Statistical Analysis of the Volatility of the Export Price of Coffee in Ethiopia

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Abstract

Ethiopia is credited as being the birthplace of coffee. In Ethiopia, the export price of coffee is among the most volatile agricultural commodity prices. This study attempted to identify and analyze the factors that are correlated with the volatility of the export price of coffee in Ethiopia using data spanning from January 2002 to June 2016. Most of the series considered in this study were found to be integrated of order one or I(1). The monthly export price return series exhibited the stylized facts of financial time series such as volatility clustering and leptokurtosis. Thus, the ARCH family models (GARCH and EGARCH models) with ARMA mean equations were fitted to the data. ARMA (1, 1)-EGARCH (3, 1) model with normal error distributional assumption was selected as the best-fit model since the asymmetric term was significant and the forecasting error as well as AIC and BIC were smaller. Among the exogenous variables considered in this study, fuel oil price, non-food price, exchange rate and some of the seasonal dummies were found to have a statistically significant effect on the volatility of the export price return series. The significance of the asymmetric term indicates that an unanticipated decrease in the export price of coffee had a significantly higher impact on price volatility than unanticipated increase in the price. Additionally, past shocks and lagged volatility of export price had statistically significant effect on the price volatility of coffee.

Keywords: *Export price of coffee, Stationarity, Volatility, ARMA, EGARCH*

1. Introduction

Most of the literature regarding commodity markets has focused on price levels rather than price volatilities. There is a need for a clear distinction between these two aspects. Most internationally traded agricultural commodities are storable so that high price volatility is indeed more likely when prices are high and stocks are low. Nevertheless, a qualified discussion of the drivers of price volatility requires a careful distinction between drivers of price levels and drivers of price volatility.

In the past, international coffee prices have been quite volatile and such volatilities were driven by a mix of climatic conditions in the largest coffee-producing countries, expectations about future prices, changes in demand and interest rates, as well as speculation (Deaton 1999). Price volatility in commodity markets has been studied extensively in the academic literature. According to Newbery (1989), commodity prices in general, and agricultural commodity prices in particular, are renowned for their continuously volatile nature.

Exchange rate can affect commodity prices through a number of channels, including international purchasing power. Using co-integration analysis, Gilbert (1989) found that domestic food price is significantly influenced by exchange rate in the long-run. According to Liefert and Persuad (2009), exchange rate movements can influence countries' domestic and export prices, thereby affecting incentives to produce, consume and trade goods.

According to the finding of Frankel (1986) using linear regression model, interest rate has a significant influence on the agricultural market in general by affecting the cost of holding inventory, investment decision (land, machinery and input purchases) and the overall farm business risks. Frankel (2006) also suggested that interest rate plays an important role in determining total commodity supply and rising interest rates often lead to a decline in commodity prices. Moreover, the study reported that the level of real interest rate affects commodity prices through a number of supply and demand channels. Hammoudeh and Yuan (2008) using GARCH model also found that rising interest rates have a dulling effect on price volatility.

Swaray (2007) found that fluctuations in business cycles and macroeconomic variables, including fuel oil prices, have significant impact on non-fuel primary commodities. Baffes (2007) found that fuel oil price affects the price of agricultural commodities. Maurice & Davis (2011) using Granger Causality models found that there is a long-run causality between oil prices and coffee. Using EGARCH model, Maurice & Davis (2011) reported that a large increase in oil prices (listed as a negative shock) has a lower impact on coffee price variability than a steep decline in oil prices (positive shock) of a similar magnitude, that is, in a world of high oil prices, coffee price volatility is not as excessive as in a context of low oil prices.

Chambers (1984) studied the extent to which macroeconomic factors alter agricultural prices and found that real, aggregated agricultural prices have not been altered by the level of general inflation. According to Moledina et al. (2003), the production of a particular agricultural commodity is dependent on growing seasons. The dependence of production of a specific commodity on growing seasons can cause seasonal variations in supply and demand. The variation in supply and demand of commodities in turn causes seasonal fluctuations in prices.

Volatility in the price of coffee influences large proportion of the population all along the coffee commodity chain in Ethiopia (Yohannes, 2010). Worako et al. (2011) have made a distinction between producer, wholesale and export prices in order to compare the price risk faced by the respective participants in the coffee chain. The study also tried to compare the price volatility of Ethiopian and Brazilian coffee (major coffee producing countries in the world) and found that coffee prices within Ethiopia were more volatile than in Brazil. Moreover, producer prices were found to be the most volatile, followed by wholesale prices and export prices.

