Staple Food Price Volatility and its Derivers in Ethiopia: GARCH Family Models

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Abstract

Food price inflation in Ethiopia commenced suffering high rates in 2004 that pose risks for poor people's livelihoods and food security. While it was not a severe challenge before the period. Accordingly, analyzing the staple food price volatility and its core drivers have noteworthy contributions to food market management and risk valuation. The unit root tests imply that all independent variables became stationary after the first differences transformation, and the three dependent return variables were stationary at level. The staple food prices revealed stylized facts of financial time series, and they confirmed ARCH effects presence in condition mean equations. Since the generalized autoregressive conditional heteroscedasticity (GARCH) family models were applied to the price series in the period of January 2000 to May 2019. Based on the model selection criteria, asymmetric effect significance and forecast error accuracy, best-fit models for monthly return prices of maize, wheat and teff were selected and modeled using ARMA(1,3)-EGARCH(1,0), AR(1)-EGARCH(1,0) and AR(1)-GARCH-M(1,1) respectively with the same normal error distribution assumptions. One month lagged shocks of the prices of maize and wheat have statistically significant effects on the current month's volatility. The asymmetric effect of maize price volatility inclines to go in response to bad news than good news while the wheat responses to good news than bad news. The impact of the price of the fertilizer and global-wheat and exchange rate on the conditional variances of the Ethiopian wheat has become stable than the general inflation rate. The influence of the price of the fertilizer and global-wheat and exchange rate on the conditional variances of the Ethiopian teff has to stabilize than the fuel oil price. Also, the global maize price decrease makes a more stable marketing environment with a more volatile Ethiopian maize price. The Ethiopian government should provide more devotion to the influential factors and must draw and execute flexible trade, investment, exchange rate, and monetary policies, which shall consider and go with the dynamic internal and global markets to sustain the Ethiopian food market.

Keywords: Ethiopia, GARCH Family Models, Price volatility and Drivers, Staple Food.

1. Introduction

The commodity prices in the world food market have been dramatically increased in recent periods, which have huge implications and impacts on financial institutions, ecological sustainability, and risk of future nutritional emergencies. In 2007–2008, as an instance period often mentioned, almost all food commodities' nominal prices boosted by more than 50 percent and after three years, in 2010–2011, the prices again fabulously surged (Kalkuhl et al., 2014). Moreover, the average cereal price in Africa has become domestically more volatile than in Asia and Latin America. It highly affected the poor because of their limited capacity to accumulate food stocks and they may be forced to buy at a time of price peaking (Cornelson et al., 2015). According to the United States' Office of National Intelligence (2014) projections report on global food security, the current conditions of agricultural commodity prices described by higher and more volatile are expected to continue for the next decade. Also, the macroeconomic conditions and climate change effects are likely to remain to make price spikes along with a cumulative risk of price volatility.

The Ethiopian economy around 2004 commenced experiencing high rates of food inflation while the food price inflation until 2004 was not a severe encounter except for price fluctuations in drought years. The staple food price such as wheat and maize was doubled and tripled, and the average inflation for food and cereals was 41 percent and 58 percent in 2007 and 2008, respectively. Annual food price inflation in mid-2008 touched a record rate of 61.1 percent (Assefa, 2014). As a result, these food price increases lead to risks of malnutrition and higher uncertainty in food markets along with reduced real income given that the share of food consumption in Ethiopia is equal to 58.6 percent of the overall consumption basket, which is greater than even from 56.6 percent in many low-income countries and 57.4 percent in fragile states like Guinea and Burundi. Thus, the food price volatility in Ethiopia has had been one of the major concerns of the government and other stack-holders in order to assure the food security in terms of food price stability and affordability (Kalkuhl et al., 2014; FAO, 2011).

Numerous food policies of Ethiopia have been implemented to reduce price hike and volatility. Some of the measures are export bans, removal of import tariff, fiscal and monetary policy, administrative and price control, releasing reserve grain stocks, grain procurement, productive safety net, increased investment in agriculture, establishing Ethiopian Commodity Exchange and other Policy Measures. However, food price hike and volatility are not still significantly reduced (Assefa, 2014; Kalkuhl et al., 2014).

