pierre Perron, 1988) is another kind of a unit root test. That is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. It builds on the DFT of the null hypothesis $\rho = 1 \; in \; \Delta Y_t = (\rho - 1) y_{t-1} + \varepsilon_t$. Where, Δ is the first difference operator. Like the ADF test, the PP test addresses the issue that the process generating data for Y_t might have a higher order of auto-correlation than is admitted in the test equation making $Y_t$endogenous and thus invalidating the Dickey Fuller t-test. Then, PP test makes a non-parametric correction to the t-test statistic.

If the time series is not stationary, we can often transform it to achieve stationary through the following approaches.

- First we use differencing data. Using y_t ; $\Delta y_t = y_t - y_{t-1}$ the differenced data will contain one less point than the original data. Mostly, we can difference the data more than once, one difference is usually sufficient.

- For the non-constant variance, taking the logarithm of the series may stabilize the variance. For the negative data, we can add a suitable constant to make the entire data positive before applying the transformation. This constant can then be subtracted from the model to obtain predicted values and forecasts for the future points.

3.3 MODELING VOLATILITY

Volatility indicates a measure of the possible variation or movement in particular macroeconomic variables from period $t - 1$ to t. This mainly to indicate how much and how quickly a value varies over time. Volatility connects two principal concepts: variability and uncertainty; the former describing overall movement and the latter referring to the movement that is unpredictable. Lack of predictability and uncertainty associated with an increased volatility may influence both producers and consumers to secure supplies and control input costs. Volatility is often measured as the sample standard deviation:

$$S = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(R_t - \hat{\mu})^2} \qquad (4)$$

Where R_t denotes the return (i.e. natural logarithm transformed and differenced series) at time tand μ is the estimated average return over period T . Since variance is the square of standarddeviation, it makes no difference which ever measure S or S^2 to compare volatilities (Antene, A. 2012).

Most of studies done in Econometrics consider returns. For instance, (Tsay, R. 2005) give two main reasons for using returns. First, for average investors, return of a series is a complete and scale-free summary of the investment opportunity. Second, return series are easier to handle than original series because the former have more attractive statistical properties. Let Ytbe the series at time index t, which often displays unit-root behavior and thus cannot be modeled as stationary, we often analyze log-returns on$Y_t$given as:

$$R_t = log\frac{y_t}{y_{t-1}} = logy_t - logy_{t-1} \qquad (5)$$

Where R_t is the log return series of y_t, and $y_{t-1}$is the series at time t-1. The returns for multivariate time series is $R_t = R_{1t} \ldots R_{kt}$ be the log returns of k series at time t and the squared returns denotes a proxy for volatility.

If there is a large variation from period t-1 to t, R_t is large and we speak of large returns or large volatility. Hence, extreme values for returns reflect extreme variation (volatility). If there is no variation over time, $R_t = log\ (y_t) - log(y_{t-1}) = 0$.

3.3.1 MULTIVARIATE GARCH MODEL

The Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) is an extension of the GARCH model. The GARCH models have featured prominently in the analysis of financial time series to solve the heteroscedasticity problem. Financial time-series such as foreign exchange rates, inflation rates and stock prices may exhibit some volatility which varies from time to time. This variation is an indicator of ARCH effects or heteroscedasticity problem. Among the numerous specifications of Multivariate GARCH (MGARCH) models, the most popular are the Vector Error Correction Heteroscedastic (VECH), the Baba, Engle, Kraft and Kroner (BEKK) of Engle and Kroner (1995), Constant Conditional Correlations (CCC) introduced by Bollerslev (1990) and Dynamic Conditional Correlations (DCC) proposed by (Tse and Tsui 2002) and Engle (2002). VECH- and BEKK-GARCH models are the models of conditional covariance matrix, whilst CCC- and DCC-GARCH are the models of conditional variances and correlations (Nelson D.B. 1991).

Let $Y_t = (Y_{1t}, Y_{2t} \ldots \ldots Y_{Nt})$ denotes a vector of returns and Y_t can be written as $\mu_t + \epsilon_t$, where μ_t indicates the mean vector and$\epsilon_t$is the error term which can be written as $\epsilon_t = z_t\sqrt{H_t}$, where z_t is a random vector and H_t is the covariance matrix of Y_t and $\sqrt{H_t}$ s obtained using Cholesky decomposition. The basic assumption of z_t is a random vector with the basic assumption E [z_t] = 0 and V [z_t] = I_N.

Before fitting any GARCH model, it is better to test for ARCH effect. According to Tsay (2005), there are two available methods to test for the ARCH effects. The first test is to apply the usual Ljung–Box statistics $Q_{(m)}$ to the ε_t^2 series. The second test for conditional heteroscedasticity is the Lagrange multiplier test of Engle (1982). In the presence of an ARCH effect or time varying variance in the residuals of a (linear) time series model, an ARCH or a GARCH model is fitted to the squared residuals of the model in order to remove the heteroskedasticity from the residuals.

BEKK-GARCH model

To ensure positive definiteness, a new parameterization of the conditional variance matrix H_t was defined by Baba, Engle, Kraft and Kroner (1990) and became known as the BEKK model. It is also considered as a restricted version of VEC mode. It achieves the positive definiteness of the conditional covariance by formulating the model in a way that this property is implied by the model structure. The BEKK model can be written as

$$H_t = CC' + \sum_{j=1}^{p} \sum_{k=1}^{k} \beta_{kj}' H_{t-j} \beta_{kj} \tag{7}$$

Where,A_{kj}, β_{kj} *and* $C$are N × N parameter matrices and C is a lower triangular matrix.

The purpose of decomposing the constant term into a product of two triangular matrices is to guarantee the positive semi-definiteness of H_t. Whenever, k > 1 an identification problem would be generated for the reason that there are not only single parameterizations that can obtain the same representation of the model.

The first-order BEKK model is

$$H_t = CC' + A'\epsilon_{t-1}\epsilon_{t-1}'A + \beta' H_{t-1} \beta \tag{8}$$

The BEKK model also has its diagonal form by assuming $A_{kj}B_{kj}$ matrices are diagonal. It is a restricted version of the DVEC model. The most restricted version of thediagonal BEKK model is the scalar BEKK one with A = aI and B = bI where, a and b are scalars. Estimation of a BEKK model still bears large computations due to several matrix transpositions. The number of parameters of the complete BEKK model is $(p+q)KN^2+N(N+1)/2,$ Even in the diagonal one, the number of parameters soon reduces to $(p + q)$ K×N+N×(N+1)/2, but it is still large. The BEKK form 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. Typically when we assume that $p = q = K = 1$, it is a BEKK form's application.

Dynamic Conditional Correlation (DCC) GARCH

An extension of the Constant Conditional Correlation (CCC)-model is the DCC-model of Engle and Sheppard (2001) where the CCC-model does not consider the correlations between the series are constant, so the model can account for possible time varying co-volatility. The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t \tag{9}$$

Where, $D_t = diag(h_{11t}^{1/2}, \ldots, h_{NNt}^{1/2})$ and each $h_{tti}$is described by a univariate GARCH model. Further,

$$R_t = diag(q_{11t}^{1/2}, \ldots, q_{NNt}^{1/2})Q_t diag(q_{11t}^{1/2}, \ldots, q_{NNt}^{1/2}),$$

Where $Q_t = (q_{ijt})$ is the N×N symmetric positive definite matrix which has the form:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\mu_{t-1}\mu'_{t-1} + \beta Q_{t-1}, \tag{10}$$

Here, $\mu_{it} = {}^{\varepsilon_{it}}\big/_{\sqrt{\mathrm{h}_{iit}}}$, α and β non-negative scalars that $\alpha+\beta<1, \bar{Q}$ is the N×N unconditional matrix of the errors μ_t.

