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Forecasting World Food Price Volatility: Performance of the GARCH Model with Different Distributions Assumptions

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Abstract

This study examines the performance of the GARCH model with two different error distribution assumptions in forecasting the volatility of the global food price indices. For this purpose, it uses the monthly series of the world food price index (FPI), Meat Price Index (MPI), Dairy Price Index (DPI), Cereals Price Index (CPI), and vegetable Oil Price Index (OPI) sourced from the FAO database over a period from 1990M1 to 2022M3. We found that the model selected by the Akaike information criteria (AIC), the Schwarz criteria (SC), and the Hannan-Quinn (HQ) criteria performs well in the prediction of the volatility of all five food price indices. Further, the in-sample and out-of-sample performance analysis revealed that the GARCH models selected by the information criteria, both the normal and student-t distributions perform equally well in forecasting volatility. Finally, the analysis of the volatility series extracted from the best-fit GRACH models shows that the world food price has witnessed unusually large and sustained volatility during the periods 1994-95, 2007-08, and 2011-12. However, the magnitude of the fluctuations in the world food price observed during the recent Covid19 pandemic period was relatively mild, with the exception of vegetable oil prices.

Keywords: World Food Price, volatility, Forecasting, GARCH, Error distributions

JEL: Q10; E31;C53

1. Introduction

Price volatility describes the magnitude of price fluctuations or the risk of large, unexpected price changes. The risk of extreme price events can intensify and contribute to broader social risks in terms of food security, human development, and political stability (Matthias Kalkuhl, 2016a). Food prices have been volatile over the last few decades reaching a new height in 2008 (Fig.1). The global food prices increased by more than 70 percent between 2005 and 2008, and during this period, the prices of maize almost tripled, wheat prices increased by 127 percent, and rice prices increased by 170 percent. According to the Food and Agriculture Organization (FAO), higher prices pushed an additional 40 million people into hunger in 2008, raising the overall number of

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undernourished people globally to 963 million, compared to 923 million in 2007 (FAO, 2008). Prices surged again in 2010–2011 as evident from Fig. 1. On average, prices of all food commodities have increased, impacting poor households severely in almost all countries, especially developing ones. In such countries the brunt of price volatility is more as households earn less income but spend more than 70% of their total income on food items. Apart from this, countries with low income also have to depend on food imports, which often raise the food import bills, affecting the balance of payments. More recently, global food prices were up 33% in August 2021 from a year earlier, with vegetable oil, grains, and meat rising (FAO, 2021).

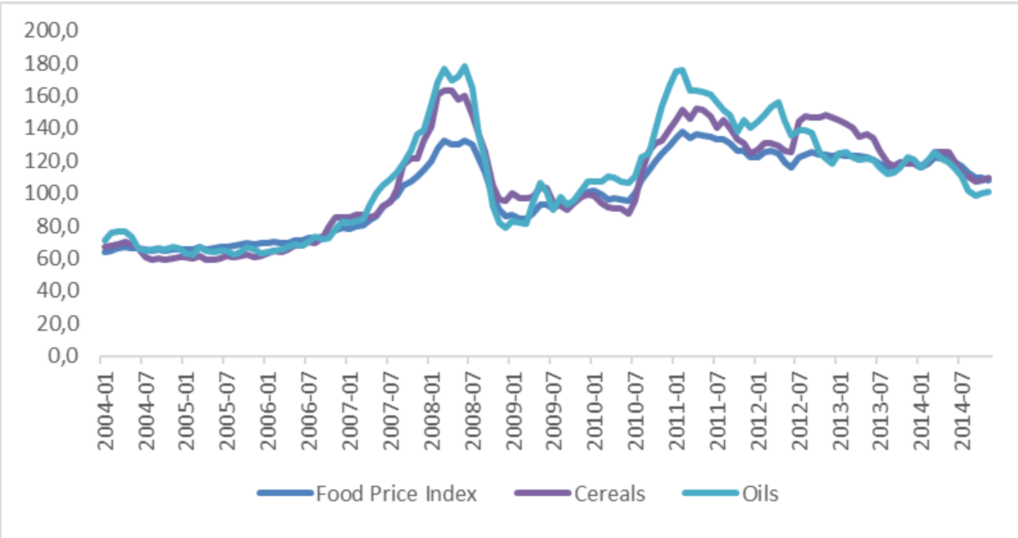

Figure 1. FAO food price indices from January 2004 to November 2011 (index: 2002-2004=100)
Source: FAO

It is a matter of grave concern and therefore needs to be addressed. Historical data confirms that food price spikes are recurrent, and consequently, much effort should go in this direction to initiate precise strategies and effective implementation. Such measures would also help formulate the policy of stabilizing prices and product enhancement (Amin Pujiati et al, 2018).

Food price movements are affected by supply and demand conditions, such as bad weather, soaring freight and fertilizer costs, shipping bottlenecks and labour shortages, and dwindling foreign currency reserves. One important factor responsible for the surge in food prices is the changing patterns of food consumption that have emerged in recent decades due to the rise in income in many countries, especially in developing countries.

Volatile prices are beneficial for some and detrimental for others. Higher prices benefit producers but hurt consumers, and low prices benefit consumers but hurt producers. The supply gets significantly affected in the latter's case. Anticipated changes are easier to cope with, because the adjustment to any changes in economic variables becomes more accessible and prevention of reduction in economic welfare accruing to consumers, producers, and market participants becomes possible. But in the case of unanticipated prices, the situation becomes complicated for both producers and consumers. In such situations, examining the changes in price distribution variance becomes central from a policy viewpoint.

Furthermore, the economic implications of the welfare and distributional shocks become stronger, in such conditions. Risk and uncertainty discourage investment which, in turn, affects supply. This may lead to an undesirable price rise, providing wrong market signals to producers and consumers. Food price surges lead poor people to limit their food consumption and shift to even less-balanced diets, with harmful effects on health in the short and long run (Habyarimana Jean Baptiste et al., 2014). Policymakers find difficulty in identifying the right package for an effective policy action that can check price volatility. Moreover, in such situations, predicting future price movements becomes difficult, creating price risk and uncertainty.

Research on food price volatility and food market dynamics in general, therefore, turn out to be quite significant in the current scenario. This would help in policy decisions and understanding the food market demand and supply dynamics. The timely monitoring of prices is important for assessing the functioning and efficiency of international and national food markets. Transparent market information is a basis for evidence-based decision-making and food security strategies. Past price volatility events demonstrate the value of timely market information and analysis, which can mitigate negative effects on low-income groups. Accurately predicting the price of agricultural commodities is important for evading market risk, increasing agricultural income, and accomplishing government macroeconomic regulation (Yongli Zhang and Sanggyun Na, 2018).

The present study attempts to forecast volatility in the selected global food price indices and, while doing so, compares the performance of the different specifications of the GARCH model with two different error distribution assumptions, standard normal and student t-distribution, to improve the predictive accuracy of the model.

The study adds to the literature in several important directions: first of all this study used 32 years of monthly frequency data starting from 1990M1 covering till the recent period i.e. 2022M3. During these periods the prices of the world food commodities have witnessed unprecedented fluctuations for instance in 2007-08 and 2010-11 steep spike in the prices and also the Covid-19 pandemic; another important contribution of this study is a detailed analysis of the volatility series of the five commodity price indices extracted from the best-fit GARCH models with reference to the demand and supply side shocks in the selected commodities groups.