Price volatility indicates the trends of food prices speedy and imprudent changes that create havoc on markets, social stability and politics than price hikes (Kharas, 2011). The idea of volatility is crucial to assessment, analysis, and management of the risk of food markets (Ahmed and Zakaria, 2011). So, volatility modeling of a market price series is an essential part of food market analyses (Cont, 2001). The commodity market volatility occurs for diverse reasons like demand changes for the commodity, supplying countries political disorder, financial innovations, different profitable expectations of the market participants (Anderson, 2009).

In the literature of volatility modeling, the model should capture characteristics of the volatile price series such as a correlation between lagged returns, jumps, fat tails and volatility clustering (Cont, 2001), the autoregressive conditional heteroskedastic (ARCH) model is originally proposed and used as a standard method (Engle, 1982) and then Bollerslev (1986) extended the ARCH model to the generalized ARCH (GARCH) model. The GARCH model captured the high-frequency price series properties that are not handled better in the former model such as volatility clustering and time-varying heteroskedasticity. The GARCH model is developed with the Gaussian distribution assumption of the series while there are scored amount of theoretical evidence suggests that the series mostly followed leptokurtic and shows heavy-tail distributional behavior (Bollerslev, 1986).

An extension of the standard GARCH model, asymmetric GARCH model was developed, which is the best fit in the volatility modeling and forecasting of the price return through its ability to overcome the two-folded characteristics of the volatile price series. First, the leverage effect is the irregularity related to volatility clustering of the series where bad news largely enhances in volatility than good news. Second, the leptokurtosis in the volatile price series that shows irregularity of the series through its fat-tails probability distribution due to outliers and non-constant conditional variance. As a result, a fat-tailed distribution like the Student's t-distribution or General Error Distribution (GED) is assumed to be consistent and employed as a solution (Nelson, 1991). Thus, the asymmetric GARCH model, a fat-tailed distribution, should be employed for empirical analyses of volatile price series.

Some empirical studies in Ethiopia are concerned with food market price and volatility modeling, while these studies have drawbacks on their methodological and analytical considerations (Abule, 2012; Jema and Fekadu, 2012; Sebsib and Emmanuel, 2018; Demisew et al., 2012). The first is the more realistic volatility model selection and the second is the distributional assumptions that best fit the volatile data. Therefore, this study, modeling and investigating the core drivers of staple food price volatility, has an undeniable impact on the existing knowledge to intervene and reduce the effect of food price volatility in Ethiopia. The reason behind the novelty of this paper is two-folded. One, It considered major food prices separately than the aggregate food price. Two, it used an asymmetric GARCH model that is a more realistic model that could handle the volatile characteristics of the food price series. Accordingly, this study investigates the staple food price volatilities and its core exogenous drivers in Ethiopia markets in order to deal and suggest the concerned market agents on behalf of understanding the financial markets current and future behaviors.

2. Methodology

2.1. Data and Variables of the study

The dependent variable in this study is monthly wholesale price returns of staple foods in Ethiopia. According to Ethiopia Price Bulletin (2019), the staple foods defined and considered in the study are Maize, Teff and wheat. The independent variables, monthly data, adopted and assumed to affect domestic price volatility from literature. These are fuel oil price-the price of one barrel crude oil in USD, exchange rate-of Birr against the US dollar, general inflation rate-the rate at which the aggregate of price changes for goods and services, fertilizer price and global wheat and maize prices- the price of foods in the international market. Where the fertilizer price computed as an average of prices of Urea and DAP which are imported and used fertilizers in Ethiopia. One year or twelve months lagged world price of fertilizer was used as proxy variable due to lack of domestic fertilizer price data. Data span in the period January 2000 – May 2019 are extracted from the National Bank of Ethiopia, Central Statistical Agency and World Food Program and World Bank Databases.

2.2. Model Selection and Specification

The Autoregressive Moving Average ARMA (s, t) mean model is specified as:

$$y_t = \phi_0 + \sum_{i=1}^{s} \phi_i y_{t-i} - \sum_{j=1}^{t} \theta_j u_{t-j} + u_t$$

Where s is moving average order, t is autoregressive order, $u_t = \sigma_t \nu_t$ and ν_t are iid normal error terms with zero mean and unit variance; y_t is the average monthly staple food price return at time t; σ_t^2 is the conditional variance of the residuals at time t (Box and Jenkins, 1976).