The shortcoming of the model is that all conditional correlations follow the same dynamic structure. The number of parameters to be estimated is (N+1) × (N+4)/2, which is relatively smaller than the complete BEKK form with the same dimension when N is small. When N is large, the estimation of the DCC model can be performed by a two-step procedure which decreases the complexity of the estimation process. In brief, in the first place, the conditional variance is estimated via univariate GARCH model for each variable. The next step is to estimate the parameters for the conditional correlation. The DCC model can make the covariance matrix positive definite at any point in time.

The advantage of DCC-GARCH model is that the number of parameters to be estimated for a conditional correlation does not depend on the number of returns in the model. When new variables are added to the system, the volatility forecasts of the original returns will be unchanged.

3.3.2 BASIC PROPERTIES OF MGARCH FAMILY MODEL

Any MGARCH should be; unique and stationary: a necessary and sufficient condition to have a unique and stationary solution is: $\sum_{j=1}^{p} \beta_k + \sum_{j=1}^{q} \theta_k < 1$, with Zero mean: any model in δ_t is measurable, the mean of ε_t is zero .i.e. E[ε_t] = 0, Correlation free: in GARCH even though it is conditional, heteroscedasticity is inevitable. Hence, the autocovariance of any pair of elements from the series is expected to be zero resulting in lack of serial autocorrelation. For K > 0, ε_t is not correlated with ε_{t+k} ; $E[\varepsilon_t\ \varepsilon_{t+k} = 0]$, and unconditional variance (Ailkaeli, 2007).

3.3.3. ORDER DETERMINATION OF MGARCH FAMILY MODEL

The model selection criterion indicates the “best approximating model” from a set of competing models. An important practical problem is the determination of the ARCH order q and the GARCH order p for a particular series. The Akaike information criterion (AIC) proposed by Akaike (1974), Schwartz Bayesian information criterion (SBIC) proposed by Schwartz (1978) and Hannan-Quinn information criterion (HQIC) by were employed. The model satisfying minimum AIC or SBIC or HQIC is most representative of the true model.

The formal expressions for the above criterion in terms of the log- likelihood are discussed:

$$\mathrm{AIC} = 2\mathrm{P} - 2\ln(\hat{\mathrm{L}}) \quad (11)$$

$$SBIC = \ln(T)\,P - 2\ln(\hat{\mathrm{L}}) \quad (12)$$

$$HQIC = \ln\ln(T)\,P - 2\ln(\hat{\mathrm{L}}) \quad (13)$$

Where = $\hat{L}$ the maximized value of the likelihood function of the model M, i.e. where $\hat{L} = P\left(\frac{R}{\hat{\theta}}, M\right)$, $\hat{\theta}$ are the parameter values that maximize the likelihood function; R denotes the observed returns; T refers to the number of data points in R, the number of observations, or equivalently, the sample size and P represents the number of parameters estimated by the model.

3.3.3 PARAMETER ESTIMATION OF MGARCH MODELS

To predict the volatility for a series, one first has to fit the GARCH model to the time series in question. This is done via estimation of the parameters in the model by MLE. As suggested by Bollerslev (1986) and Tsay (2005), the estimation of GARCH models is usually carried out using MLE method for VECH and BEKK-GARCH models, whilst two step estimation method for CCC- and DCC-GARCH models. However, obtaining a handleable likelihood function is not straightforward. In MLE the distributional assumption on residual is the core point. Financial time series data possess volatility clustering and leptokurtosis characteristics which lead to the use of different distributional assumptions for residuals such as: Gauss and Student-t.

Suppose that R_t (for t = 1… T) is the vector of returns with conditional mean, conditional variance matrix and conditional distribution are respectively $\mu_t(\theta_0)$ *and* $H_t(\theta_0)$ *and* $P\left(\frac{R_t}{\varsigma_0}, \Omega_{t-1}\right)$. Where $\varsigma_0 = (\theta_0 \eta_0)$ is a r-dimensional parameter vector and η_0 is the vector that contains the parameters of the distribution of the innovations z_t (there may be no such parameter). Importantly, to justify the choice of the estimation procedure, the model to be estimated encompasses the true formulations of $\mu_t(\theta_0)$ *and* $H_t(\theta_0)$.

The most commonly employed distribution in the literature is the multivariate normal, uniquely determined by its first two moments (so that $\varsigma = \theta$ since η is empty). In this case, the sample log-likelihood is:

$$L_T(\theta) = \frac{-1}{2}\sum_{t=1}^{T}[kln(2\pi) + ln|H_t| + (R_t - \mu_t)' {H_t}^{-1}(R_t - \mu_t)] \qquad (14)$$

Where T is the number of observations, k is the number of return, θ is the vector of parameters to be estimated.

3.2.3 MODEL ADEQUACY CHECKING

After a GARCH family model has been fit to the data, the adequacy of the fit has been evaluated using a number of graphical and statistical diagnostics. There are different methods for examining the adequacy. From these method the following were used in this study;

- The standardized residuals are assumed to be IID standard normal distributions (Tsay, 2005). This was checked through Jarque-Bera test.
- The Ljung-Box test is another approach which widely used lack-of-fit tests, that is, a test for the appropriateness of the fitted model. It was developed by Box (1970) and modified by (Li and Mcleod, 1993).

A multivariate version of Ljung-Box test statistic is given by:

$$Q_m = T^2 \sum_{j=1}^{m} (T-j)^{-1} tr C_{Rt}^{-1}(0) C_{Rt}(j) C_{Rt}^{-1}(0) C'_{Rt}(j) \tag{15}$$

Where R_t is the vector of observed returns and $C_{Rt}(j)$ is the sample auto covariance matrix of order j. Under the null hypothesis shows there is no serial correlation in R_t, Q_m is asymptotically distributed as a $\chi^2(K^2m)$. Li and Mcleodpropose an alternative portmanteau statistic to detect misspecification in the conditional mean of an ARMA model. So, the modified version of their statistic $Q^*_{(m)} = Q_m + \frac{k^2m(m+1)}{2n}$ is asymptotically distributed as $\chi^2(K^2(m-s))$, where m is the lag order, and $s = p + q$ is the ARMA order (AR+MA orders). Thus, if the statistic Q_m at all lags was found to be non-significant indicating absence of autocorrelation in the residuals, then the model selected fits the data well.

3.6 FORECASTING

In the class of multivariate ARCH/GARCH models and their extensions, the covariance matrix is no longer constant over time. After such model has been estimated, it is always meaningful to get and understand the mechanism that how the future series can be generated and whether they fit well with the real series. Forecasting by the BEKK-GARCH model, in the conditional covariance equation of the BEKK-GARCH model is given by:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{16}$$

H_t Is a function of the past information, i.e., H_{t-1} and ε_{t-1} for this reason, the parameter estimation of MGARCH models can be used to predict the future covariance matrix.

Forecasting by the DCC-GARCH model

The forecast of the covariance matrix of the DCC model is implemented in a two-step procedure. The prediction of the diagonal matrix of the time-varying standard variation through the univariate GARCH models and the forecast of the conditional correlation matrix of the standardized residuals are dealt with separately. Under the assumption that the volatility at time *t* is known, what is its forecast value at time *t* + *k*. In a four-variable case, the answer when *k* = 1 is given by;

$h_{ii,t+1} = \omega + \alpha\varepsilon_{it}^2 + \beta h_{ii,t}$, where, i =1, 2, 3, 4 (17)

To obtain the forecast $h_{ii,t+1}$at time *t* + *k*, one just needs to repeat the substitution successively.

Under the assumption that $\hat{R} = \hat{Q}$ and $R_{t+i} = Q_{t+i}$ for *i* = 1…*k*, a successive calculation as before can be performed to derive R_{t+k}.MGARCH models can be used for forecasting. However, by analyzing the relative forecasting accuracy of the two formulations BEKK and DCC, it can be deduced that the forecasting performance of the MGARCH models is not always satisfactory. Many studies e.g. see (Andersen and Bollerslev (1998)), reveals 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.

