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Original Research

The Application of Garch Family Models for Agricultural Crop Products in Amhara Region, Ethiopia

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Abstract

In the recent past, the price of general commodities has increased in Ethiopia as well as in the world. The main objective of this study is to identify and analyze the factors that affect the average monthly price volatility of pulses (bean and pea) in Amhara National Regional State over the period of December 2001 to June 2012 GC. The return series considered exhibited typical characteristics of financial time series such as volatility clustering, leptokurtic distributions and asymmetric effect and thus, can suitably modeled using GARCH family models. Among such models entertained in this study, ARMA(4,4)-EGARCH(2,3) with GED for bean and ARMA(1,0)-EGARCH(1,2) with student-t for pea were chosen to be the best fit models. From the results, exchange rate and general and food inflation rates were found to be an increasing effect on price volatility of bean and pea. On the other hand, rainfall was found to have a stabilizing effect on the price volatility of these crops. Moreover, saving interest rate has a decreasing effect on the price volatility of bean. The results also revealed that price volatility has seasonal variation. The asymmetric terms were found to be significant in all GARCH models considered. Thus, price volatility tends to over-react in response to bad news as compared to good news. Furthermore, the significance of the EGARCH terms provides strong evidence of volatility spillover from one period to another.

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INTRODUCTION

In Ethiopia, agriculture accounts for almost 41% of the gross domestic product (GDP), 80% of exports, and 80% of the labor force. Many other economic activities depend on agriculture, including marketing, processing, and export of agricultural products. Production is overwhelmingly by small-scale farmers and enterprises and a large part of commodity exports are provided by the small agricultural cash-crop sector. Principal crops include coffee, pulses (*e.g.,* bean and pea), oilseeds, cereals, potatoes, sugarcane and vegetables. Exports are almost entirely agricultural commodities, and coffee is the largest foreign exchange earner. In 2005/2006 Ethiopia's coffee exports represented 0.9% of the world export, and oil seeds and flowers each represent 0.5% (IMF, 2009).

Agricultural households in developing countries face a variety of risks. The most visible manifestation of these risks is high food price instability, which, because of its inherent economic and political implications, has attracted the attention of almost all actors in food policy making over the past few decades. However, all actors agree on one point, i.e. the direct consequences of price instability on consumers, producers, as well as on overall economic growth. For poor consumers, consequences of price instability are severe. Since a large share of their income is spent on food, an unusual price increase forces them to cut down food intake, take their children out of school, or, in extreme cases, simply to starve. Even when such price shocks are temporary, they can have long term economic impacts in terms of nutritional well-being, labor productivity, and survival chances (Hoddinott, 2006; Myers, 1993).

Variability in food prices can also have important effects even if average prices remain constant. This might happen if fluctuations in food production become more common or larger but average production remains the same. This would lead to more frequent and larger price changes, which might be predictable or unpredictable. If the increased variability were largely predictable, this would cause fewer problems than if the changes were unpredictable. However, price changes are generally less predictable than might be imagined. Unstable prices for staple foods are likely to have larger negative effects than unstable prices for other agricultural commodities because staple foods are important for both poor farmers and poor consumers. On the consumer side, staple foods account for a large share of the expenditures of the poor. On the producer side, they are the most widely planted crops in developing countries, especially on smallholdings (FAO, 2011).

It is crucial to examine the pattern of price volatility and identify its determinant on cereal crops. According to

Jordaan *et al*. (2007), the accurate measurement of the stochastic component in prices may contribute to the decision maker being able to make more informed decisions when choosing one crop over another. It may also contribute to policy decisions regarding the possible implementation of commodity price stabilization programs. Examining the underlying causes of pulse price volatility has great role for managing price instability for producers, consumers, whole sellers and agricultural price policy reforms for the country as well.

In Amhara National Regional State (ANRS), agriculture contributed to about 55.8% of the total regional GDP. The main field crops in the Amhara region are cereals (wheat, barley, teff, sorghum, maize, etc), pulses (field pea, chickpea, bean, etc) and oil crops (sesame, rape seed, sunflower, etc). Cereals account for more than 80 % of cultivated land and 85 % of total crop production. About 33 % of the livestock and 25-30 % of crop production in Ethiopia are from the Amhara region (BoFED, 2011).

As many studies indicated price volatility of agricultural commodities has a negative impact on the economy of the country through income instability for producers, consumers and whole sellers and also leads to a major decline in future output if the price changes are unpredictable and erratic. Therefore, this study was an attempt to identify the pattern of average monthly price volatility of pulse seed (pea and bean) in Amhara Region by developing appropriate time series models that can fit financial data.

Therefore, this study has attempted to address the following problems (1) is there volatility in the price of some selected agricultural crops products (cereal and pulse seed)? (2) which agricultural commodities under consideration have highly volatile prices? (3) which model is a good fit to data on price of agricultural crop products?