The Generalized Autoregressive Conditional Heteroscedastic GARCH (p, q) model with independent variables for the variance of the residuals at time t is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + X_t' \gamma$$

where $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ are imposed restrictions in order for the variance σ_t^2 to be positive; α_0 indicates long term volatility; $\alpha_1, \alpha_2, ..., \alpha_q$ show the effect of past shocks regardless of their sign and $\beta_1, \beta_2, ..., \beta_p$ show the influence of past volatility on the current volatility; q is ARCH order, p is GARCH order and σ_t^2 is variance of a random shock at time t; $\gamma = (\gamma_1, \gamma_2, .., \gamma_k)'$ is a vector of independent variables coefficients and $X_t = (X_{1t}, X_{2t}, X_{3t}, ..., X_{kt})'$ is a vector of independent variables at time t (Bollerslev, 1986). The GARCH family models enable to handle dynamic structures of conditional variance of the financial series, which are of counting heteroscedasticity in the estimation method and sanctioning parameters estimation simultaneously (Bollerslev, 1986).

According to literature like Nelson (1991), the aforementioned symmetric GARCH model has drawbacks which are the non-negativity restrictions might be disrupted and the leverage effects cannot be explained. To overcome the limitations, Nelson (1991) developed the Exponential GARCH (EGARCH) model that permit asymmetric effects of returns of the positive and negative values and ease the coefficients positivity restriction using logged conditional variance. The asymmetric GARCH model, assuming that price volatility changes asymmetrically for an increase and decrease in price, EGARCH (p, q) model with independent variables for the variance of residuals at time t is:

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left| \frac{u_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \delta_k \left(\frac{u_{t-k}}{\sigma_{t-k}} \right) \sigma_{t-j}^2 + \sum_{j=1}^{p} \beta_j \log(\sigma_{t-j}^2) + X_t' \gamma$$

Where q, p and r is the order of ARCH, GARCH and asymmetric respectively; $\delta_1, \delta_2, ..., \delta_r$ indicate the magnitude of asymmetric effects. The coefficients have no imposed restrictions because the logarithm disables the positivity restriction. The leverage effects existence can be tested by the hypothesis that $\delta_k \neq 0$.

The assumptions of the model are: $E(u_t) = 0$; heteroscedasticity of the errors, $var(u_t) = \sigma_t^2$; the error terms u_t are assumed to follow normal, student-t or a generalized error distribution (GED) with mean zero and variance σ_t^2; the multicollinearity is not severe among the independent variables ; the error terms u_t are serially uncorrelated.

The standard procedure to build a GARCH family model includes four econometric tests. Firstly, unit root tests check the series' stationarity that includes the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron (PP) test (Phillips and Perron, 1987). When the series is the unit root, their difference must be used to reach stationarity. Secondly, ARCH effect tests show whether the errors are significantly Heteroscedastic, which are the Ljung-Box test checks for the existence of a joint serial correlation in the standardized and squared standardized residuals for the first k lags and the Lagrange Multiplier (LM) test checks the serial correlation in the squared residuals for the first q lags. Thirdly, the normality test, Jarque-Bera test is applied to check the time series normality since most financial series data may have thick-tailed distribution. Fourthly, order selection for GARCH family models identify appropriate orders of the models using the Akaike Information Criteria (AIC) and Schwarz Bayesian Information Criteria (SBIC) given the ARCH effects are verified.

2.3. Model Estimation, Adequacy and Accuracy

To estimate the parameters of the GARCH family model, the maximum-likelihood (ML) estimation method is used with a distributional assumption about error terms, the normal, student-t and Generalized Error Distribution (GED). The ML estimation is efficient to estimate the not constant variance of the error terms and the model non-linearity in conditional variance than the ordinary least square estimation. And then, the distribution of the fitting residual in the mean equation is verified via the forecasting ability of the models.