2. Literature Review

The recurrent occurrences of food price volatility have attracted much academic attention for research in this area. Habyarimana Jean Baptiste et al. (2014) applied a Vector Autoregressive Model that combined monthly prices of Sorghum, Maize, Rice, Wheat, Irish Potato, and Beans from January, 2007 to December, 2013, to forecast food prices volatility in Rwanda and to find out which food commodities' price volatility granger cause price volatility in the other food commodities. To evaluate the model's forecasting accuracy, the study used RMSE and RSquare. To determine whether the trend of analysed food prices is deterministic or stochastic, it used a test for non-stationary (unit root) of time series. Similarly, Amin Pujiati et al (2018) made an observation and analysed price fluctuations of food commodities using the ARIMA (Autoregressive Moving Average) Model to predict food price in a short period of time, as well as early detection of food price fluctuation using data for the period ranging from 2015 to 2018. The research showed that the ARIMA Model predicted the price of some food commodities (i.e chicken meat, eggs, red chili peppers and shallots) in the study area, i.e, Semarang city. Priyanka et al, (2016) used the Wavelet and artificial neural network (Wavelet-ANN) hybrid models for multistep-ahead forecasting of monthly WPI of pulses. A comparative assessment of hybrid models and individual counterparts revealed that the hybrid models give significantly better results than the classical artificial neural network (ANN) model for all tested situations. Another study by Priyanka Anjoy and Ranjit Kumar Paul (2017) also used the Wavelet-based modelling and forecasting technique to find the volatility of potato price as an alternative to the traditional forecasting models, such as, the Autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroscedastic (GARCH) model and found that the combinatory Wavelet-GARCH hybrid model outperforms the individual ARIMA and GARCH model. Onour et al (2011) captured the volatility in global food commodity prices by using two competing models, the thin-tailed normal distribution, and the fat-tailed Student t-distribution models. The study showed that the t-distribution model outperforms the normal distribution model, suggesting that the normality assumption of residuals which are often taken for granted for its simplicity may lead to unreliable results of the conditional volatility estimates. The study also showed that the volatility of food commodity prices is mean reverting. Yongli Zhang and Sanggyun Na (2018) proposed a novel agricultural commodity price forecasting model which combined the fuzzy information granulation, mind evolutionary algorithm (MEA), and support vector machine (SVM) and the empirical analysis showed that the MEA-SVM model was effective and had higher prediction accuracy and faster calculation speed in the forecasting of the agricultural commodity price. Kwas and Rubaszek (2021) used an alternative model for forecasting commodity prices: the random walk, no-change forecast. The study showed that futures-based forecasts should supplement the random walk benchmark in forecasting nominal commodity prices at shorter horizons. And, in forecasting real commodity prices, the random walk benchmark should be supplemented, if not substituted, by forecasts from the local projection models. In both cases, the alternative benchmarks deliver comparable forecasts and, in many cases, superior accuracy. In another study by Teddy Mutugi Wanjuki et al. (2021), suggested that the monetary policy committee ought to control inflation through monetary or fiscal policy, strengthening food security and trade liberalization. The study, fitted and forecasted the food and beverages price index (FBPI) in Kenya using seasonal autoregressive integrated moving average (SARIMA) models. Capitanio et al. (2020) examined the shock transmission between the world cereal market and Morocco's market. Huang et al (2012) used the Realized GARCH model developed by Hansen, Huang and Shek (2012) to estimate and forecast price volatility in agricultural commodity futures. Empirical evidence, both in-sample and out-of-sample, show that the Realized GARCH model and its variants outperform the conventional volatility models that only use daily price data, such as GARCH and EGARCH. The study also considered skewed student's t-distribution to account for the skewness and fat-tail in the agricultural futures prices.

Literature on the subject sheds light on the methods employed to forecast food price volatility. It has been evident that most empirical studies primarily applied the GARCH model to forecast food price volatility. A few studies have used the Wavelet models and found that these have provided better results than the other classical models in some situations.

3. Data and methodology

3.1. Data

The FAO Food Price Index is an important indicator of global food commodity price movements. The FAO Food Price Index (FFPI) measures the monthly change in international prices of a basket of food commodities. It consists of the average of five commodity group price indices weighted by the average export shares of each of the groups over 2014-2016. The FAO Food Price Index (FFPI) was introduced in 1996 as a public good to help monitor developments in the global agricultural commodity markets.

This study attempts to forecast the general price volatility of food items. For this purpose, the study uses monthly series of the world food price index (FPI)[1], Meat Price Index (MPI), Dairy Price Index (DPI), Cereals Price Index (CPI) and vegetable Oil Price Index (OPI)[2] sourced from the FAO database. The period of study is from 1990M1 to 2022M3. To test the out-of-sample forecasting performance of the developed model, ten observations from 2021M5 to 2022M3 are reserved.

3.2. Methodology

This study uses the ARIMA-ARCH/GARH model to forecast volatility in the five major world food price indices. For this purpose, first, we calculate the rate of change in the price indices (R_t) using the following formula

$$R_t = ln(P_t/P_{t-1})$$

Where 'P_t' is the price index value at period t and P_{t-1} stands for the price index value at period 't-1'. 'ln' stands for natural logarithm.

Testing Stationarity

The time-series property of the index returns series is tested using the Augmented Dickey Fuller (ADF) method. This test is an improvement over DF test (1979) as it includes higher order regressive process.

$$y_t = \alpha + \beta y_{t-1} + \theta_i \sum_{i=1}^{m} \Delta y_{t-i} + e_t$$

Where 'm' is the lags of the differenced term which takes care of the serial independence of e_t. The null hypothesis of the test is H0: $\beta = 0$, implying that y_t is nonstationary.

Mean Model

This study assumes that y_t follows a stationary ARMA (p,q) process and considers different ARMA specifications as mean equations. The time series model ARMA is a combination of AR and MA models and often

1 Consist of the averages of five commodity group price indices i.e. Meat, Dairy Cereals, Vegetable and Sugar. For a detailed discussion on the methodology of construction of the world food price index and its sub-categories visit https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

2 Since we find no evidence for ARCH effect in the Sugar Price Index we excluded it from the study.

called a stationary time-series model (Box et al., 1970). The specification of ARMA (p,q) model takes place as follows:

$$y_t = \mu + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{q} \beta_i e_{t-i} + e_t$$

ARCH effects

The presence of autoregressive conditional heteroskedasticity (ARCH) in the residuals from the mean equation is examined using the ARCH Lagrange multiplier (LM) test. In this test the squared residual from the mean equation is fitted on constant and lagged squared residuals up to order 'q'. This test specifies the null hypothesis as there is no ARCH up to order 'q' in the residuals. The rejection of the above hypothesis confirms the presence of the 'ARCH effect' in the residual. This means that there is evidence to suggest that the variance of the residuals is not constant but exhibits conditional heteroskedasticity.

ARCH/GARCH model

ARCH (Autoregressive Conditionally Heteroscedastic) and GARCH (Generalized Autoregressive Conditionally Heteroscedastic) models are widely used in analyzing and forecasting volatility in the financial time series. The ARCH model proposed by Engle (1982) assumes that the conditional variance of the error term at each time point is a function of past squared residuals. Engle and Bollerslev (1986) extended the ARCH model by incorporating lagged values of both squared residuals and conditional variances, known as the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. This extension allows for a more flexible representation of time-varying volatility.

ARCH (q) process can be specified as follows

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2$$

where $\alpha_0 > 0$, and $\alpha_i \geq 0$, $i > 0$.