In the past, coffee prices have exhibited high inter-year (seasonal) variations in Ethiopia. These variations are a combined effect of the factors reflecting domestic supply and the periodic trends of the global coffee demand and supply situation (ECX, 2012). Coffee production and marketing in Ethiopia have influenced the export price of coffee due to low quality, poor market infrastructure, and long and traditional marketing channels. These could cause sudden fluctuations in export price of coffee, worsen price instability and create serious problems in the national income.

Price volatility does not usually affect a single market, but spillovers abound. Zerihun & Worako (2011) studied the interrelationships among producer, auction and world prices based on monthly price data ranging from October 1992 to September 2006 in Ethiopia. Using VAR and VECM models, they found that there is a unidirectional transmission of shocks from the world price to the auction price and then to the producer price. The study also revealed the presence of asymmetries in price transmissions and adjustments in the auction market, and weak interrelationship between producer and world prices causing producer prices to be less responsive to changes in the world price. In general, their results suggest that coffee growers benefit little from positive changes in the world price compared to participants in the auction markets.

Worako et al. (2008) studied the price of the producer, auction and Free-On-Board price (FOB) using data that extend from October 1992 to September 2006. The price data included in the analysis were comprised of four major Ethiopian coffee types by original growing region (Sidama, Harar, Wollega and Jimma). Using ECM, they found that there is a strong, long-run relationship among growers, wholesaler and exporter prices. The estimation of the ECM shows the transmission of price shocks from the world price to the auction price and then to the product price. According to Worako et al. (2008), the domestic price of coffee in Ethiopia adjusts more rapidly to world price changes.

Several studies related to the price of coffee have been conducted in Ethiopia (e.g., Bart et al., 2014; Worako et al., 2011). However, as to the authors' knowledge, none of them have focused on identifying significant drivers of the export price volatility of coffee. To fill this gap, this study attempted to investigate the potential factors that affect the volatility of the export price of coffee in Ethiopia by utilizing financial time series models.

2. Materials and Methods

2.1 Variables considered in the study

The response variable in this study is the monthly export price return of coffee in Ethiopia. The explanatory variables that are assumed to affect the export price volatility of coffee in Ethiopia include the following:

- Exchange rate (US Dollar to Birr).
- Saving interest rate: the interest rate paid to deposit account holders for accounts like certificates of deposit and savings accounts
- Fuel oil price: the price of one metric ton fuel oil (in Birr).
- Inflation rate for food items: A quantitative measure of the rate at which the average price level of a basket of food items in an economy increases over a period of time
- The inflation rate for non-food items: A quantitative measure of the rate at which the average price level of non-food items in an economy increases over a period of time
- Domestic price: the price of Ethiopian coffee in the Ethiopian market.
- GDP: total output or the output values of goods and services at market prices excluding net income from abroad (in millions of Birr).
- Total government revenue: revenues earned by the government which are received from sources such as taxes levied on the incomes and wealth accumulation of individuals and corporations and on the goods and services produced, exports and imports, non-taxable sources such as government-owned corporations' incomes, central bank revenue and capital receipts in the form of external loans and debts from international financial institutions.

2.2 Statistical model specification

2.2.1 Mean model

The Autoregressive Moving Average (ARMA (p, q)) model is given by (Box and Jenkins, 1976):

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad \text{......} (1)$$

where Y_t is the average monthly export price return of coffee at time t, ε_t is a white noise random error term, and p and q are the autoregressive and moving average orders, respectively.

2.2.2 Variance Model

The Generalized Autoregressive Conditionally Heteroscedastic (GARCH (r, m)) model for the conditional variance of the residuals at time t is given by (Bollerslev, 1986):

$$\varepsilon_t = \sigma_t \upsilon_t$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2 \quad \text{...} \; (2)$$

where $\{\upsilon_t\}$ is a sequence of independent and identically distributed random variables with mean zero and variance one, $\sigma_t^2 = E(\varepsilon_t^2 \mid \psi_{t-1})$, and r and m are the ARCH and GARCH orders, respectively. Here ψ_{t-1} denotes the information set up to and including time (t−1). The restrictions $\alpha_0 > 0$, $\alpha_i \geq 0$ for $i = 1, 2, \ldots, r$ and $\beta_j \geq 0$ for $j = 1, 2, \ldots, m$ are imposed to ensure that the conditional variance is positive. The process is covariance stationary if and only if $\sum_{i=1}^{r} \alpha_i + \sum_{j=1}^{m} \beta_j < 1$. The GARCH (r, m) model with explanatory variables is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2 + f(X_t \,,\, \Upsilon) \quad \text{.....................................} \; (3)$$