The adequacy of the specified model must be confirmed through the next econometrics tests. The first is the squared standardized residuals have to be indicative of a white noise process using the Autocorrelation Function (ACF) and Partial ACF (PACF). The second is even if student-t and GED are presumed, the standardized residuals have to be IID as standard normal distribution by the Jarque-Bera test (Nelson, 1991). Finally, the absence of autocorrelation for the first k lags must be confirmed using the Ljung-Box test.

The predictive accuracy of ARCH-GARCH family models are assessed through the standard criteria. These are the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Theil

Inequality Coefficient (U). A better model forecasting ability is achieved with the smaller the error statistic.

3. Results and discussion

3.1 Descriptive statistics

The staple food prices of wheat, maize and teff in Ethiopia showed an increasing trend of prices in level and a highly fluctuating return prices over the sample period, January 2000 to May 2019.

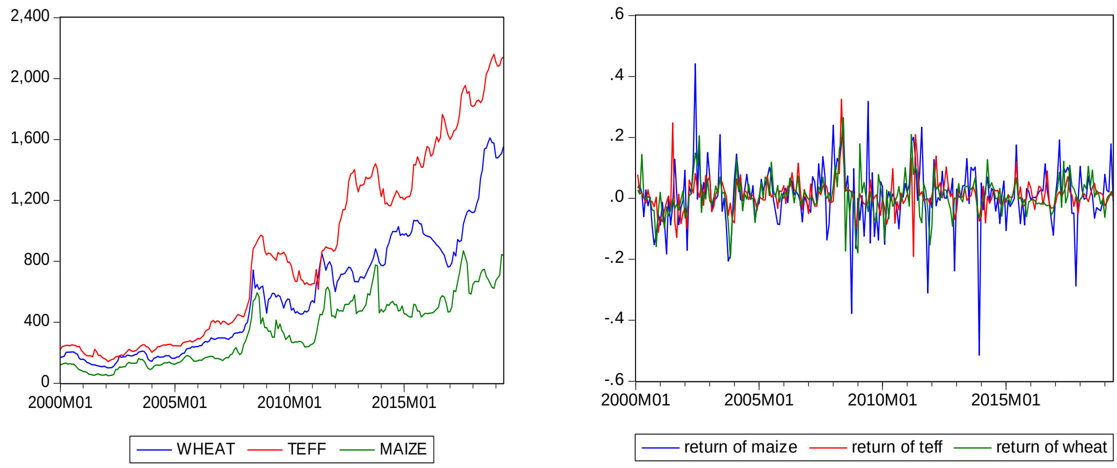

Figure 4.1 staple food prices span January 2000 to May 2019 in level and return, respectively.

3.2. Unit Root Tests

All the endogenous variables, return of maize, wheat, and teff, are stationary at level, but the exogenous variables: exchange rate, general inflation rate, price of crude oil, fertilizer, global wheat, and global maize reached integrated of order one, I(1), series at one percent level of significance as the Augmented Dickey-Fuller (ADF) and Phillip–Perron (PP) tests in Table 1.

3.3. Conditional Mean Model Specification

To compare and find the best estimate of Box–Jenkins models, ARMA (p,q), by the ML method with smallest information criteria, the Schwarz–Bayesian information criterion (SBIC) and AIC, the 15 combinations of ARMA (p,q) are compared and found that the models for monthly return prices of maize with ARMA(1,3), wheat with ARMA(1,0) and teff with ARMA(1,0) were selected.

Table 1: Stationarity tests of the variables in level and difference

Series	**ADF**		**PP**	
	Test statistic	**P-value**	**Test statistic**	**P-value**
Return of maize	-12.894	<0.001	-12.932	<0.001
Return of wheat	-11.808	<0.001	-11.866	<0.001
Return of teff	-12.889	<0.001	-13.044	<0.001
Exchange rate	-14.872	<0.001	-14.872	<0.001
Fuel oil	-9.759	<0.001	-9.740	<0.001
Gene. Inflation	-5.307	<0.001	-11.422	<0.001
Fertilizer (-12)	-4.703	<0.001	-8.471	<0.001
Global wheat	-5.850	<0.001	-12.176	<0.001
Global maize	-12.520	<0.001	-12.671	<0.001
	Test critical value			
	1%	5%	10%	
	-3.458594	-2.87386	-2.573413	