A generalized GARCH (q,p) model can be specified as follows

$$\sigma_t{}^2 = \mu + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

Where μ, α and β are parameters that need to be estimated and must be positive. Further, it should satisfy the condition that $\alpha + \beta < 1$. 'p' and 'q' are the lag order of the model.

Some of the previous literature on forecasting volatility based on the GARCH model has found that the assumption of error distribution significantly impacts the model performance (Wilhelmsson, 2006; Podobnika, Horvaticd, Petersena, & Stanleya, 2009). Originally the GARCH model was constructed based on the 'normal distribution assumption. However, the literature suggests that the low-frequency financial/price series could also follow a leptokurtic distribution and exhibit heavy-tail behaviour (Bollerslev, 1987; Stanley, Plerou, & Gabaix, 2008; Susmel & Engle,1994). Considering the above, while estimating the GARCH model the present study allows the error term to be distributed according to a normal and Student's *t* distributions and provides a comparison of the forecasting performance of these models.

Model Selection Criterion

The selection of the final mean model and ARCH/GARCH model among the different specifications of the model is done based on the Akaike information criteria (AIC), the Schwarz criteria (SC), and the Hannan-Quinn (HQ) criterions.

$$AIC = -2\left(\frac{l}{T}\right) + 2\left(\frac{k}{T}\right)$$

$$SC = -2\left(\frac{l}{T}\right) + k\log(T)/T$$

$$HQ = -2\left(\frac{l}{T}\right) + 2k\log(\log(T))/T$$

Where *'(T)'*, *'k'* and *'l'* stand for the sample size, the number of parameters and the lag length. According to the above criterion, the best fit model is one that minimizes the above information.

Forecast Performance Analysis

This study analyses the performance of the GARCH models with two different distributions assumption in forecasting world food price volatility using two loss functions namely Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{y}_t - y_t)^2}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|\hat{y}_t - y_t|$$

Where N is the sample size, y_t is the actual return at time t, and $\hat{y}_t$ is the forecasted return at time t. The smaller the value of the RMSE and MAE, the higher the model's predictive accuracy.

4. Result and Discussion

This study attempts to forecast the volatility of global food price. For this purpose, the study considered five food price indices, including the aggregate food price index (FPI) of FAOs. The rate of change in the global food price indices (return/inflation) indicate that the prices of the different categories of the global food items have seen increased fluctuations during the 2007-08 periods. The rate of change observed in the food indices during the covid19 period (2019-21) was relatively mild compared to the 2007-08 and 1993-94 fluctuations.

Table 1 reports descriptive statistics of the food price return series. The highest average price change rate is observed for edible oil. Among the six-return series under the study, a standard deviation is found relatively higher in the case of edible oil. Skewness of all the return series of the food crop indices except CPI (which is positively skewed) is found to be

Table 1. Descriptive Statistics

Statistics	FPI	CPI	DPI	MPI	OPI
Mean	0.0012	0.0013	0.0016	0.0004	0.0029
Median	0.0014	-0.0020	0.0017	0.0034	0.0019
Maximum	0.0743	0.1701	0.1576	0.0765	0.1998
Minimum	-0.1446	-0.1777	-0.2330	-0.1019	-0.2683
Std. Dev.	0.0253	0.0394	0.0414	0.0264	0.0536
Skewness	-0.6541	0.2351	-0.5640	-0.5249	-0.3719
Kurtosis	6.5268	5.5631	8.0693	4.3179	5.2287
Jarque-Bera	221.0807	106.0979	421.4066	44.3578	86.2566
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Authors' own calculation using FAO data

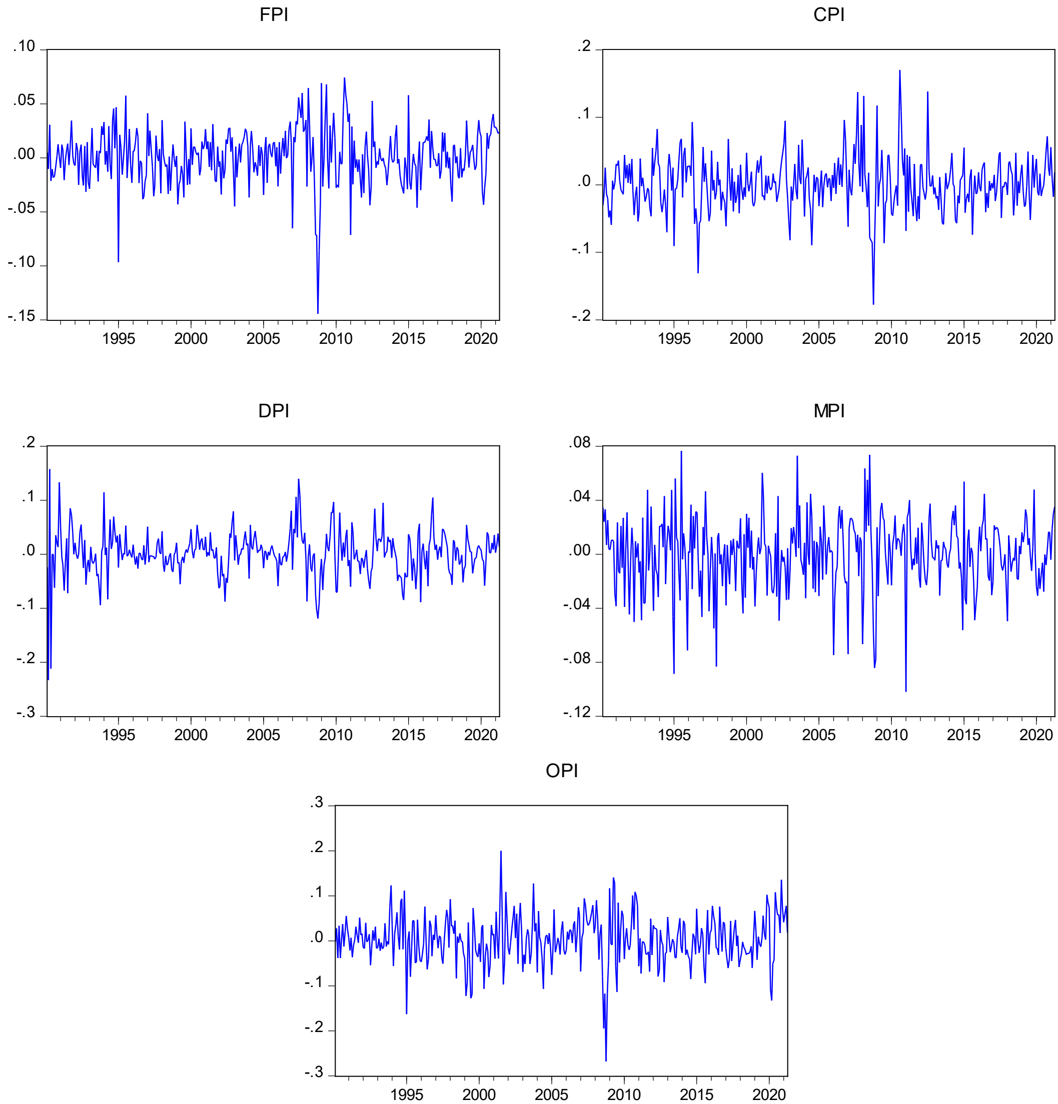

Figure 2. Rate of change in the global food price indices
Source: Authors' own calculation using FAO data

negatively skewed and the kurtosis is greater than 3, indicating that all the series under the present study are leptokurtic and thick-tailed. Further, the Jarque-Bera test rejects the null hypothesis of normality in all the cases.