Here the function $f(X_t \,,\, \Upsilon)$ is assumed to be strictly positive, where $X_t = (X_{1t}, X_{2t}, \ldots, X_{kt})'$ is a vector of explanatory variables at time t and $\Upsilon = (\gamma_1, \gamma_2, \ldots, \gamma_k)'$ is a vector of regression coefficients that quantify the effect of explanatory variables on the conditional variance.

A variant of the GARCH model which allows for asymmetric effects is the Exponential GARCH (EGARCH) model introduced by Nelson (1991). The EGARCH (r, m) model for the conditional variance of the residuals at time t is given by:

$$\varepsilon_t = \sigma_t \upsilon_t$$

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{r} [\alpha_i \mid \upsilon_{t-i} \mid + \; \delta_i \upsilon_{t-i}] + \sum_{j=1}^{m} \beta_j \ln(\sigma_{t-j}^2) \quad \text{...........................} \; (4)$$

Here $\delta_1, \delta_2, \ldots, \delta_r$ quantify the magnitude of asymmetric effects. No restriction is imposed on the coefficients of the model since the logarithmic transformation overcomes the positivity constraint. The presence of leverage effects can be tested by the hypothesis that $\delta_i \neq 0$, $i = 1, 2, \ldots, r$.

GARCH family model building process takes into account the following tests:

a) Test for the presence of a unit root

Unit root tests need to be performed to examine the stationarity of the series under study. In this regard, the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips-Perron (PP) test (Phillips and Perron, 1988) have been used for the said purpose.

b) Test for ARCH effects

In financial time series, ARCH effect is common (Asteriou and Hall, 2007). In this study, the Lagrange Multiplier (LM) test was used to check for the presence of ARCH effects by testing the significance of serial correlations in the squared residuals for the first few lags.

c) Test of normality

Financial time series often have thick tailed distribution indicating a departure from the normal distribution. Thus, the Jarque-Bera test was used to test the normality of the time series under consideration.

2.2.3 Order selection for GARCH family models

Once we are certain that ARCH effects are present in the financial time series under study, the next step involves identifying the appropriate orders for GARCH family models using Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC).

2.2.4 Parameter estimation for GARCH family models

Since GARCH family models are no longer of the usual linear from, OLS cannot be used for model estimation. One of the reasons is that OLS minimizes the residual sum of squares which depends only on the parameters of the conditional mean equation, and not on the parameters of the conditional variance equation. Another reason is that, under the presence of ARCH effects, OLS estimation is not efficient since the conditional variance of the errors is not constant. Due to these reasons, the maximum-likelihood (ML) estimation method was used to estimate the parameters of GARCH family models by assuming normal, student-*t* and Generalized Error Distribution (GED) for the error term.

The log-likelihood functions under different distributional assumptions are:

a) If $\varepsilon_t \sim N(0, \sigma_t^2)$, the log-likelihood function is given by:

$$\ln(L) = \sum_{t=1}^{T}\left(-\frac{1}{2}\log(2\pi) - \frac{1}{2}\ln(\sigma_t^2) - \frac{\varepsilon_t^2}{2\sigma_t^2}\right) \quad \ldots\ldots (5)$$

b) If $\varepsilon_t \sim t(0, \sigma_t^2, \nu)$, where ν is the number of degrees of freedom, then the log-likelihood function is given by:

$$\ln(L) = \sum_{t=1}^{T}\left[\log\left(\Gamma\left(\frac{\nu+1}{2}\right)\Big/\Gamma\left(\frac{\nu}{2}\right)\right) - \frac{1}{2}\ln\left(\frac{\pi(\nu-2)}{\sigma_t^2}\right) - \left(\frac{\nu+1}{2}\right)\ln\left(1 + \frac{\varepsilon_t^2}{\sigma_t^2(\nu-2)}\right)\right] \quad \ldots\ldots (6)$$

where $\Gamma(\bullet)$ is the Gamma function.