The following are the commonly used error functions (Tsay, R, 2005)

- Mean Error (ME) $ME_{vj} = \frac{1}{n}\sum_{k=1}^{n}(\sigma_{ik} - \hat{\sigma}_{ik})$ (18)
- Mean Square Error (MSE) $MSE_{vj} = \frac{1}{n}\sum_{k=1}^{n}(\sigma_{ik} - \hat{\sigma}_{ik})^2$ (19)
- Mean Absolute Error (MAE) $MAE_{vj} = \frac{1}{n}\sum_{k=1}^{n}|\sigma_{ik} - \hat{\sigma}_{ik}|$ (20)
- Root Mean Square Error (RMSE) $MSE_{vj} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(\sigma_{ik} - \hat{\sigma}_{ik})^2}$ (21)

4. RESULTS AND DISCUSSIONS

In this chapter, the results obtained from the study along its discussion are explained. First, the results of both descriptive and inferential statistics will be explained. Following this, the results of the study along its advantage as compared to other related works is taken into account. In this work, 132 total numbers of observations were taken from January 2010 to December 2020. Finally, the entire datasets considered in this thesis, were analyzed using STATA14 and E-views 9.

4.1. Descriptive analysis

In this work, a total of 132 observations were included. In this empirical analysis, four aggregate series namely, the general consumer price index (CPI), food price index (FPI), non-food price index (NFPI) and exchange rate (ER) were illustrated in Figure 4.1. Some descriptive statistics including the mean, the standard deviation, the coefficient of variation, minimum and maximum values of the series under study were also summarized as shown in Table 4.1. The results show that the values of summary statistics are more or less similar except standard deviation which indicates relatively high dispersion for FPI.

Table4.1: Summary Results of Series

Series	Obs	Mean	Std.Dev	Min	Max	Skewness	Kurtosis	CV
CPI	132	97.65985	36.80256	41.6	182.2	.594587	2.690765	0.377
FPI	132	100.1159	38.40871	44.4	195.1	.7863051	2.983133	0.384
NFPI	132	95.56742	34.0256	42.9	171	.4913092	2.387864	0.356
EX_R	132	22.10848	6.06937	12.1111	37.8733	.6801653	2.868725	0.2745

4.2. UNIT ROOT PROPERTIES OF INDIVIDUAL SERIES

Prior going to further statistical analysis, first, we need to test the basic assumption of time series analysis. This can be done through checking stationary before one can attempt to fit a suitable model. That is, variables have to be tested for the presence of unit root(s) there by the order of integration of each series is determined. Therefore, the result illustrated in Figure 4.1 suggests that the series of the endogenous variables display a non-stationary behavior.

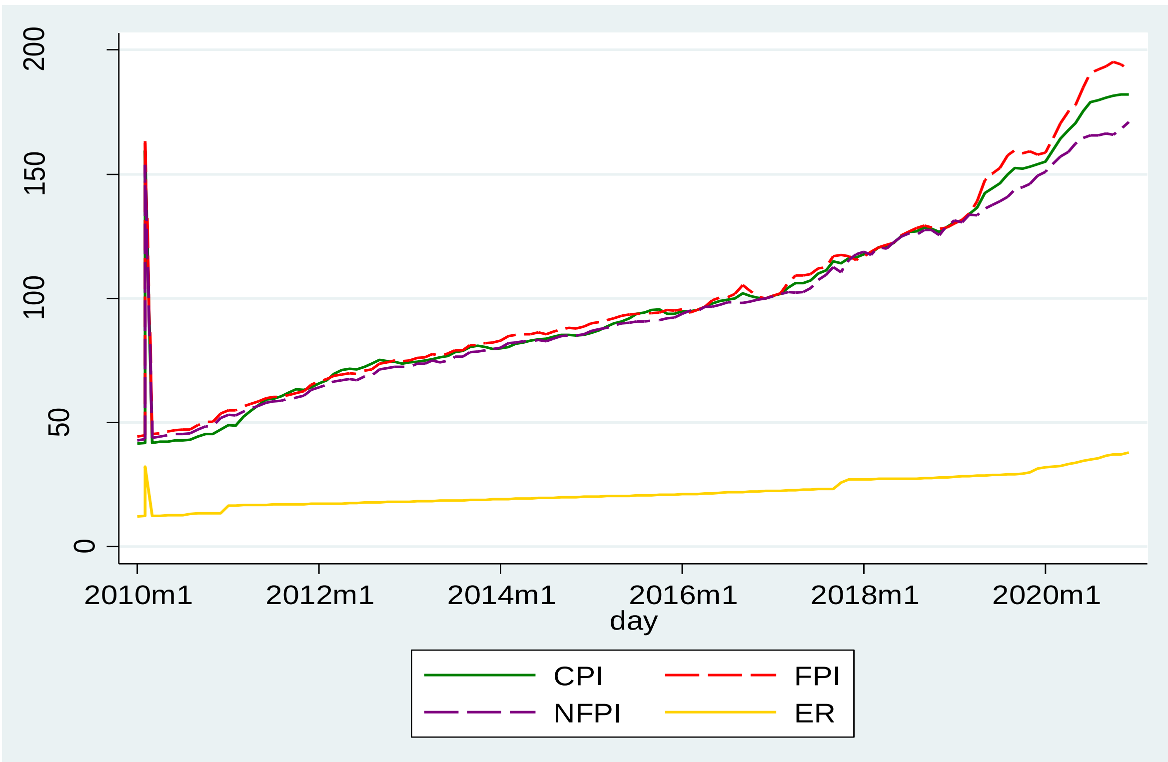

Figure 4.1 Time series plot of CPI, FPI, NFPI and ER

To further justify the issue of stationary, additionally, the stationary of the series of the analysis also numerically tested through an Augmented Dickey-Fuller test and a Phillips and Perron test (PP). The hypothesis to be tested is:

H_0: The series is non-stationary Vs. H_1: The series is stationary

Thus, the results corresponding to this test are given in Table 4.2 and Table 4.3, from which we note that ADF and PP tests, with intercept but no trend, and with intercept and trend both at level and log return for each series attained. The critical values used for the tests are the McKinnon (1996) critical values. The test result corresponding to stationary indicates that the null hypothesis which reveals that the series in levels contain unit root could not be rejected for all the four series. That is, the respective p-values are greater than conventional significance levels(α) = 0.05.

As the null hypothesis is not rejected (shown in Table 4.2), revealing integration of the non-stationary time series, the same tests were applied to their first differences (Fig 4.2), from which we note that the order of integration is the number of unit roots that should be contained in the series to be stationary.

Table 4.2: 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	1.0000	1.00
FPI	3.495	1.740	1.00	1.00	1.062	1.856	1.0000	1.00
NFPI	3.310	1.244	1.00	1.00	1.028	1.959	1.0000	1.00
ER	2.448	1.849	0.999	0.999	1.000	2.643	1.0000	1.000
Critical value 5%	-2.888				-3.446			

The results shows in Table 4.3 reveals that the null hypothesis is rejected for the log retur of the four sires due the p-values is less than at 5% level of significance with intercept and trend in PP test and ADF test. There by, the results corresponding to ADF and PP test reveal that all series are non-stationary in the levels, and stationary in the log return (see Table 4.3).