In time-series modelling it is necessary to confirm the stationary property of the series under the study, to avoid the issue of spurious regression. Hence, we conducted the ADF test and the outcome of the analysis is provided in Table 2. The result indicates that the null hypothesis that the 'return series has a unit root' has been rejected at a 1% level of significance, in all the cases implying that these series are stationary.

Table 2. ADF-Test Result

Null Hypothesis: Variable has a unit root	
Variable	**Test Stat**
CPI	-13.441***
DPI	-14.754***
FPI	-14.343***
MPI	-16.980***
OPI	-12.904***

Source: Author's own calculation using FAO data;
Note: *** represent significance at 1% level

Having confirmed the stationary property, the next step in modelling volatility is to fit a mean equation to the return series. The present study uses different ARMA specifications for the mean equation. The best ARMA model is selected based on the AIC, BIC and HQC criteria i.e. the best model is the one with smallest AIC, BIC and HQC values or at least when two of the above criteria are smallest for that model.

Based on the above criteria we have selected ARMA (1,0) model for FPI, CPI, MPI series and ARMA (0,1) for OPI and ARMA (1,2) for MPI.

Table 3. ARMA Model Selection

Variable	**Selection criteria**	**ARMA(1,0)**	**ARMA(0,1)**	**ARMA(1,1)**	**ARMA(2,1)**	**ARMA(1,2)**	**ARMA(2,2)**
FPI	AIC	-4.591	-4.576	-4.594	-4.591	-4.591	-4.526
	SC	-4.560	-4.545	-4.552	-4.549	-4.549	-4.485
	HQC	-4.579	-4.564	-4.578	-4.574	-4.574	-4.510
CPI	AIC	-3.743	-3.725	-3.738	-3.738	-3.738	-3.631
	SC	-3.711	-3.694	-3.696	-3.696	-3.696	-3.589
	HQC	-3.730	-3.713	-3.721	-3.721	-3.722	-3.614
DPI	AIC	-3.588	-3.567	-3.616	-3.624	-3.625	-3.585
	SC	-3.557	-3.535	-3.574	-3.582	-3.583	-3.543
	HQC	-3.575	-3.554	-3.599	-3.607	-3.609	-3.568
MPI	AIC	-4.433	-4.432	-4.429	-4.429	-4.429	-4.412
	SC	-4.402	-4.401	-4.387	-4.387	-4.388	-4.370
	HQC	-4.421	-4.420	-4.412	-4.413	-4.413	-4.395
OPI	AIC	-3.108	-3.128	-3.123	-3.123	-3.123	-3.004
	SC	-3.076	-3.097	-3.081	-3.081	-3.081	-2.962
	HQC	-3.095	-3.116	-3.106	-3.107	-3.106	-2.988

Source: Author's own calculation using FAO data

In the next stage, we test the residual from the mean equation for the presence of the ARCH effect. This study used the ARCH LM test (Engle, 1982)) with the null hypothesis 'there is no ARCH effect', for this purpose. The outcome of the ARCH LM test is provided in Table 3. In all the cases the null hypothesis is rejected at a 1% level of significance, indicating the presence of the ARCH effect in all the series.

Table 4. Result of the ARCH LM test

Variable	F-statistic
CPI	2.551***
DPI	2.644***
FPI	3.132***
MPI	5.685***
OPI	2.330***

Source: Authors' own calculation using FAO data; Note: *** represent significance at 1% level

Once we confirm the ARCH effect in the return series, the next step is to fit an ARCH/GARCH model for each case. When estimating the GARCH model we have allowed the error term to be distributed according to a normal distribution and also as a Student's *t* distribution. Among the models estimated for all the return series with these two distribution assumptions, we select the best GARCH specification based on the smallest AIC, SC and HQC criteria. Table 5 provides the AIC, SC and HQC values for all the different GARCH specifications considered for the return series with the assumption of normal error distribution. Based on the above-specified criterion we select a GARCH (1, 0) specification for FPI, CPI, MPI and OPI series and a GARCH (1, 1) specification for DPI.

Table 5. GARCH Model Selection: Normal Distribution

Variable	Selection criteria	GARCH (1,0)	GARCH (1,1)	GARCH (2,1)	GARCH (1,2)	GARCH (2,2)
FPI	AIC	-4.6533	-4.3939	-4.5118	-4.4742	-4.5711
	SC	-4.6113	-4.3415	-4.4488	-4.4113	-4.4977
	HQC	-4.6366	-4.3731	-4.4868	-4.4492	-4.5420
CPI	AIC	-3.7590	-3.5111	-3.7328	-3.7262	-3.7348
	SC	-3.7170	-3.4586	-3.6698	-3.6633	-3.6614
	HQC	-3.7423	-3.4903	-3.7078	-3.7012	-3.7057
DPI	AIC	-3.8747	-3.9718	-3.5474	-3.5406	-3.7519
	SC	-3.8223	-3.9088	-3.4739	-3.4671	-3.6679
	HQC	-3.8539	-3.9468	-3.5182	-3.5114	-3.7185
MPI	AIC	-4.4423	-4.2434	-4.4408	-4.4418	-4.4370
	SC	-4.4004	-4.1910	-4.3778	-4.3788	-4.3635
	HQC	-4.4257	-4.2226	-4.4158	-4.4168	-4.4078
OPI	AIC	-3.1323	-2.9079	-3.1183	-3.0595	-3.1065
	SC	-3.0904	-2.8556	-3.0554	-2.9967	-3.0332
	HQC	-3.1156	-2.8871	-3.0933	-3.0345	-3.0774

Source: Authors' own calculation using FAO data

Table 6 provides the values of AIC, SC and HQC for all the different GARCH specifications with the assumption of Student's *t* distribution. The AIC, SC and HQC criteria suggest the GARCH (1, 0) model for FPI, CPI and DPI and GARCH (2, 1) for MPI and GARCH (1, 1) for OPI.

Table 6. GARCH Model Selection: t- Distribution

Variable	Selection criteria	GARCH (1,0)	GARCH (1,1)	GARCH (2,1)	GARCH (1,2)	GARCH (2,2)
FPI	AIC	-4.614	-4.189	-4.530	-4.397	-4.504
	SC	-4.561	-4.126	-4.456	-4.324	-4.420
	HQC	-4.593	-4.164	-4.501	-4.368	-4.471
CPI	AIC	-3.745	-3.306	-3.719	-3.698	-3.736
	SC	-3.693	-3.243	-3.645	-3.625	-3.652
	HQC	-3.724	-3.281	-3.689	-3.669	-3.703
DPI	AIC	-3.817	-3.248	-3.309	-3.260	-3.619
	SC	-3.754	-3.175	-3.225	-3.176	-3.524
	HQC	-3.792	-3.219	-3.276	-3.227	-3.581
MPI	AIC	-4.446	-4.057	-4.458	-4.435	-4.453
	SC	-4.394	-3.994	-4.385	-4.362	-4.369
	HQC	-4.425	-4.032	-4.429	-4.406	-4.419
OPI	AIC	-3.172	-3.222	-3.221	-3.219	-3.216
	SC	-3.120	-3.160	-3.148	-3.145	-3.132
	HQC	-3.152	-3.197	-3.192	-3.189	-3.182

Source: Authors' own calculation using FAO data

Once we select the best-fit GARCH specification with standard normal and student *t* distribution assumptions, we do an in-sample and out-of-sample forecasting of variance/volatility of the selected 5 global food price indices. We found that the in-sample and out-of-sample forecasted variances are well within the prediction interval (+/-2SE) (see Appendix figure 1 to 4). The performances of the forecasted variance of these food price indices are analysed using the loss function such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The result of the forecasting performance of the best GARCH model with normal and student t distributions assumptions are reported in Table 7 and 8, respectively.