Table 2: Mean Models' Breusch-Godfrey Serial Correlation LM Test

Models	**(q)**	**Chi-square statistic**	**F-statistic**	**SBIC**
Return of Maize (ARMA (1,3))	ARCH1	0.02495 (0.93)	0.122249 (0.98)	-1.70675
	ARCH2	0.24863 (0.78)	0.322249 (0.851)	-1.68539
	ARCH3	2.175246 (0.37)	0.768292 (0.513)	-1.6699
Return of Wheat (AR (1))	ARCH1	1.926188 (0.1675)	1.917159 (0.1652)	-2.72102
	ARCH2	2.537549 (0.2812)	1.260653 (0.2854)	-2.70013
	ARCH3	3.461944 (0.3257)	1.146181 (0.3313)	-2.68062
Return of Teff (AR (1))	ARCH1	1.266202 (0.2605)	1.256646 (0.2635)	-2.96539
	ARCH2	1.279189 (0.5275)	0.632019 (0.5325)	-2.94189
	ARCH3	4.395106 (0.2218)	1.461125 (0.226)	-2.93199

Note: p-values are inside parenthesis.

For the best conditional mean equations, the Breusch–Godfrey serial correlation LM test was used to check the presence of serial correlation in the residuals, in which the null hypothesis states that there is no serial correlation in the residual series up to lag 3. The test results, in Table 2, show no serial correlation in the residuals. The Jarque–Bera test of normality indicated the residuals of the fitted best mean models are normally distributed. Also, the ARCH effect test for the squared residuals of the models was conducted with the null hypothesis of no ARCH effect in the first three lags of residuals and found that there was a heteroscedasticity or ARCH effect in Table 3. So, the GARCH family models enable to handle the non-constant variance or ARCH effect.

Table 3: Mean Models' LM Test of ARCH Effect Test for Squared Residuals

Models	(q)	Chi-square statistic	F-statistic	SBIC
Return of Maize (ARMA (1,3))	ARCH1	12.32575 (<0.001)	11.656 (<0.001)	-6.40192
	ARCH2	14.07385 (<0.001)	6.323 (<0.001)	-6.29171
	ARCH3	14.00384 (<0.001)	4.323 (<0.001)	-6.18171
Return of Wheat (AR (1))	ARCH1	21.75573 (<0.001)	23.80979 (<0.001)	-6.84442
	ARCH2	26.34821 (<0.001)	14.68448 (<0.001)	-6.83989
	ARCH3	26.2401 (<0.001)	9.7061 (<0.001)	-6.82849
Return of Teff (AR (1))	ARCH1	11.32575 (<0.001)	11.80656 (<0.001)	-6.60192
	ARCH2	15.07385 (<0.001)	7.960323 (<0.001)	-6.59171
	ARCH3	15.01682 (<0.001)	6.960323 (<0.001)	-6.56271

Note: p-values are inside parenthesis.

3.4. GARCH Family Models: Order and Error Distribution Selection

Given the ARCH effect in the conditional mean models was occurred, the best GARCH family models should be identified concerning their minimum SBIC, forecast error accuracy, and asymmetric effect significance. Accordingly, out of the GARCH family models, the GARCH, GARCH-M, and EGARCH models for the three price return series were considered and estimated by ML method with the normal, student's t, and GED error distribution assumptions. The study considered different orders and error distributions and found nine candidate models for each price volatility of maize, wheat and teff based on their minimum SBIC as summarized in Table 4. Then, a best-fit model for each price volatility models was identified by their forecasting performance or RMSE, remaining ARCH effect and significance of the asymmetric effect.