Table 4.3: Unit root test results (log 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
CPI	-7.303	-76.742	0.000	0.00	-7.717	-84.300	0.00	0.00
FPI	-6.504	-67.195	0.00	0.00	-6.763	-73.211	0.00	0.00
NFPI	-11.615	-134.59	0.00	0.00	-12.508	-144.24	0.00	0.00
ER	-8.954	-100.78	0.00	0.00	-9.250	-104.75	0.00	0.00
Critical value 5%	-2.888				-3.446			

4.2. MODELING VOLATILITY

4.2.1. CHECKING AND TESTING FOR THE PRESENCE OF ARCH EFFECT

Prior examining the issue of inflation volatility in Ethiopia, testing the existence of ARCH effect is highly advisable. Thus to test the existence of ARCH effect, the Y axis denotes the observation while the X axis indicates day. As noted from Fig. 4.2, the Y-axis limits are the same for each plot; this shows an opportunity to compare the volatility of different series. Thus, the return FPI, CPI, NFPI and ER indicates the first, second, third and fourth most volatile, respectively. Moreover, it can be observed as the ER seems to be the least volatile. However, the graphical analysis does not give an indication of how volatility reacts to positive and negative news.

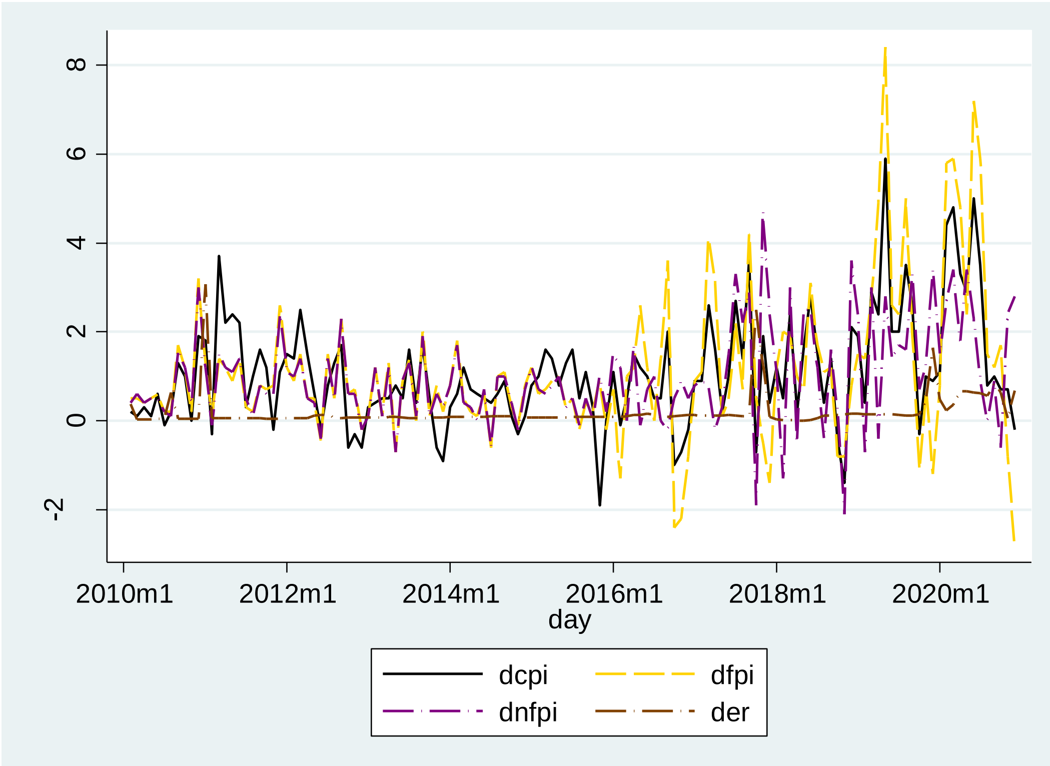

Figure 4.2: Time series plot for the log return series of FPI, NFPI, EX and CPI

4.2.2. ARCH effect test

To estimate optimal parameters of different GARCH models, first we need to test the presence of ARCH effects. This is done by performing the ARCH Lagrange Multiplier (LM) test in which the null hypothesis indicates as there is no ARCH effects (that is the issue of homoskedasticity) in the residuals. Under this, we need to test the hypothesis which says the null hypothesis no ARCH effect while the alternative hypothesis show there is an existence of ARCH effect. The result corresponding to this is effect is summarized in Table (4.4). The result corresponding to Chi2-statistic reveals that the presence of ARCH effects at 5% significance level. Thus, it can be noted that there is volatility clustering, from which it is possible to estimate the optimal parameters of MGARCH family models.

Table (4.4): Lagrange Multiplier (LM) test for Autoregressive Conditional Heteroskedasticity (ARCH)

Lags(p)	Chi2	Df	Prob.
1	90.109	1	0.000

H0: no ARCH effect vs. H1: has ARCH effect

Parameter estimation of volatility

Cogently identifying the Lag length selection before fitting any MGARCH model has strong implications in choosing models. For determining an appropriate lag length for MGARCH model through using Akaike information criterion(AIC), Schwartz information criterion (SBIC) and Hannan-Quinn information criterion (HQIC). Because; too many lags results in loss of degree freedom, insignificant coefficients' and multicollinearity, and too few lags results in specification errors (Lutkephol, H. 2005). The result is summarized in the Table (4.5) below.

Table 4.5: Lag Selection for DCC and BEKK GARCH Models

	Lags		T log-likelihood	SBIC	HQIC	AIC
Lag Selection for DCC	0	0	131408.8	-16.2	-16.4	-16.5
	0	1	131 799.24	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	131 688.66	-16.02	-16.16	-16.30
	0	2	131 704.01	-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	131 715.62	-16.08	-16.42	-16.64
	2	2	131 716.01	-16.02	-16.42	-16.58

(*)indicates the lag selected by the criterion.

Table 4.5 indicates the results of Lag selection corresponding to DCC and BEKK GARCH models. The information criterions are given in Table (4.5) from which, both $BEKK(1,1)$and $DCC(1,1)$ GARCH models are taken into consideration. But, since the values of information criterion are comparable and small for DCC- GARCH model, then DCC (1, 1) is relatively better than the BEKK (1, 1). This is due to the DCC-GARCH model is more flexible of univariate GARCH models coupled with parsimonious parametric models for the correlations. They are not linear but can often be estimated very simply with univariate or two step methods based on the likelihood function. Additionally, the DCC-GARCH algorithm outperforms to the BEKK-GARCH due to is easy to compute and the numbers of parameters that are estimated in the correlation process are independent on the number of series that are to be estimated. It is shown that they perform well in a variety of situations and give sensible empirical results. Thus, in this thesis, we don’t consider the BEKK for further analysis. Taking this into account, analysis on wards only consider the best multivariate generalized autoregressive conditional heteroscedastic model adopted for this study.

Table 4.6: Estimated Parameters of DCC-GARCH Model

		Coefficient	Std.Error	t-value	t-prob
Part: CPI	Cst(V)	3.372	1.365	2.470	0.0031
	ARCH(θ)	0.782	0.132	5.924	0.0001
	GARCH(β)	0.092	0.017	5.412	0.0002
Part: FPI	Cst(V)	0.703	0.030	23.43	0.0000
	ARCH(θ)	0.010	2.5e-03	4.00	0.0000
	GARCH(β)	0.086	0.009	9.555	0.0000
Part: NFPI	Cst(V)	0.693	0.195	3.553	0.0380
	ARCH(θ)	0.496	0.220	2.254	0.0050
	GARCH(β)	0.485	0.180	2.694	0.0190
Part: EX-Ret	Cst(V)	0.004	0.009	0.444	0.2770
	ARCH(θ)	0.080	0.089	0.899	0.2720
	GARCH(β)	0.174	0.039	4.463	0.0050
Part: Correlation	ρ_{21}	0.692	0.101	6.851	0.000
	ρ_{31}	0.628	0.072	8.722	0.000
	ρ_{41}	0.504	0.094	5.33	0.000
	ρ_{32}	0.703	0.082	8.57	0.000
	ρ_{42}	0 .552	0.083	6.651	0.000
	ρ_{43}	0.513	0.074	6.932	0.000
	θ	0.179	0.014	12.41	0.000
	β	0.702	0.015	47.36	0.000

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.