The main objective of this study is to identify and analyze the factors that affect the price volatility of bean and pea seeds in Amhara Regional. Specifically, this study tries to address the following key issues (1) to fit and select an appropriate GARCH family models for the price volatility of pulse seeds (bean and pea), (2) to assess the pattern of their price volatility and (3) to estimate and forecast the price volatility of bean and pea seeds.

MATERIALS AND METHODS

Source and Type of Data

To assess the average monthly price volatility and its determinants on certain pulse seeds (beans and pea), the data were obtained from Central Statistical Agency (CSA), National Bank of Ethiopia (NBE) and National Metrological Agency of Ethiopia, on monthly basis from December 2001 to June 2012 G.C.

Average monthly price of pulse seed (bean and pea) is used as dependent variables. Exchange rate, saving interest rate, lending interest rate, general inflation rate, food inflation rate, non-food inflation rate, average temperature (in degree Celsius) and average rain fall (in mm) are used as independent variables. Since the data are not seasonally adjusted also seasonal dummies are used.

(G) ARCH Models

The Box-Jenkins time series model such as Autoregressive (AR), Moving Average (MA) and ARMA are often very useful in modeling general time series data. However, they all require the assumption of homoskedasticity (or constant variance) for the error term in the model. Autoregressive Conditional Heteroskedasticity (ARCH), separate GARCH, TGARCH and EGARCH models have been employed in this study to investigate the pattern of price volatility and its determinants.

Model Specification: Stationarity and Unit-Root Problem

A given series is said to be stationary if its mean and variance are constant overtime and the value of the covariance between any two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed.

Generally the concept of stationarity can be summarized by the following conditions. A time series $\{y_t\}$ is said to be stationary if:

$$E(y_t) = E(y_{t-s}) = \mu,$$
$$E(y_t-\mu)^2 = E(y_{t-s}-\mu)^2 = \sigma_y^2,$$
$$E(y_t-\mu)(y_{t-s}-\mu) = E(y_{t-j}-\mu)(y_{t-j-s}-\mu) = \gamma(s),$$

where μ, σ_y^2 and $\gamma(s)$ are all time invariant.

The assumption of stationarity is somewhat unrealistic for most macro economic variables. A non-stationary process arises when at least one of the conditionsfor stationarity does not hold. Let us consider an autoregressive process of order one (AR (1) process):

$$y_t=\rho y_{t-1}+\varepsilon_t, \qquad [1]$$

where ε_t denotes a serially uncorrelated white noise error term with a mean of zero and a constant variance. Non-stationarity can originate from various sources but the most important one is the presence of so-called "unit roots". Equation (1) is said to be a unit root process when $\rho= 1$.

If a variable is stationary in level, i.e. without running any differencing, then the variable is said to be integrated of order zero, denoted by $I(0)$. Similarly, if it becomes stationary by differencing d times, then the variable is said to be integrated of order d, written as I(d), d= 1, 2, 3, …. Unit-root test helps to detect whether a variable is stationary or not. It also provides the order of integration at which the variable can be stationary.

Let p_t, t= 1, 2, 3… be the price of a commodity at time period t (t in days, months, etc). Instead of analyzing p_t, which often displays unit-root behavior and thus cannot be modeled as stationary, we often analyze log- returns on p_t (Fryzlewicz, 2007):

$$Y_t = \log p_t - \log p_{t-1} = \log\left(\frac{p_t}{p_{t-1}}\right) = \log\left(1+\frac{p_t-p_{t-1}}{p_t}\right).$$

The series y_t, log- return series, displays many of the typical characteristics in financial time series such as volatility, clustering and leptokurtosis.

The Mean Model

ARMA Model

Autoregressive moving average (ARMA) modeling is a specific subset of univariate modeling in which a time series is expressed in terms of past values of itself plus current and lagged values of a 'white noise' error term. ARMA (p, q) mean model (Box-Jenkins, 1976) is given by:

$$y_t=\Phi_o+\sum_{i=1}^{p}\Phi_i y_{t-i}-\sum_{j=1}^{q}\theta_j\varepsilon_{t-j}+\varepsilon_t, \qquad [2]$$

Where y_t is average monthly log return price of selected crops at time t, Φ_0 is constant mean, Φ_1, Φ_2, …….,Φ_p are autoregressive parameters, ε_t, ε_{t-1},… are white noise error with mean zero and variance and σ^2_t and θ_1, θ_2, ……., θq are moving average parameters.

ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) model was introduced by Box and Jenkins in 1960s for forecasting a variable. ARIMA models consist of unit-root non-stationary time series which can be made stationary by the order of integration 'd'. The general form of ARIMA (p, d, q) is written as:

$$\Delta^d\psi_p(B)Y_t = \Phi_o+\Theta_q(B)\varepsilon_t, \qquad [3]$$

Where $\psi_p(B)$ = 1-Φ_1B-……-$\Phi_p B^p$, $\Theta_q(B)$ = 1-θ_1B-……-$\theta_q B^q$,Δ = 1-B, d is the order of integration and B is the backward shift operator.