First, we evaluate the in-sample performance of the best GARCH model assuming normal and student *t* error distributions. The in-sample performance analysis result is provided in table 7 and it shows that RMSE and MAE values are smaller for all the price indices under the present study. This indicates that the model can accurately predict the global food price variance. Further, the result also indicates no significant difference in the in-sample performance of the models based on the two different error distribution assumptions.

We also evaluated the out-of-sample performance of the best-fit GARCH model, assuming normal and t error distributions. The out-of-sample performance analysis (table 8) reveals that all five price indices have smaller RMSE and MAE values. This indicates that the model can accurately predict the global food price variance. Further, the result shows that in the case of CPI and DPI the GARCH model based on the t-distribution slightly outperform

Table 7. In-sample Volatility Forecasting Performance

Variable	Selection criteria	Normal distribution	t- distribution
FPI	RMSE	0.0243	0.0249
	MAE	0.0184	0.0186
CPI	RMSE	0.0370	0.0370
	MAE	0.0278	0.0278
DPI	RMSE	0.0332	0.0333
	MAE	0.0243	0.0243
MPI	RMSE	0.0261	0.0261
	MAE	0.0195	0.0195
OPI	RMSE	0.0503	0.0503
	MAE	0.0379	0.0379

Source: Authors' own calculation using FAO data

Table 8. Out-of-sample Volatility Forecasting Performance

Variable	Selection criteria	Normal distribution	t- distribution
FPI	RMSE	0.0249	0.0249
	MAE	0.0201	0.0208
CPI	RMSE	0.0310	0.0310
	MAE	0.0278	0.0278
DPI	RMSE	0.0236	0.0232
	MAE	0.0184	0.0181
MPI	RMSE	0.0233	0.0158
	MAE	0.0181	0.0140
OPI	RMSE	0.0643	0.0645
	MAE	0.0534	0.0535

Source: Authors' own calculation FAO data

the model assuming normal error distribution. In the other cases (FPI, MPI and OPI) we found no significant difference in the out-of-sample performance of the two models.

Further, in this study we make an attempt to analyse the volatility in the world food price indices with reference to the different demand and supply shocks. For this purpose, we produce the volatility series of the commodity indices extracted from best-fit GARCH models with the Normal and Student-t distribution assumptions in figure 3 and figure 4. It is evident from these figures that the World Food price has witnessed unusually large and sustained volatility especially during three time periods-1994-95, 2007-08, and in 2011-12. Although the prices of the sub-categories of the food items have also witnessed a similar trend, there are differences in the instances and depth of volatility observed across these indices. Among the sub-indices the vegetable OPI witnessed a high-intensity volatility during the study period.

The increased fluctuation in the world food price could be attributed to multiple factors. FAO (2022) notes that since 1990 the annual growth rate of production of foodgrains and oilseeds has declined by 1.3 percent. The factors that led to the slowing of output growth are reduced state intervention and overall investment in agriculture in developing countries, and marginal state expenditure in R&D in the agriculture sector. Resource scarcity issues such as climate change and water depletion, droughts, floods, and freezing weather have also impacted agricultural output adversely (IPCC,2023). Australia, the European Union (EU), and Ukraine which are the major grain and oilseed-producing areas suffered from adverse weather conditions in 2006 and 2007 (WMO,2006). Another reason is the high energy prices, which increased the cost of production for overall food grains and particularly for corn, soybeans, and wheat by around 21.7 percent between 2002 and 2007 (Harris et al, 2009). The main reason for the fall in the world cereal stock can be attributed to the changes in the policy environment in the Uruguay Round Agreements. These changes pertain to the size of reserves to be held by public institutions, the cost of storage, the cost of risk management, etc.

Some of the major demand side factors that caused the unprecedented fluctuations in the food prices especially during 2008 are identified as the higher income growth rate in most emerging economies and speculative investment opportunities in commodity markets (Mittal, 2009). These have put tremendous upward price pressure on food and energy commodities during this period.

Over and above, the increase in oil prices during the 2007-08 periods resulted to an increased conversion of food grains for biofuels which is also responsible for the 70–75 percent increase in food prices during 2007-08 (Baier et al, 2009).

Figure 3 and 4 also show that among the sub-indices Dairy price (DPI) has witnessed Large and sustained volatility during the major portion of the study period. The reason for the fluctuations in dairy prices can be attributed to the perishable nature of milk and also the seasonal variation in the production of milk (FAO,2022). As the demand for dairy products is inelastic, a slight scarcity causes prices to rise. Moreover, the production cycle in dairy farming is prolonged causing supply constraints. Another reason for the high dairy prices is the increased globalisation of dairy commodity trade during this period.

Finally, the figures clearly indicate that overall, the instances of increased volatility in the world Food price index were more during the post-2008 period (Tadesse, 2014). These findings in fact question the argument that the liberalization and globalization measures should bring down the commodity price volatility especially through increased variety and reduced cost of food.

5. Summary and conclusion

GARCH models are known for their better performance in the short-run volatility forecasting. This study used different specifications of the GARCH model with two different error distribution assumptions to forecast the volatility in the five selected global food price indices. The performance of the GARCH models is examined using two loss functions: Root Mean Square Error