Table 4: Selected Candidate GARCH family model with error distribution for the returns series

	ARMA(1,0)-WHEAT		**ARMA(1,0)-TEFF**		**ARMA(1,3)-MAIZE**	
Distribution	**Specification**	**SBIC**	**Specification**	**SBIC**	**Specification**	**SBIC**
Normal	GARCH (3,3)	-2.88966	GARCH (1,1)	-3.13636	GARCH (1,0)	-1.692413
t	GARCH (1,1)	-2.93166	GARCH (1,1)	-3.33515	GARCH (1,0)	-1.875129
GED	GARCH (1,1)	-2.96587	GARCH (1,1)	-3.32150	GARCH (1,1)	-1.893727
Normal	GARCH-M(2,1)	-2.83035	GARCH-M(1,1)	-3.11287	GARCH-M(2,2)	-1.729853
t	GARCH-M(1,1)	-2.91081	GARCH-M(1,1)	-3.31192	GARCH-M(1,2)	-1.858887
GED	GARCH-M(1,1)	-2.94325	GARCH-M(2,1)	-3.30700	GARCH-M(1,0)	-1.879405
Normal	EGARCH(1,1)	-2.81073	EGARCH(3,2)	-3.18176	EGARCH(1,0)	-1.740837
t	EGARCH(1,2)	-2.89487	EGARCH(1,1)	-3.31096	EGARCH(2,1)	-1.882376
GED	EGARCH(1,1)	-2.94351	EGARCH(3,1)	-3.30430	EGARCH(1,1)	-1.893455

Table 5: Forecast accuracy measures for the candidate models of the staple foods price

	AR(1) WHEAT		AR(1) TEFF		ARMA(1,3) MAIZE	
Distribution	**Specification**	**RMSE**	**Specification**	**RMSE**	**Specification**	**RMSE**
Normal	GARCH (3,3)	0.062061	GARCH (1,1)	0.053946	GARCH (1,0)	0.100396
t	GARCH (1,1)	0.062192	GARCH (1,1)	0.054000	GARCH (1,0)	0.100999
GED	GARCH (1,1)	0.062263	GARCH (1,1)	0.053941	GARCH (1,1)	0.100994
Normal	GARCH-M(2,1)	0.063820	**GARCH-M(1,1)**	**0.053923**	GARCH-M(2,2)	0.100984
t	GARCH-M(1,1)	0.063964	GARCH-M(1,1)	0.054123	GARCH-M(1,2)	0.104426
GED	GARCH-M(1,1)	0.062423	**GARCH-M(2,1)***	**0.053895**	GARCH-M(1,0)	0.101088
Normal	**EGARCH(1,1)**	**0.062013**	**EGARCH(3,2)***	**0.053891**	**EGARCH(1,0)**	**0.100352**
t	EGARCH(1,2)	0.062397	EGARCH(1,1)	0.054019	EGARCH(2,1)	0.100991
GED	EGARCH(1,1)	0.062293	EGARCH(3,1)	0.054094	EGARCH(1,1)	0.100527

Note: *the models are with the smallest accuracy measures but insignificant asymmetric effect

According to Table 5, using the model selection criteria-merely SBIC presented, forecast accuracy measures-only RMSE displayed, and asymmetric effect significance, a best-fit models for monthly return prices of maize, wheat and teff were selected as ARMA(1,3)-EGARCH(1,0), AR(1)-EGARCH(1,0) and AR(1)-GARCH-M(1,1) respectively with the same normal error distribution assumptions. While the EGARCH (3, 2) and GARCH(2,1) were with the smallest forecast accuracy measures but the insignificant asymmetric effect and remaining ARCH effect respectively.

3.5. Results of Fitted Models

The best GARCH family models with similar normal error distribution were identified and estimated as the return of maize with ARMA (1,3)-EGARCH(1,0), return of wheat with AR (1)-EGARCH(1,1) and return of teff with AR (1)-GARCH-M(1,1).

As Table 6 (in maize column) displays, the variables exchange rate, and global maize price are statistically significant in explaining current month maize price volatility in Ethiopia at the ten percent significant level. Whereas, all the remaining variables show a non-significant impact on the current month maize price volatility. The coefficient estimate of global maize price and the exchange rate was negative and positive respectively. Consequently, the global maize price decrease and exchange rate depreciation tip to the increase in the current month maize price volatility. This shows that the money market and global substitute commodity influence the domestic maize market. The results are in line with Zheng et al. (2008) and Abule (2012) under the exchange rate and Worako et al., (2008) under global maize price. Additionally, the result indicates that one month lagged maize price volatility, EGARCH lagged order one, is statistically significant at the one percent level and affected the current month maize price volatility. On the other hand, the asymmetric positive and significant effects show that the maize price volatility rises to turn in response to bad news (an unanticipated increase in the price) than impact good news (an unanticipated decrease in the price).