c) Under the assumption that the errors follow independent GED with mean zero, variance $\sigma_t^2 > 0$ and degree of freedom (shape parameter) $\nu > 0$, that is, $\varepsilon_t \sim GED(0, \sigma_t^2, \nu)$, we have:

$$\ln(L) = \sum_{t=1}^{T}\left[\ln\left(\frac{\nu}{\lambda}\right) - \ln\left(\Gamma\left(\frac{1}{\nu}\right)\right) - \frac{1}{2}\ln\left(\sigma_t^2\right) - \left(1 + \frac{1}{\nu}\right)\ln(2) - \frac{1}{2}\left(\frac{\varepsilon_t^2}{\lambda^2\sigma_t^2}\right)^{\nu/2}\right] \quad \ldots\ldots (7)$$

The appropriate distribution for the residuals in the mean equation can be determined based on the forecasting ability of the models under the specified error distribution. The Root Mean Square Error (RMSE) and Theil Inequality Coefficient (U) are among the measures of the forecasting accuracy of ARCH-GARCH models.

2.2.5 Model adequacy checking

After fitting GARCH family models, it is necessary to check that the model actually does provide an adequate description of the time series under consideration. If the final model is good-fit to the data, then the partial autocorrelation function (PACF) of the squared standardized residuals should be indicative of a white noise process. The Ljung-Box test could be used in this regard. Moreover, the standardized residuals should be independent and identically distributed as standard normal even if the Student-t or the GED are assumed (Tsay, 2005). This can be checked using the Jarque-Bera test.

3. Results and Discussion

3.1 Descriptive analysis

The data set used in this study consist of the monthly export price of coffee (in Birr per Kg), the domestic price of coffee (in Birr per Kg), food inflation, nonfood inflation, fuel oil price (in Birr per metric ton), real GDP (in millions of Birr), exchange rate (US dollar to Birr), saving interest rate and total government revenue (in millions of Birr) in Ethiopia from January 2002 to December 2016. Summary statistics of the export price of coffee and selected macro-economic variables are presented in Table 1 below.

The average monthly export price of coffee was Birr 44.494 ($1.58) per kg with a standard deviation Birr 28.329 ($1.01). The coefficient of variation of about 64% tells us that there is large variation in the monthly export price of coffee. Moreover, the coefficient of kurtosis is indicative of excess kurtosis (leptokurtic distribution). These features are also shared by most of the other covariates. The presence of a considerable variation within independent variables across time might induce volatility in the export price of coffee.

Table 1: Summary statistics for macroeconomic variables

Variable	Mean	Median	Std. Dev.	Coe. of Var.	Skewness	Kurtosis
Export price of coffee	44.49	32.46	28.33	63.67	2.59	16.64
Domestic price of coffee	45.53	37.10	28.59	62.80	4.79	46.08
Food inflation	15.35	11.85	15.60	101.61	1.13	3.97
Non-food inflation	11.22	0.44	7.62	67.93	0.21	1.92
Fuel oil price	47588.98	7337.09	27887.30	58.60	3.43	14.59
Exchange rate	13.08	10.34	4.81	36.73	0.44	1.48
Saving interest rate	4.11	4.25	0.92	22.48	-0.15	1.44
GDP	386086.50	274480.82	324329.02	84.00	0.63	1.83
Revenue	74261.66	47788.29	365667.03	492.40	0.97	2.75

Time series plot of the monthly export price of coffee (Birr per Kg) is shown in Figure 1. In general, the export price of coffee exhibited an increasing trend from 2002 up to 2016. Some fluctuations (ups and downs) are observed from 2009 to 2012 and around the end of the study period.

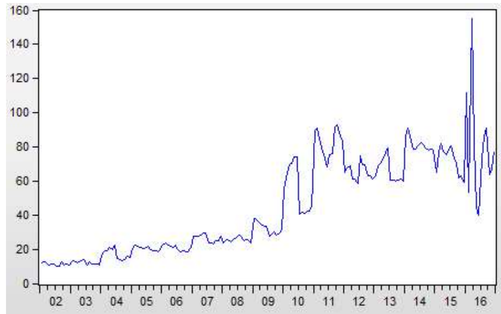

Figure 1: Time series plot of the monthly export price of coffee

The export price return series is plotted in Figure 2. We can observe that the return series revolves around a constant mean with no apparent trend. Moreover, the monthly export price return series exhibited the stylized facts of financial time series such as volatility clustering, that is, periods of high volatility followed by high volatility, and similarly for low volatility processes.