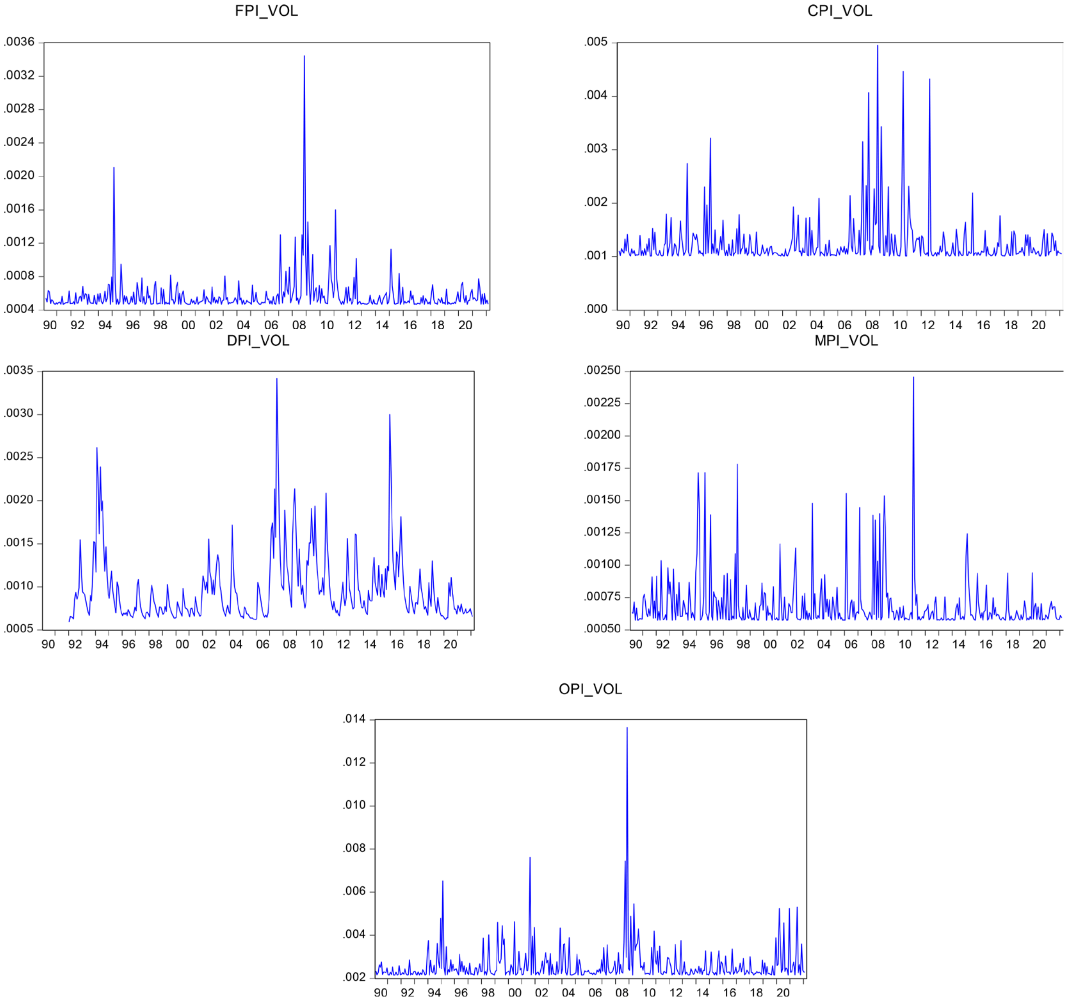

Fig. 3. Volatility series extracted from the best-fit GARCH model under the Normal distribution assumption

Source: Authors' own calculation FAO data. Note:

(RMSE) and Mean Absolute Error (MAE). The results show that the best models selected using the model selection criteria namely AIC, SC and HQC were able to predict the volatility of all the five food price indices accurately. Further, the in-sample and out of the sample performance analysis revealed that the best GARCH model with both the normal and student-t distributions perform equally well in forecasting volatility.

An analysis of the volatility series extracted from the best-fit GARCH models of all the food price indices under the present study revealed that the World Food price has witnessed unusually large and sustained volatility especially during three time periods - 1994-95, 2007-08, and in 2011-12. Further, the volatility in the world food price is found relatively larger during the post-2008 period. However, we found that the magnitude of the

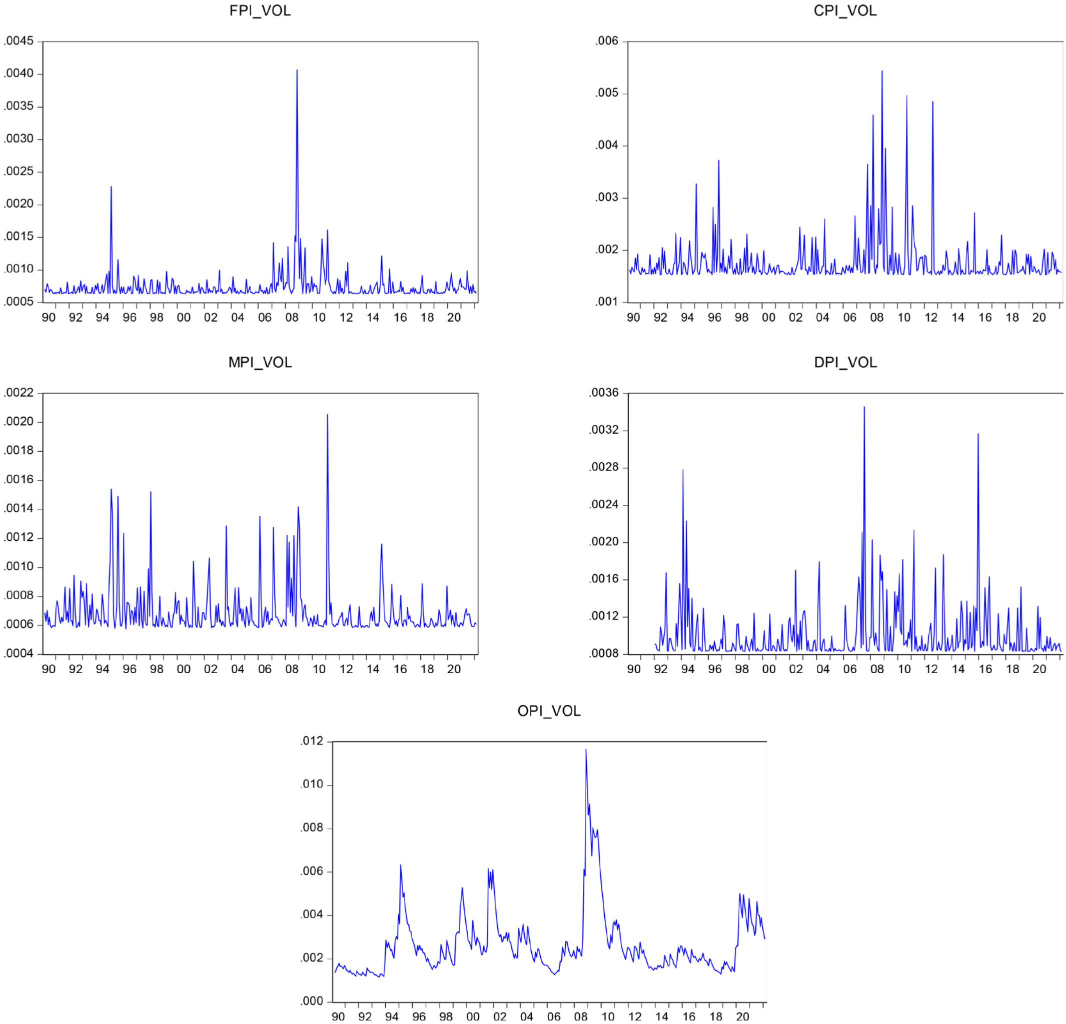

Fig. 4. Volatility series extracted from the best-fit GARCH model under the student-t distribution assumption

Source: Authors' own calculation FAO data. Note:

fluctuations in the world food price observed during the recent Covid19 pandemic period was relatively mild.

Volatility matters because volatile food prices are closely linked with the stability dimension of food and nutrition security. The risk of future price shocks reduces investments in agricultural production, which has negative long-run impacts on food supply. Volatile food prices increase political risks which could induce governments to adopt ill-designed ad hoc market interventions (Matthias Kalkuhl, 2016c). Policymakers may employ the appropriate method for forecasting the price volatility which would provide a guiding tool to perceive different risks. The present work mainly focuses on the performance of models to be employed while analysing food price volatility and it deemed to be extended by an improvement in forecasting methodology and evaluation criteria.