Depending on the results given in Table (4.6), we can write DCC-GARCH models as follows:

$$\hat{\delta}^2_{CPI,t} = 3.372 + .092\hat{\delta}^2_{CPI,t-1} + .782\hat{\varepsilon}_{\mathrm{CPI,t-1}} \quad (24)$$

$$\hat{\delta}^2_{FPI,t} = .703 + .086\hat{\delta}^2_{FPI,t-1} + .010\hat{\varepsilon}_{\mathrm{FPI,t-1}} \quad (25)$$

$$\hat{\delta}^2_{NFPI,t} = .693 + .485\hat{\delta}^2_{NFPI,t-1} + .496\hat{\varepsilon}_{\mathrm{NFPI,t-1}} \quad (26)$$

$$\hat{\delta}^2_{EX-Ret,t} = .174\hat{\delta}^2_{EX-Ret,t-1} \quad (27)$$

$\hat{\delta}_{(FPI,CPI),t} = \rho(FPI,CPI)\sqrt{\hat{\sigma}^2_{FPI,t}\hat{\sigma}^2_{CPI,t}}$ Where $\rho(FPI,CPI) = 0.692$

$\hat{\delta}_{(NFPI,CPI),t} = \rho(NFPI,CPI)\sqrt{\hat{\sigma}^2_{NFPI,t}\hat{\sigma}^2_{CPI,t}}$ Where $\rho(NFPI,CPI) = 0.628$

$\hat{\delta}_{(EX-Ret,CPI),t} = \rho(EX,CPI)\sqrt{\hat{\sigma}^2_{EX-Ret,t}\hat{\sigma}^2_{CPI,t}}$ Where $\rho(EX-Ret,CPI) = 0.504$

$\hat{\delta}_{(NFPI,FPI),t} = \rho(NFPI,FPI)\sqrt{\hat{\sigma}^2_{NFPI,t}\hat{\sigma}^2_{FPI,t}}$ Where $\rho(NFPI,FPI) = 0.703$

$\hat{\delta}_{(EX-Ret,FPI),t} = \rho(EX-Ret,FPI)\sqrt{\hat{\sigma}^2_{EX-Ret,t}\hat{\sigma}^2_{FPI,t}}$ Where $\rho(EX-Ret,FPI) = 0\,.552$

$\hat{\delta}_{(EX-Ret,NFPI),t} = \rho(EX-Ret,NFPI)\sqrt{\hat{\sigma}^2_{EX-Ret,t}\hat{\sigma}^2_{NFPI,t}}$ Where $\rho(EX-Ret,NFPI) = 0.513$

All coefficients of the conditional variance specification meets the stability condition of $0 < \theta_k < 1,\ 0 < \beta_k < 1\ and\ \theta_k + \beta_k < 1$. This indicates that the volatility of inflation is neither permanent nor explosive, which means, 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 (Sinah,D.(2007). This result entails clearly the setup presence of time varying conditional volatility of returns, and it denotes 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 models from (Table 4.6), the

ARCH coefficients are lower than the coefficients of the GARCH term coefficients, revealing further evidence of high rate of change in conditional volatility and significant time dependent. The DCC-GARCH estimates are $\theta = 0.1794059$ and $\beta = 0.7022735$ and both estimators are statistically significant at 5% level of significance which satisfy the condition of $\beta + \theta < 1$ suggesting that the conditional variance is mean reverting toward its equilibrium level.

In previous Table 4.6 the coefficient of the series in FPI there is greater coefficient of DCC-beta it indicates that FPI have greater impact for today's volatility. And in CPI and NFPI there is greater coefficient of DCC-alpha, so we expected today's correlation to be that of yesterday's correlation. And there is a positive association among CPI, FPI, NFPI and ER.

4.2.3. DCC-GARCH MODEL ADEQUACY CHECKING

Once fitting the DCC-GARCH model, the Ljung Box statistics (Q-test) and Li-Mcloed (Q*-test) were employed for residuals to check and examine model adequacy. The result which corresponds to (Table 4.7) to test the null hypothesis which says there is no serial correlation. The overall result showed that the model perform well statistically as its P-values is insignificant. It means that the null hypothesis which says no serial correlation in the residuals is accepted.

Table 4.7: DCC-GARCH Model Adequacy Checking

	Q-Test		Q*-Test	
	Value	probe	Value	probe
DCC-GARCH	17.2548	0.1924	17.2106	0.1903

H_0 : $There\ is$ no serial correlation VersusH_1 : $There\ is$ serial correlation

Here Q-test statistics is non-significant indicating absence of autocorrelation in the residuals, then the model selected fits the data well based on Table 4.7.

4.2.3 FORECASTING

One of the fundamental applications of time series analysis or developing a time series model is forecasting inflation volatility by DCC model. Thus, the Mean Squared Error (MSE), Mean Error (ME), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to examine the accuracy performance of forecasting.

Table 4.8: Volatility Forecast Evaluation Measures

Forecast Evaluation Measures	Variance
Mean Squared Error(MSE)	6.187e-006
Mean Error(ME)	-0.002271
Mean Absolute Error(MAE)	0.002271
Root Mean Squared Error(RMSE)	0.002487
Mean Absolute Percentage Error(MAPE)	106.5

The result shown in Table 4.8 indicates that the MSE, ME, MAE, RMSE and MAPE are small. This implies that the volatility forecasting from the fitted DCC-GARCH model is good enough. The computational complexity in estimating the parameters related to the two algorithms is also computed and summarized in Appendix, from which the DCC algorithm is more efficient as compared to the BKK-GARCH algorithms (See Appendix Table (a) Time complexity). To further justify the issue of forecasting the results were also depicted in Fig 4.3.