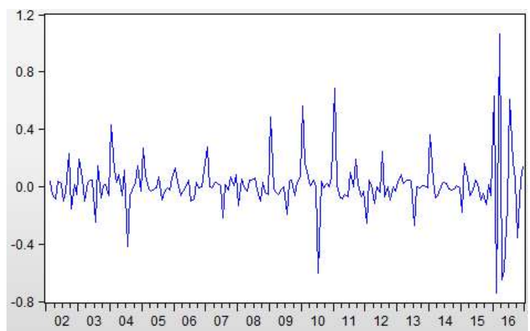

Figure 2: Time series plot of the monthly export price return of coffee

3.2 Tests of normality

Different literatures indicate that the distribution of price returns exhibit features such as leptokurtosis and volatility clustering (Cornew et al., 1984). In this study, the Jarque-Bera (JB) test has rejected the null hypothesis of normality for the monthly export price return series at the 1% level of significance. The non-normality of the return series might be due to the existence of excess kurtosis that we have observed from the descriptive statistics in Table 1.

3.3 Unit-root tests

The series should be stationary in order to fit a suitable time series model. The augmented Dickey-Fuller (ADF) test was used to check whether the series under consideration are stationary or not. It tests the null hypothesis that the series has a unit-root versus the alternative that the series is stationary. The ADF test results are presented in Table 2. The results indicate that domestic price of coffee and food inflation are stationary at level, while all other macroeconomic variables are stationary at first difference.

Table 2: Unit-root test results

	At level		First difference	
Variables	ADF test statistic	p-value	ADF test statistic	p-value
Export price of coffee	-2.817	0.215	-20.426	0.000
Domestic price of coffee	-3.934	0.002		
Food inflation	-5.192	0.009		
Non-food inflation	11.218	0.245	-7.898	0.000
Fuel oil price	-2.879	0.245	-15.532	0.000
Exchange rate	1.584	0.999	-11.299	0.000
Saving interest rate	-2.282	0.179	-13.273	0.000
GDP	-0.056	0.951	-13.236	0.000
Revenue	2.554	1.000	-13.429	0.000

3.4 Mean equation specification and selection

In order to model the volatility of the return series, we need to specify their mean equation first. In the specification of the mean equation, the sample ACF and PACF plots of the stationary series can be used to tentatively identify the order of autoregressive terms and/or moving average terms. However, the final model is often selected based on information criteria.

In most applications, lower order ARMA models are often considered. Thus, the 15 combinations of AR (0 - 3) and MA (0 - 3) models were fitted in this study. Among these candidate models, ARMA (1,1) model was found to have the smallest AIC and SBIC, and hence, was used as the mean equation for the export price return of coffee. The fitted mean model is shown in Table 3 below.

Table 3: The fitted mean equation for average monthly export price return series

Variable	Coefficient	Std. error	T-statistic	p-value
C	0.011	0.003	3.451	0.000
AR (1)	0.565	0.094	6.008	0.000
MA (1)	-0.898	0.051	-17.574	0.000

3.5 Tests for the presence of ARCH effects

ARCH effect is commonly found in financial time series (Cotter and Stevenson, 2006). Based on the residuals from the mean equation, it is possible to test for the existence of ARCH effects using the ARCH LM test. The results of the ARCH LM test for the residuals of the fitted ARMA (1,1) model for the export price return series indicated that the current squared residual is significantly correlated with first two lags of squared residuals. Consequently, we need to use GARCH family models.

3.6 GARCH-family model selection

Even though ARCH models have attractive properties, a large number of lags (q), and thus, a large number of parameters, are required to obtain a good model fit. A GARCH model with low orders, on the other hand, results in a more parsimonious representation of the conditional variance process (Anderson, 2009). To choose the best-fit GARCH model among candidate volatility models, Akaike Information Criterion (AIC) and Schwarz Bayesian information Criterion (SBIC) are often used. Note that the AIC and BIC of the GARCH models are obtained by estimating the mean and variance equations simultaneously.