Table 6: The Best Volatility Models of Staple foods with ML Parameter Estimates

Variables	Maize	Wheat	Teff
Sqrt(GARCH)	-	-	0.2525 (0.1714)
Constant	0.0204 (<0.001)	0.0122 (0.0065)	-0.0010 (0.9011)
AR(1)	0.9469 (<0.001)	0.2290 (0.0003)	0.1396 (0.0800)
MA(1)	-0.7497 (<0.001)	-	-
MA(2)	-0.0820 (0.4057)	-	-
MA(3)	-0.1453 (0.0730)	-	-
Constant	-0.8509 (0.0007)	-5.2084 (<0.001)	0.0014 (0.0010)
ARCH(-1)	-	0.5531 (<0.001)	0.0627 (0.0337)
GARCH(-1)	-	-	0.4404 (0.0085)
Asymmetric(-1)	0.3342 (<0.001)	-0.1762 (0.0729)	-
EGARCH(-1)	0.8204 (<0.001)	0.1695 (0.1528)	-
Exchange rate	0.2185 (0.0922)	-0.9485 (0.0186)	-0.0006 (<0.001)
Fuel oil	0.0047 (0.6016)	0.0037 (0.8686)	0.0001 (<0.001)
General inflation	-0.0033 (0.8613)	0.1685 (0.0060)	0.0001 (0.3811)
Fertilizer (-12)	-0.0016 (0.1151)	-0.0038 (0.0569)	-0.0001 (0.0079)
Global wheat	-0.0023 (0.5874)	-0.0165 (0.0101)	-0.0001 (<0.001)
Global maize	-0.0100 (0.0683)	0.0205 (0.0281)	0.0001 (<0.001)

Note: p-values are inside parenthesis.

As a result in Table 6 (in a wheat column) shows, all variables except crude oil are statistically significant in explaining the current month price volatility of wheat in Ethiopia at different percent significant level. The coefficient estimate of prices of the general inflation rate and global maize were positive. As a result, the general inflation rate and global maize increase tip to the increase in the current month price volatility of wheat. These show that the money market and global substitute commodity impact the domestic wheat market which was in line, respectively, with the result of Zheng et al. (2008) and Worako et al., (2008). The global wheat price, fertilizer price and exchange rate, ETB against USD, coefficient were negative and significant at different percent level, which revealed a decrease in the fertilizer price, global wheat price and depreciation of the exchange rate had a noteworthy contribution to the rise in the price volatility of wheat. These finding are in line with Worako et al., (2008), Abule (2012) and Regmi, H. R. (2008) who stated that the wheat prices had no significant association with the global wheat price, exchange rate and fertilizer price respectively. Explicitly, the findings indicate that wheat volatility returns to the money market and global commodity input and substitute variables. Moreover, the result shows that the first month lagged shock, ARCH lagged order one, of the wheat price, is statistically significant at the one percent level and influenced the current month wheat price volatility. Also, an asymmetric negative and significant effect shows that the wheat price volatility inclines to turn in reaction to good news (an unanticipated decrease in the price) than bad news (an unanticipated increase in the price).