4.2.4. In and out of samples volatility forecasting

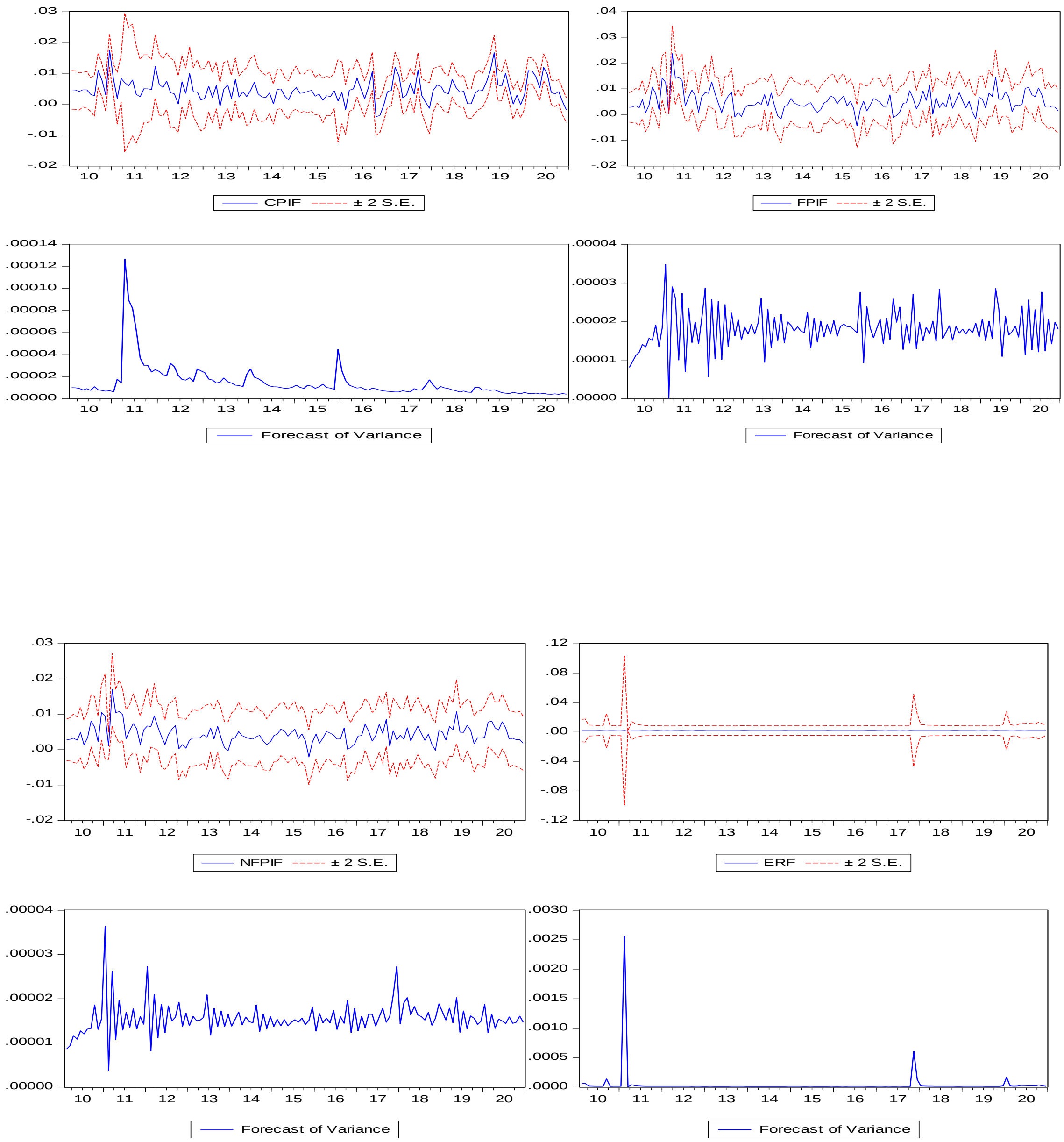

Figure 4.3: In Samples Forecasted Volatility

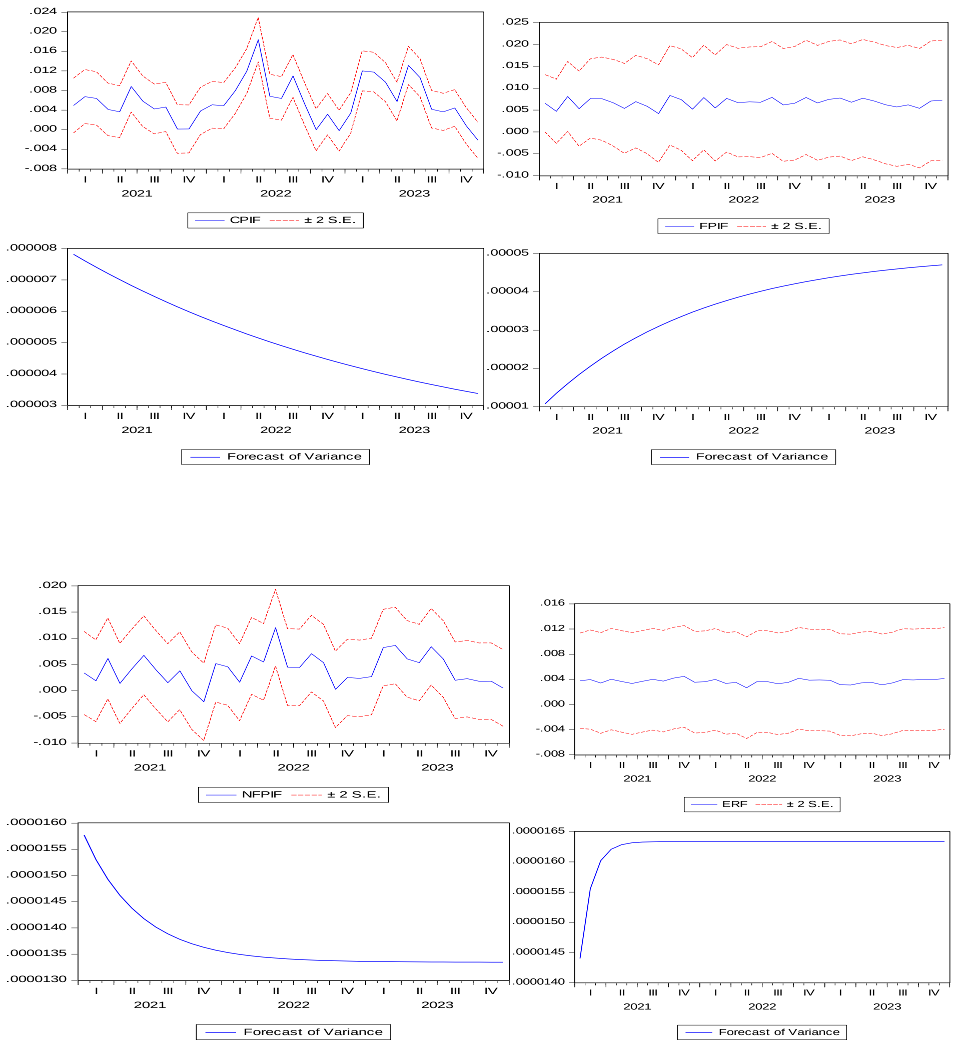

Figure 4.4: Out Samples Forecasted Volatility

The result corresponding to in samples volatility forecasting from January 2010 to December 2020 and out of samples volatility forecasting from January 2021 to December 2023 were illustrated in Figure 4.3 and 4.4 respectively, which shows the forecasts lie within plus and minus two standard error bands with 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 stable for the rest of twenty four months and ER will increase for the first four months and stable for the rest of thirty two months. Therefore, analyzing and forecasting volatility is helpful as it informs investors a measures of risk involved in holding an asset, because investors are not only interested in the average returns.

4.3. DISCUSSION

In this study, multivariate GARCH algorithms BEKK-GARCH and DCC- GARCH models were considered to examine the inflation volatility forecasting in Ethiopia, from which we note that the DCC (1, 1) relatively better fits than the BEKK (1, 1) model based on AIC, SBIC and HQIC information criterions. The finding of our study is more similar with (Ezekiel N, et al 2015). DCC GARCH method outperforming in forecasting inflation volatility as compared to the BEKK-GARCH method. This is due to the number of parameters in BEKK-GARCH is more than the DCC-GARCH algorithms. Additionally, the summation of error accumulated by each parameter of the BEKK-GARCH models tends to be larger than that of the DCC-GARCH models (Wenjing .S and Yiyu .H, 2010).

The current work is more similar as compared to the work of (Nyoni. T, 2018) in modeling the inflation rates based on monthly inflation rate volatility in Zimbabwe over the period July 2009 to July 2018; however it lacks considering more indications of inflation volatility. The finding of this study is more similar with our work in estimating the AR (1) – GARCH (1, 1) model; is indeed an AR (1) – IGARCH (1, 1) process. The advantage of our work as compared to Nyoni, T (2018) is first we consider the issue of inflation volatility through including more indicators of inflation into account.

Our research finding goes beyond the research conducted by (Demile, A, 2015) which pointed inflation growth nexus in Ethiopia indicating the existence of threshold effect between two variables based on annuals data through Hansen's Threshold Autoregressive (TAR) model. However our work addresses an inflation volatility forecasting through incorporating four indicators of the inflation in Ethiopia.

Our research work mainly focuses on modeling and forecasting inflation volatility, while (Fekadu D, 2012) addressed the relationship between inflation and economic growth in Ethiopia, through an empirical analysis, 1980-2011 via using the VEC. The research finding of our study goes beyond (Fekadu D, 2012) in the aspect of considering inflation volatility through comparing two popular MGARCH models.