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Appendix

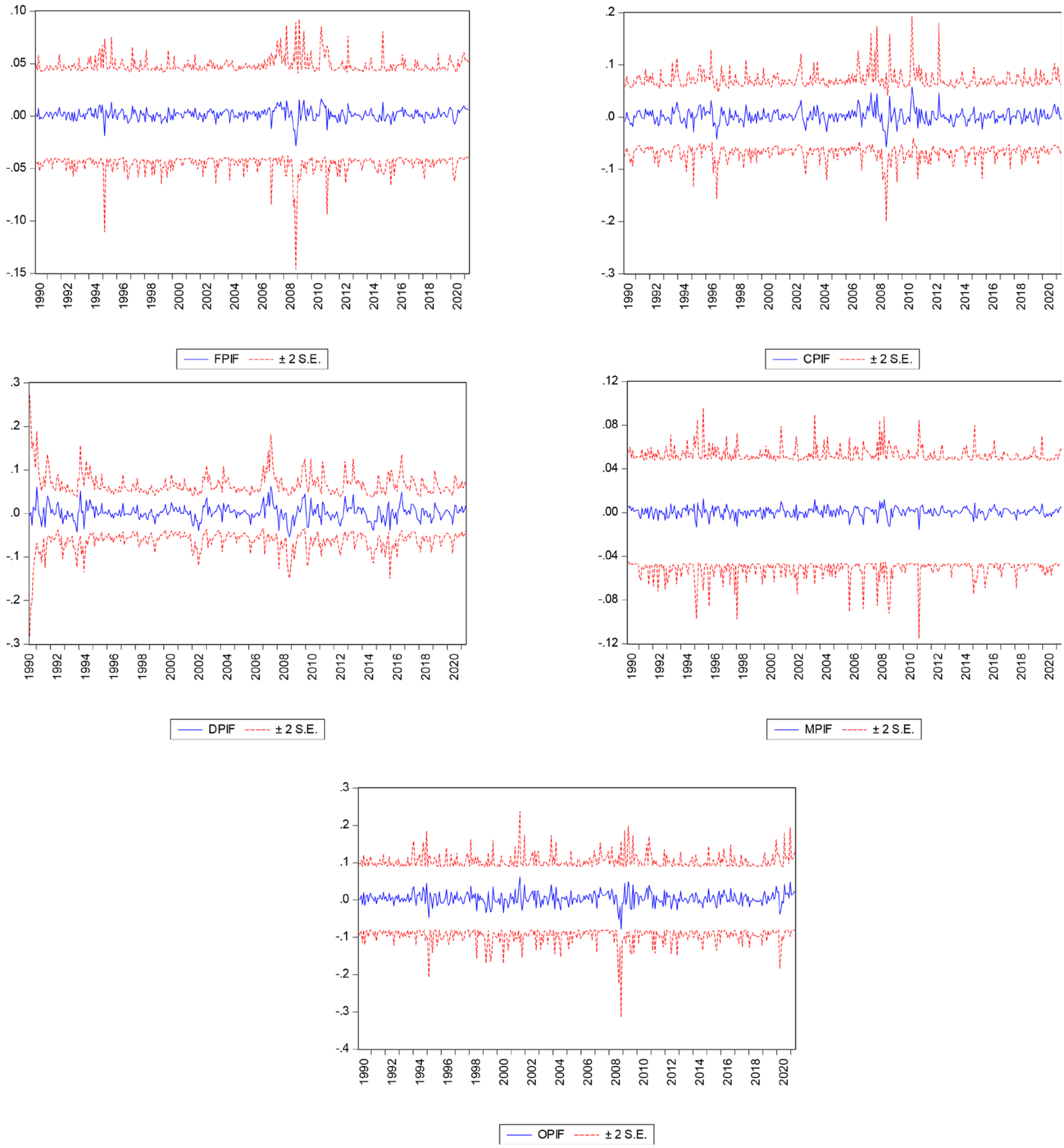

Figure 1. In-sample forecasted variance, GARCH Model assuming Normal error distribution

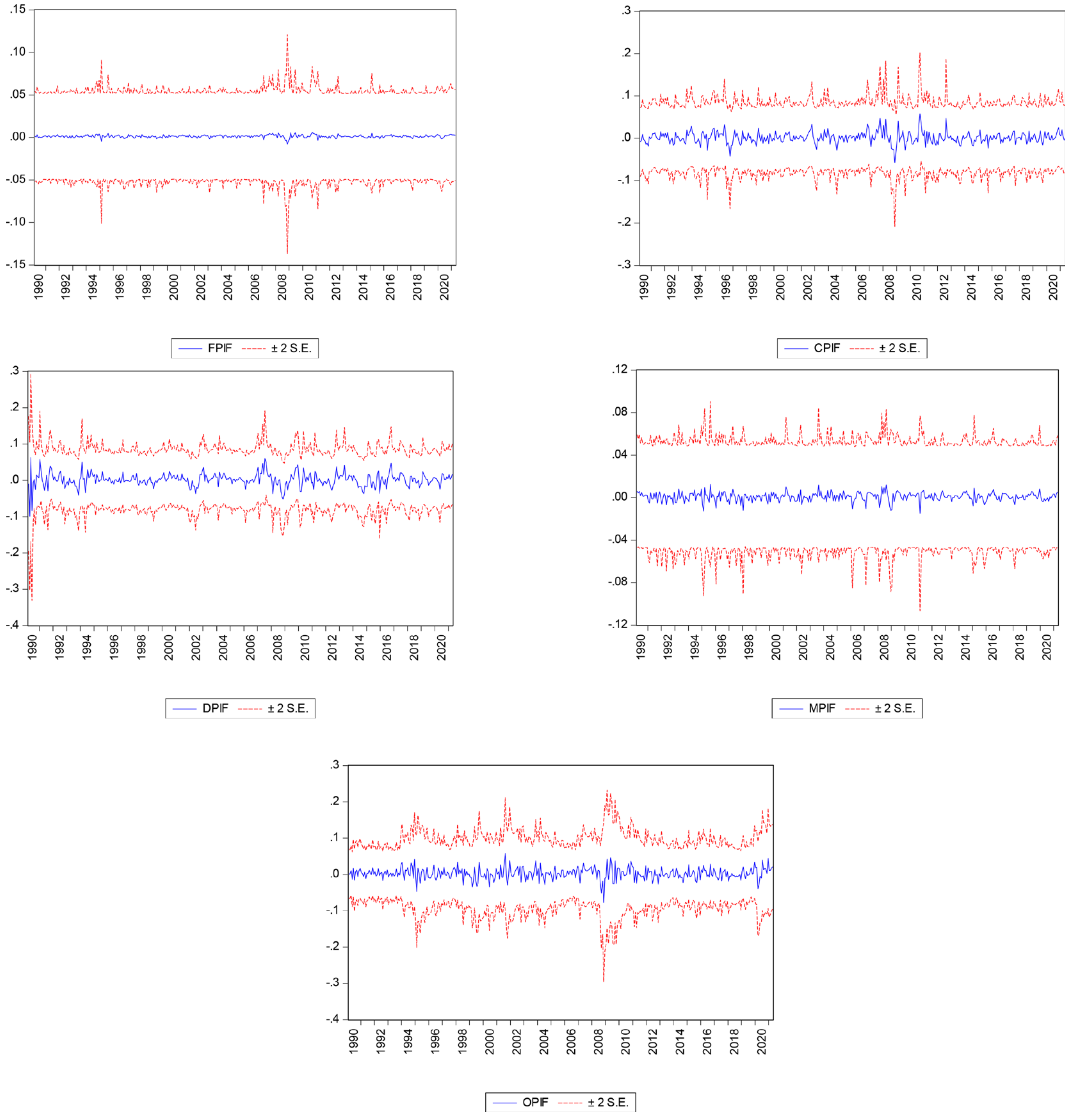

Figure 2. In-sample forecasted variance, GARCH Model assuming student t distribution