As a result in Table 6 (in teff column) shows, all variables except general inflation are statistically significant in explaining current month price volatility of teff in Ethiopia at the 1 percent significant level. While, the variable general inflation rate displays a non-significant impact on the current month teff price volatility, which is in line with the results of Zheng et al. (2008) who stated that the general inflation rate has no significant impact on the teff price volatility, but it is not in line with the results of Khin (2010). The coefficient estimate of prices of crude oil and global maize was positive. As a result, the price of crude oil and global maize increases tip to the increase in the current month price volatility of teff. These show that the energy market and global substitute commodity impact the domestic teff market which was in line with the result of Baffes (2017)and Zheng et al. (2008), and inconsistent with Khin (2010). The coefficient of fertilizer price, the exchange rate (ETB against USD) and global wheat price were negative, that is, the price volatility of teff could increase as the depreciation of the exchange rate and price of fertilizer and global wheat decreases. This finding was in line with Zheng et al. (2008) who stated that the prices of the commodity produced merely domestically are associated with the prices of global input for and substitute to the commodity. On the other hand, this finding was not consistent with Khin (2010) who stated that the domestically produced commodity prices had no significant association with the price of the global commodity. Explicitly, the findings indicate that teff volatility returns to global commodity input and substitute variables. Moreover, the finding shows that the first month lagged shock, ARCH lagged order one, of teff price, is statistically significant at the five percent level and influenced the current month teff price volatility. Likewise, one month lagged teff price volatility, GARCH lagged order one, is statistically significant at the one percent level and affected the current month teff price volatility.

The remaining ARCH effect tests were made as in Table 7. The null hypotheses: no ARCH effects were failed to reject the standardized residuals of the fitted volatility models. Therefore, the fitted variance models had no significant remaining ARCH effects.

Table 7: Remaining ARCH effect tests for the estimated variance models

Models	ARCH(q)	Chi-square statistic (q)	F-statistic
Return of maize (ARMA (1,3)-EGARCH(1,0))	ARCH1	0.0009 (0.976)	0.0008 (0.976)
	ARCH2	1.0127 (0.603)	0.5019 (0.606)
	ARCH3	1.2699 (0.736)	0.4182 (0.740)
Return of wheat (AR (1)-EGARCH(1,1))	ARCH1	0.0573 (0.811)	0.0568 (0.812)
	ARCH2	1.5301 (0.465)	0.7601 (0.469)
	ARCH3	2.9150 (0.405)	0.9670 (0.409)
Return of teff (AR (1)-GARCH-M(1,1))	ARCH1	1.9630 (0.161)	1.9627 (0.162)
	ARCH2	2.2804 (0.319)	1.1366 (0.322)
	ARCH3	2.4003 (0.493)	0.7944 (0.498)

Note: p-values are inside parenthesis.

4. Conclusion and Policy Implications

Analyzing the staple food price volatility and its core drivers have important contributions to food market management and risk valuation. Since the food price inflation in the Ethiopian economy commenced suffering high rates in 2004 that pose risks for poor people's livelihoods and food security. The staple food prices revealed stylized facts of financial time series and confirmed ARCH effects presence in condition mean equations. Since the generalized autoregressive conditional heteroscedasticity (GARCH) family models were applied to the price series in the period of January 2000 to May 2019. The ADF and PP unit root tests imply that all independent variables became stationary after the first differences transformation and the three dependent price return variables were stationary at level. A best-fit models for monthly return prices of maize, wheat and teff were selected and modeled using ARMA(1,3)-EGARCH(1,0), AR(1)-EGARCH(1,0) and AR(1)-GARCH-M(1,1) respectively with the same normal error distribution assumptions based on the model selection criteria using AIC and SBIC; forecast error accuracy using the MAE, MAPE, and RMSE; and asymmetric effect significance. One month lagged shock of the price of maize has statistically significant effects on the current month's volatility. The maize price volatility inclines to go in response to bad news than good news while the wheat responses to good news than bad news. One month lagged shocks of the price of wheat has statistically significant effects on the current month's volatility. The impact of the price of the fertilizer and global-wheat and exchange rate on the conditional variances of the Ethiopian wheat has become stable than the general inflation rate. The influence of the price of the fertilizer and global-wheat and exchange rate on the conditional variances of the Ethiopian teff has to stabilize than the fuel oil price. Also, the global maize price decrease makes a more stable marketing environment with a more volatile Ethiopian maize price. As a merely economic policy implementer, to sustain the Ethiopian food market, the Ethiopian government should provide more devotion to the influential factors, and must draw and execute flexible trade, investment, exchange rate, and monetary policies which shall consider and go with the dynamic internal and global markets.

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Author contributions

WT considered of the study, performed the statistical and econometric analysis. The author reads and approved the final manuscript.

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Competing interests

The author declares that he has no competing interests.

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