(Gofere, Solomon Mosisa (2013)) addressed the relationship between inflation and foreign prices through VAR model. The result of the study indicates that monetary and fiscal fundamentals were considered as important determinants of price dynamics in the short run. However, considering more structural indicators of inflation as a future work but our work mostly focus on forecasting the inflation volatility taking four indicators of inflation into account. But, our work is more resembled with the work of (Geda, Alemayehu and Tafere, Kibrom (2008)).

Habtamu G (2015) addressed Modeling the Growth of Ethiopian Inflation and Its Dynamic Behavior over Time via VECM based on 1980 to 2012. The study found that the effect of supply side, monetary and external factors were highly significant to explain price inflation through their long run co-integrating (equilibriums) relationships, while our work is focused to forecast inflation volatility considering more indicators of inflation volatility.

Many studies were conducted with CPI and NFPI variables like (Seifu.N 2010) but the issue of inflation volatility is not taken into account. (Rana. E, 2018) the study found that food inflation in many countries is transmitted into non-food inflation in a significant and important way, and again, this is particularly so in developing economies.

The result of our study relatively better indicating inflation volatility through considering more indicators of inflation as compared to the study conducted by (Virginia Wairimu Gathingi, 2014) which aimed to model inflation over the period 2005-2013 using two auto regressive models via Autoregressive Integrated Moving Average (ARIMA) model and the Vector Auto regression (VAR) model.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study focuses on forecasting inflation volatility using the data obtained from NBE for the period January 2010 to December 2020 (i.e. 11 years), and the data uses monthly data and transformed to natural logarithm to make analysis easy which considers about 132 observations.

In this study, all the series were identified to be non-stationary using the Augmented Dickey Fuller and Phillips Peron unit root tests to avoid problems related to using non-stationary data. Thereby, the result showed that all the series are volatile and non-stationary. Therefore, non-stationary series are log returned to make them stationary.

Following this, we proposed two popular Multivariate GARCH models, DCC and BEKK to forecast inflation volatility in Ethiopia, from which we note that the DCC-GARCH model is found to be the best in forecasting inflation volatility based on different tests and information criterion. Based on the findings of our work, the following conclusions are made:

There is evidence showing existence of volatility clustering based on the ARCH Lagrange Multiplier test, following this, DCC-GARCH model parameter estimation was taken into account. Additionally, it is noted that result of the ARCH coefficients lower than that of GARCH term coefficient based on FPI, from which we noted that evidence of high rate of change in conditional volatility and significant time dependent is observed. Similarly, it is observed that the result of GARCH coefficient is lower than ARCH term coefficient for NFPI and CPI variables. However, the result of ARCH coefficient is found insignificant in ER. Finally, the result of the forecast from the model showed as FPI increase at high rate, CPI decrease at the low rate, NFPI will decrease for the first twelve months and stable for the rest of twenty four months and EX increase for the first four months and stable for the rest of thirty two months. The DCC- GARCH algorithm is more efficient as compared with BKK-GARCH algorithm based on time computational complexity.

5.2. RECOMMENDATIONS

Based on the conclusions, the following recommendations were drawn:

- It is advisable if the researchers, to use DCC-GARCH model to forecast inflation volatility in multivariate case.
- Since there is inflation volatility in the market, thus the government and policy makers need to give a due attention inflation volatility in Ethiopia.
- The government should put attention in reducing the high volatility in FPI.