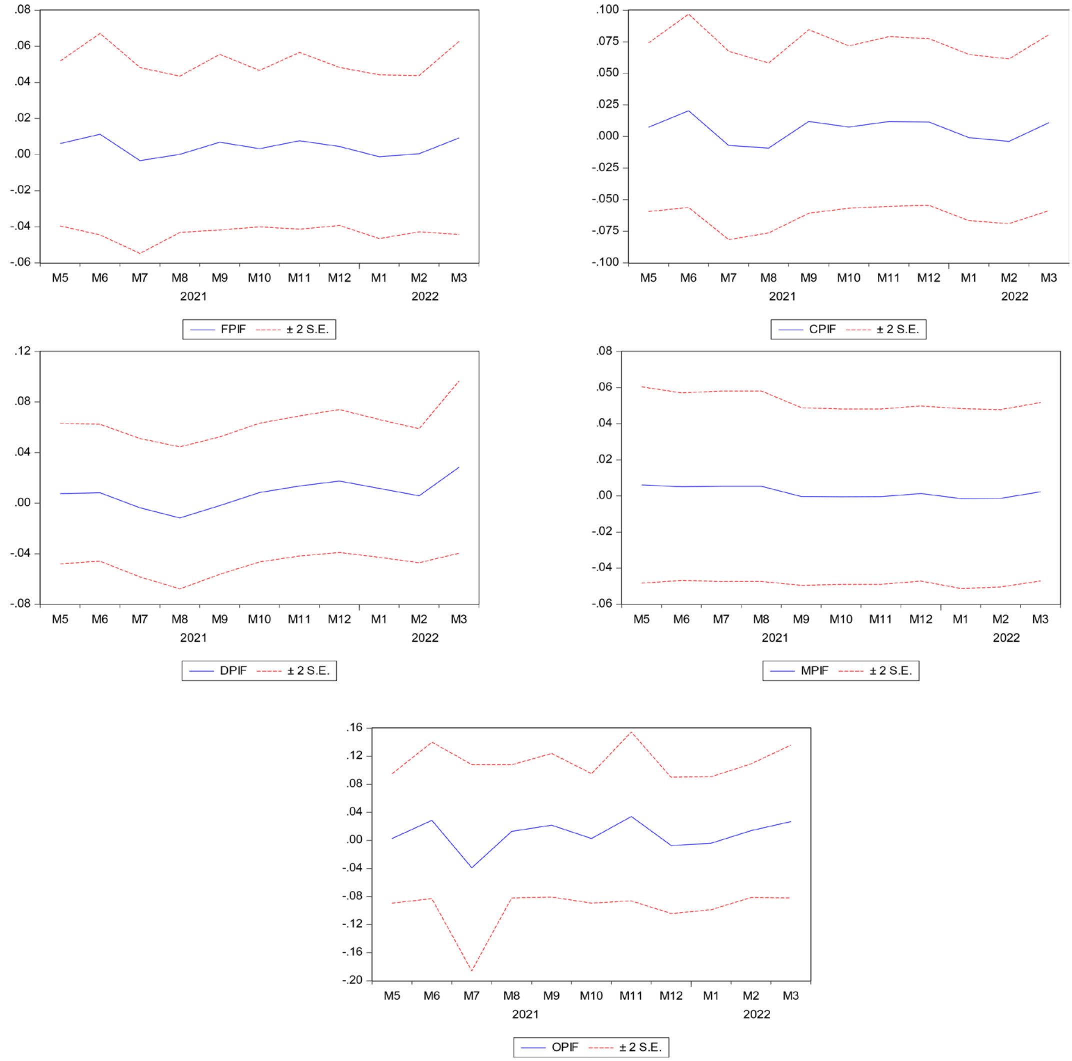

Figure 3. Out-of sample-forecasted variance, GARCH Model assuming Normal error distribution

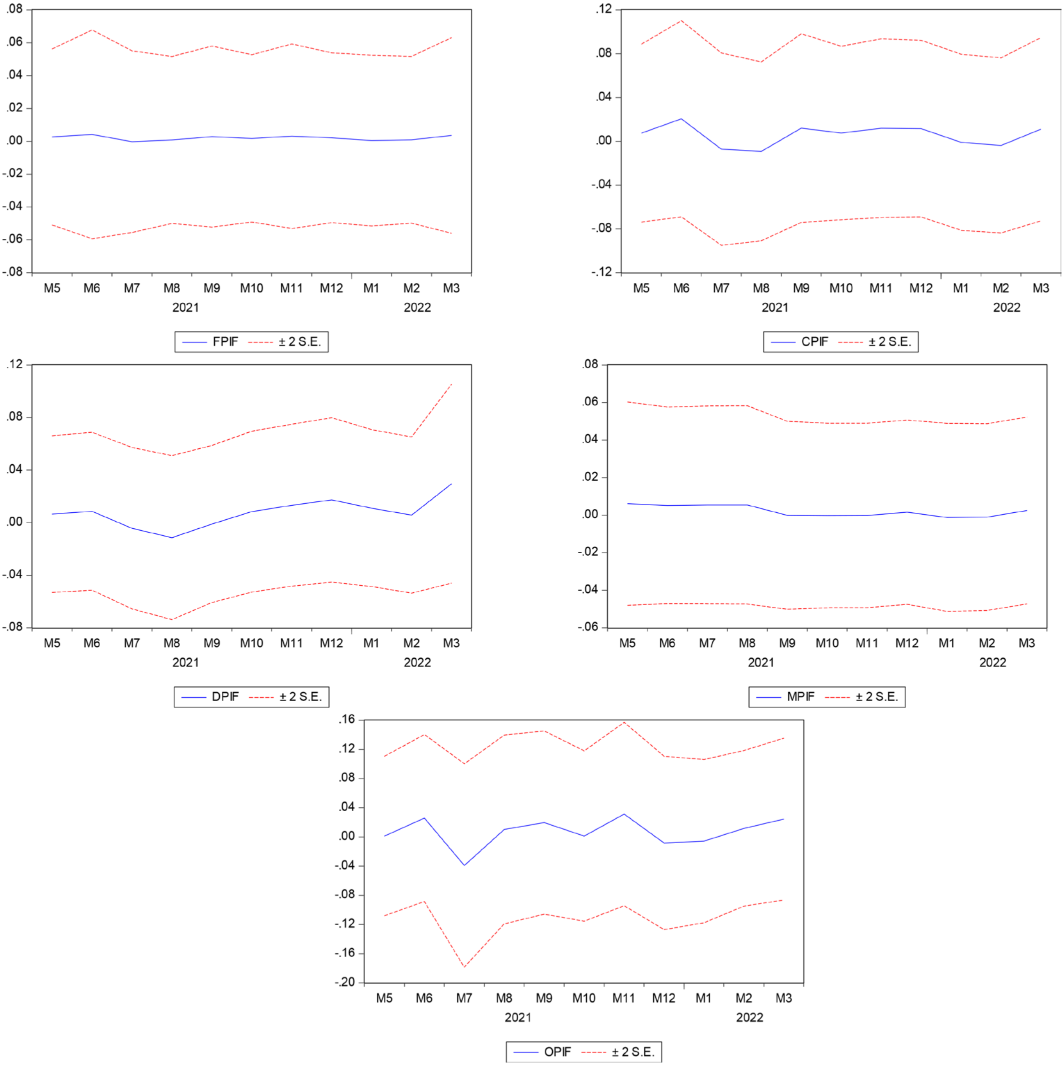

Figure 4. Out-of-sample forecasted variance, GARCH Model assuming student t distribution