In our model selection procedure, various low order GARCH family models were considered. Among these models, ARMA (1,1)-EGARCH (3,1), ARMA (1,1)-EGARCH (2,3) and ARMA (1,1)-EGARCH (3,3) models with normal, Student's-t and GED distributional assumptions for the residuals, respectively, were selected for the export price return volatility of coffee. To select the appropriate conditional volatility model among these candidate models, we considered their forecasting performance. The forecasting performance of the fitted GARCH family models was evaluated by RMSE and Theil inequality coefficients.

A summary of forecast accuracy measures for the candidate GARCH-family models is given in Table 4. We can observe that EGARCH (3,1) model with normal distributional assumption for the residuals possesses the smallest forecast accuracy measures, and that the asymmetric effect is significant. Thus, this model was selected to describe and analyze the export price volatility of coffee.

Table 4: Summary of forecast accuracy measures

Model	Error distribution	Forecast accuracy measures		Asymmetric effect
		RMSE	Theil	
ARMA (1,1)-EGARCH (3,1)	Normal	0.190	0.958	Significant
ARMA (1,1)-EGARCH (2,3)	GED	0.191	0.993	Insignificant
ARMA (1,1)-EGARCH (3,3)	Student-t	0.191	0.974	Insignificant

3.7 Parameter estimation

Once the ARMA (1,1)-EGARCH (3,1) model with normal distributional assumption for the residuals is selected, then the next step is to estimate the parameters of the model using the maximum likelihood approach. The results are given in Table 5.

Table 5: Fitted ARMA (1,1)-EGARCH (3,1) model under normal distributional assumption of the residuals for the return series of export price of coffee

	Variables	Coefficients	Std. Error	Statistic	P-value
Mean equation	Constant	0.014	0.003	4.116	0.000*
	AR (1)	-0.989	0.005	-210.171	0.000*
	MA (1)	0.987	0.005	204.407	0.000*
Variance equation	Constant	-0.852	0.679	-1.255	0.210
	ARCH (-1)	0.958	0.182	5.272	0.000*
	Asymmetric (1)	0.233	0.097	2.408	0.016**
	EGARCH (-1)	1.376	0.082	16.878	0.000*
	EGARCH (-2)	-1.235	0.064	-19.252	0.000*
	EGARCH (-3)	0.638	0.077	8.242	0.000*
	Domestic price of coffee	-0.014	0.026	0.013	0.068
	Exchange rate	0.401	0.132	3.027	0.003*
	Food inflation	0.041	0.041	0.995	0.320
	Fuel oil price	0.045	0.030	-1.243	0.044**
	Non-food inflation	1.325	0.639	2.072	0.038**
	Saving interest rate	-0.119	0.306	-0.388	0.699
	Gov't revenue	0.001	0.001	1.121	0.262
	GDP	0.000	0.000	0.963	0.336
	April	-3.223	0.933	-3.455	0.674
	August	2.885	0.848	-3.402	0.001*
	October	3.004	0.970	-3.096	0.002*
	November	-4.014	0.641	-6.260	0.000*
	December	-2.727	0.769	-3.547	0.009
	March	-2.172	0.730	-2.975	0.283
	February	0.467	1.046	-0.447	0.066
	May	3.859	0.674	-5.726	0.000*
	July	0.195	0.864	0.225	0.082
	June	4.075	0.768	-5.306	0.000*
	September	1.103	0.701	-1.573	0.012**

* and ** indicate significance at 1% and 5% level, respectively

3.8 In-sample forecast of price volatility

One of the fundamental applications of developing GARCH family models is forecasting. A plot of the dynamic in-sample forecasts based on the fitted ARMA (1,1)-EGARCH (3,1) model is shown in Figure 3. We can observe that there was high export price volatility of coffee around 2012, 2015 and 2016.