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Appendix

Table (a) Time complexity

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

Figure (a) plot of residual

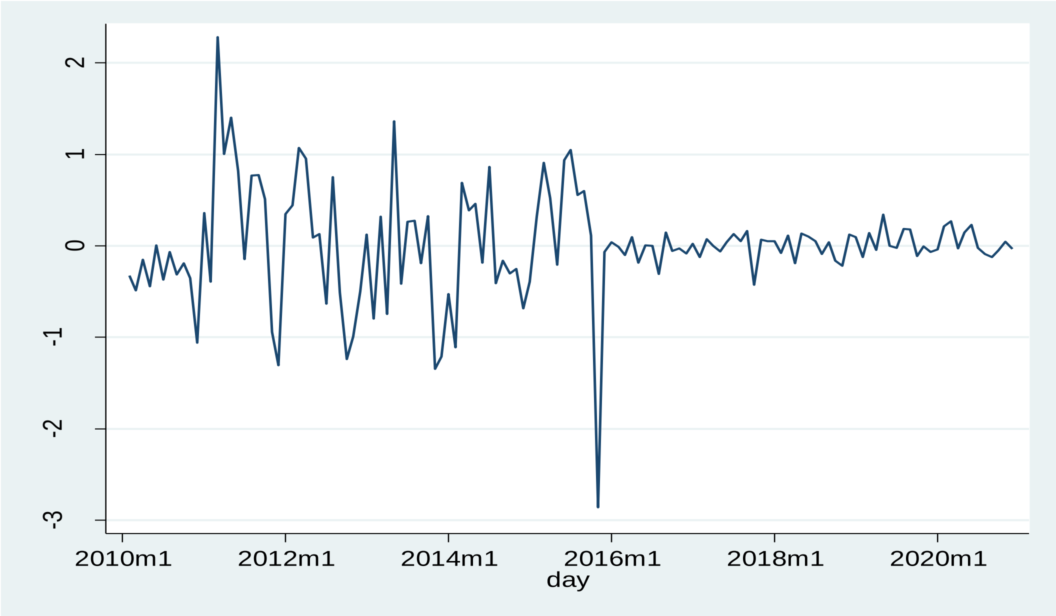

Figure (b) Plot of returned CPI

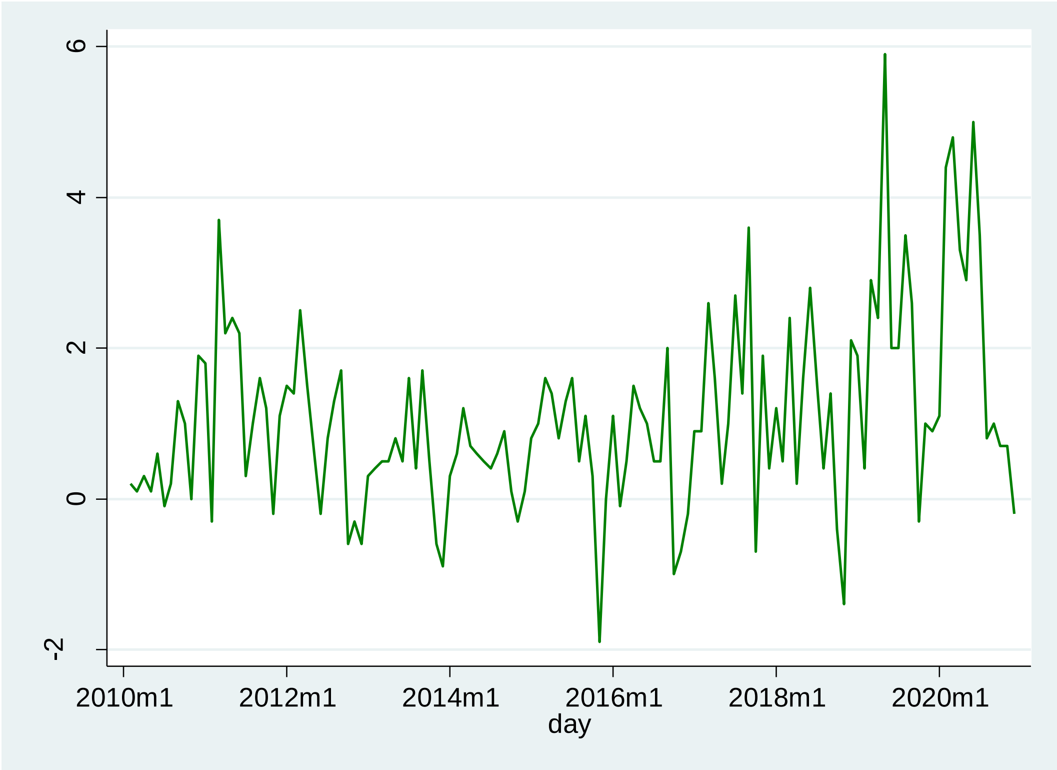

Figure (c) Plot of returned FPI

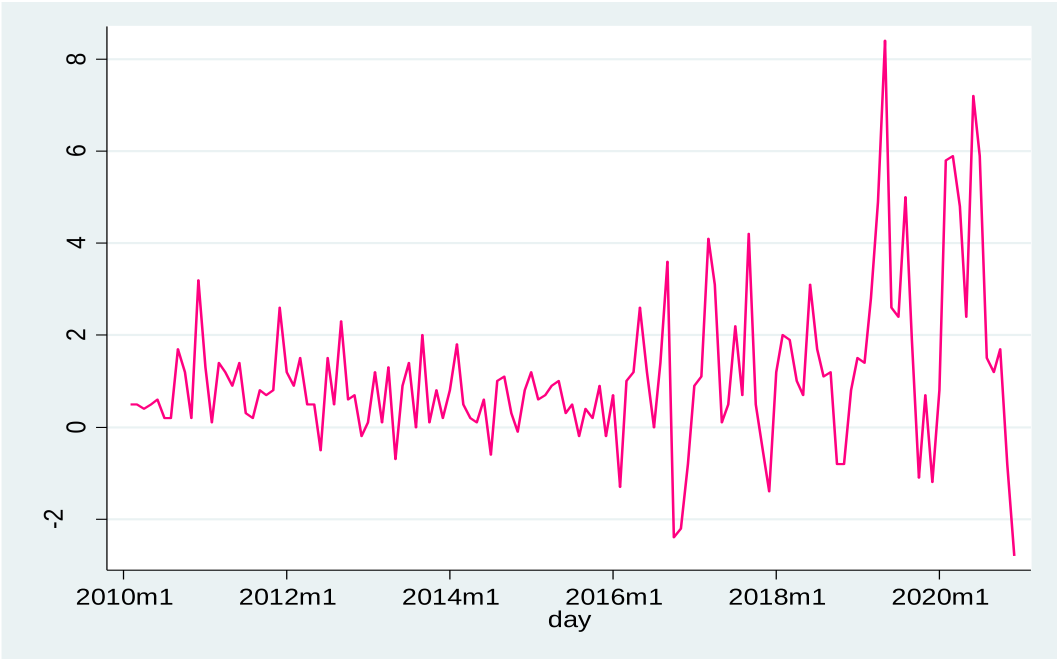

Figure (d) Plot of returned NFPI

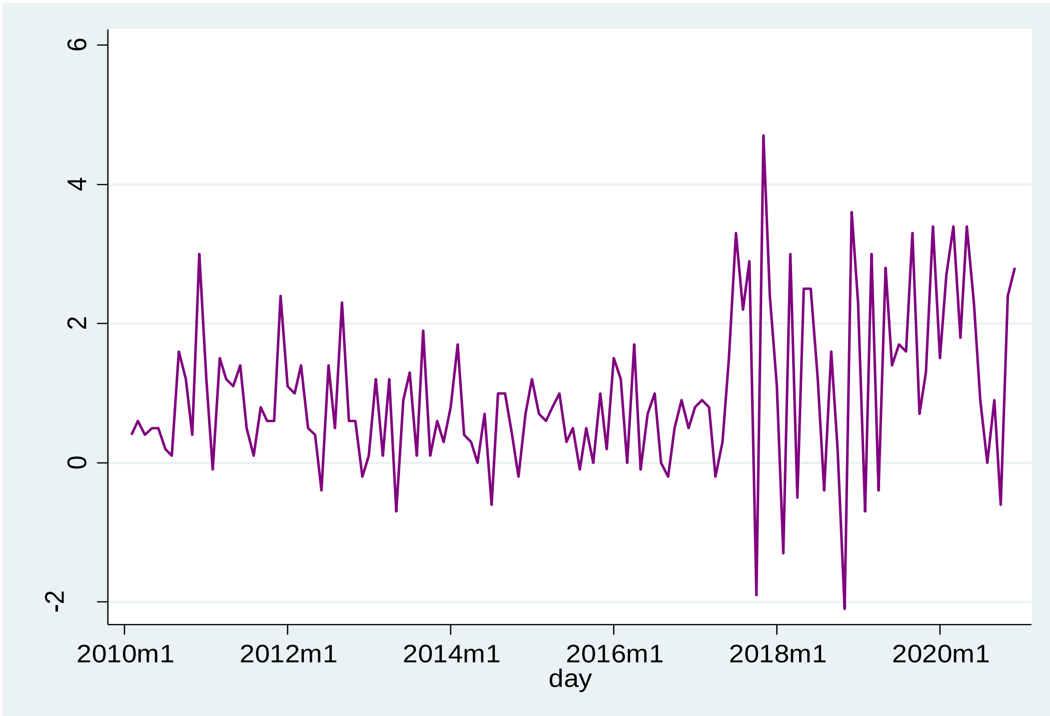

Figure (e) Plot of returned ER

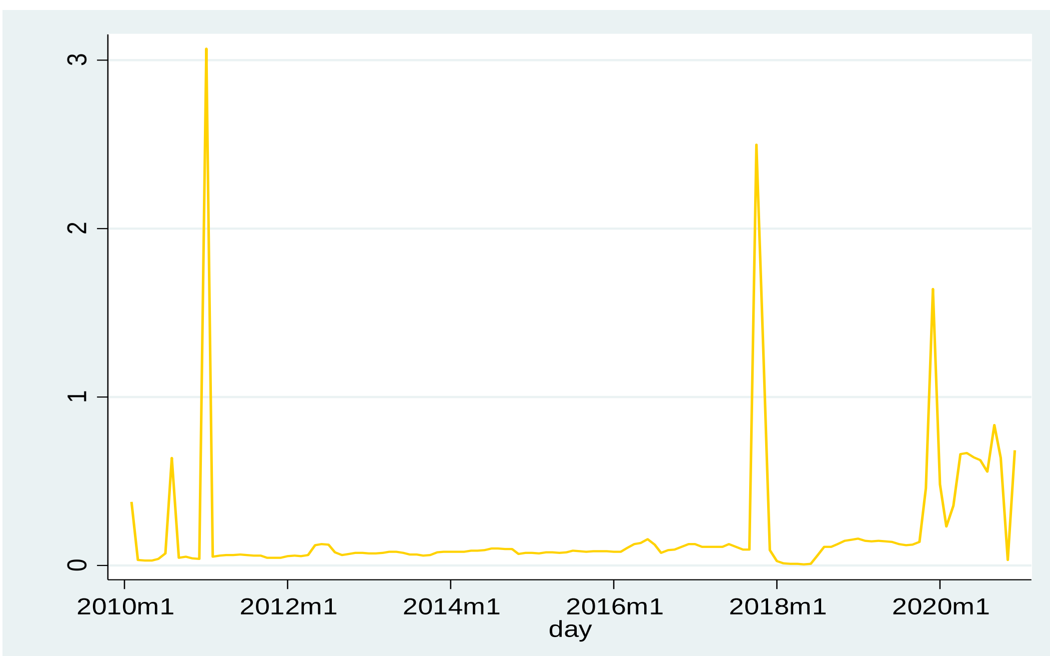

Figure (f) conditional Variance and covariance plot of CPI, FPI, NFPI and ER