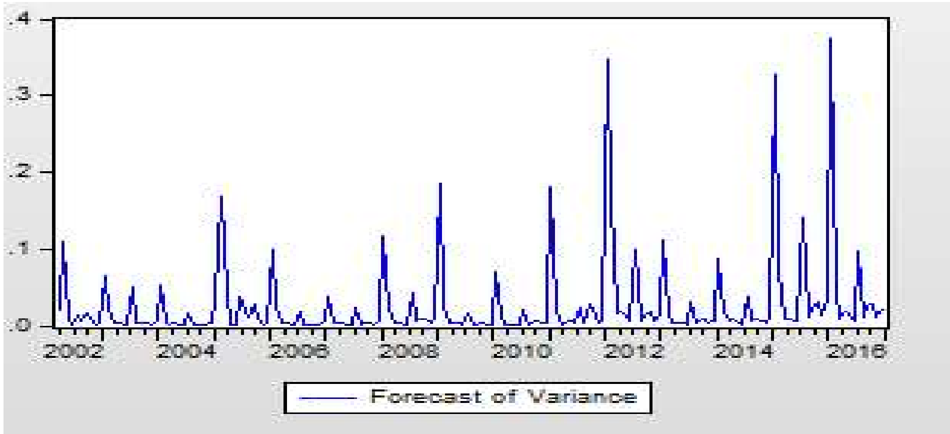

Figure 3: In-sample forecast of monthly export price volatility of coffee

3.9 Model diagnostics

The presence of remaining ARCH effects in the ARMA (1,1)-EGARCH (3,1) model was tested using the ARCH LM test. The test statistic was found to be insignificant, and hence, we do not have enough evidence to reject the null hypothesis that there is no ARCH left in the residuals. The Jarque-Bera test was used to test the normality of the residuals in the fitted EGARCH model. The result indicated that the null hypothesis of normality of the residuals cannot be rejected. Moreover, the skewness and kurtosis coefficients of the standardized residuals from the fitted model were 0.258 and 2.687, respectively, indicating that the skewness and excess kurtosis have been considerably reduced.

3.10 Discussion

Among the explanatory variables which were considered in this study, domestic price of coffee, exchange rate, fuel oil price, non-food inflation rate and some of the seasonal dummies were found to be significant. On the other hand, food inflation rate, saving interest rate, total government revenue and GDP were found to have no significant influence on the current month export price volatility of coffee. The results also revealed significant effects of lagged innovations and lagged volatilities on the current conditional return volatility (see Table 5).

The coefficients of non-food inflation rate and exchange rate are positive and statistically significant. This indicates that increases in non-food inflation rate and exchange rate lead to an increase in the monthly export price volatility of coffee.

The coefficient of fuel oil price is also positive and statistically significant at the 5% level. The implication is that an increase in fuel oil price leads to an increase in the monthly export price volatility of coffee. Coffee production is increasingly mechanized and uses various chemical fertilizers which are byproducts of the petroleum industry. Fuels are also required for storage and transportation thus directly enhancing the potential transmission effect of oil prices on coffee prices. These results are consistent with the findings of Swaray (2007) and Baffes (2007).

The results from the seasonal dummies indicate that prices during May, June, August, September and October had increasing effect on the current month variability of export price of coffee, while prices during November and December had a decreasing effect. The link between those months and export price volatility is likely to be related to the seasonal pattern of coffee price. Jordaan et al., (2007) stated that fluctuations in prices may be characterized by lower prices at harvest compared to prices during other seasons.

The results also show that lagged shocks (represented by ARCH (-1)) of the monthly price of coffee have statistically significant effect on the current month price volatility of coffee. Similarly, EGARCH (-1), EGARCH (-2) and EGARCH (-3) terms are statistically significant at the 1% level. This indicates that the current month price volatility of coffee is affected by its past (lagged) price volatilities.

The asymmetry coefficient in the variance equation is positive and statistically significant. This indicates that positive shocks (unexpected decreases in the export price of coffee) have a more prominent effect on the volatility of the export price of coffee than negative shocks (sharp increases in coffee prices). A study by Maurice & Davis (2011) also revealed that coffee Arabica and Robusta price volatilities are more affected by positive shocks than negative shocks.

4. Conclusion and Recommendations

This study has analyzed the export price of coffee and major macroeconomic variables that determine its volatility based on monthly data from January 2002 to December 2016. The results from the fitted EGARCH model revealed that non-food inflation rate, exchange rate and fuel oil price had a significant effect on the volatility of the export price of coffee in Ethiopia. Moreover, recent past shocks and lagged volatilities were found to increase the contemporaneous volatility of the same. Thus, potential stakeholders should work hard to minimize the fluctuation on the aforementioned drivers so that coffee export price volatility could be optimized at a reasonable level.

Based on the findings of this study, the following recommendations are forwarded:

- ✓ The volatility of export price returns of coffee was influenced by macroeconomic factors such as exchange rate, non-food inflation rate, and price of crude oil. Therefore, concerned bodies should give due attention to these factors during policy formulation.

- ✓ Further studies that consider some potential variables that may have significant linkage with price volatility of coffee (such as climatic conditions and world demand-supply related factors) are recommended.

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