ARCH Model

The autoregressive conditional hetroskedasticity model for the variance of the errors, denoted by ARCH (Q), was proposed by Engle (1982). The conditional variance is given by:

$$\varepsilon_t = \sigma_t u_t \quad \text{and} \quad \sigma^2_t=\alpha_0+\sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-I}, \qquad [4]$$

where u_t is IID normal residual with mean zero and unit variance and σ_t^2 is the conditional variance of the residuals at time t, i.e., σ_t^2 =Var ($\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2},….$). We impose the non-negativity constraints α_0,α_i>0 i = 1, 2, …., Q.

GARCH Model

ARCH model was generalized by Bollerslev (1986) as GARCH(P,Q) which allows the conditional variance to be dependent upon previous own lags. Then ARMA(p,q) - GARCH(P,Q) model is given by:

$$y_t = \Phi_o+\sum_{i=1}^{p}\Phi_i y_{t-i}-\sum_{j=1}^{q}\theta_j\varepsilon_{t-j} + \varepsilon_t,$$

$$\sigma^2_t=\alpha_0+\sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-i}+\sum_{j=1}^{P}\beta_j\sigma^2_{t-j} \qquad [5]$$

Restrictions: α_0>0, α_i≥ 0, β_j ≥ 0 for i=1, 2, …, Q and j=1, 2, …, P.

The conditional variance equation of GARCH(P,Q) with explanatory variables for wheat seed is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-i} +\sum_{j=1}^{P}\beta\sigma_{t-j}^2 + \boldsymbol{\gamma}'X_t, \qquad [6]$$

where X_t = (x_{1t}, x_{2t},.., x_{kt})′ is a vector of explanatory variables and **γ** = (γ_1, γ_2,.., γ_k)′ is a vector of regression coefficients of the explanatory variables.

EGARCH Process

In order to capture possible asymmetry exhibited by financial time series, a new class of models, termed the asymmetric ARCH models, was introduced. The most popular model proposed to capture the asymmetric effects is Nelson's (1991) exponential GARCH, or EGARCH model. The ARMA(p,q)-EGARCH (P,Q) model is given as:

$$y_t = \Phi_o+\sum_{i=1}^{p}\Phi_i y_{t-i}-\sum_{j=1}^{q}\theta_j\varepsilon_{t-j} + \varepsilon_t,$$

$$\ln(\sigma_t^2)=\alpha_0+\sum_{i=1}^{Q}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{R}\lambda_i\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)+\sum_{j=1}^{P}\beta_j\ln(\sigma^2_{t-j}) \qquad [7]$$

In this model specification, β_1, β_2,…. β_P are the GARCH parameters that measure the impact of past volatility on the current volatility.

TGARCH Process

The TGARCH model with mean and conditional variance equations is given as:

$$y_t = \Phi_o+\sum_{i=1}^{p}\Phi_i y_{t-i}-\sum_{j=1}^{q}\theta_j\varepsilon_{t-j} + \varepsilon_t,$$

$$\sigma_t^2=\alpha_0+\sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-i}+\sum_{i=1}^{Q}\lambda_i d_{t-i}\varepsilon^2_{t-i}+ \sum_{j=1}^{P}\beta_j\sigma^2_{t-j}, \qquad [8]$$

where d_{t-i}= 1 if ε_{t-i}≥ 0, and d_{t-i}= 0 otherwise. The TGARCH model allows a response of volatility to news with different coefficients for good and bad news.

In this study, the general inflation rate, food inflation rate, non-food inflation rate, exchange rate, saving interest rate, lending interest rate, temperature, rain fall and monthly seasonal dummies were introduced into the conditional variance equation as independent variables in order to determine the impact of these variables on the volatility of average monthly price returns under consideration. The conditional variance equation of GARCH(P,Q) with explanatory variables for each cereal crops and pulse seeds is given by:

$$\sigma_t^2=\alpha_0+\sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-i}+\sum_{j=1}^{P}\beta\sigma_{t-j}^2+ \boldsymbol{\gamma}'X_t, \qquad [9]$$

where X_t = (x_{1t}, x_{2t},.., x_{kt})′ is a vector of explanatory variables and **γ** = (γ_1, γ_2,.., γ_k)′ is a vector of regression coefficients of the explanatory variables.

Assuming the presence of asymmetric effect on the GARCH family model, the conditional variance equations for EGARCH (P,Q) and TGARCH(P,Q) with explanatory variables are given by:

$$\ln(\sigma_t^2)=\alpha_0+\sum_{i=1}^{Q}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{R}\lambda_i\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)+\sum_{j=1}^{P}\beta_j\ln(\sigma^2_{t-j})+\boldsymbol{\gamma}'X_t, \qquad [10]$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{Q}\alpha_i\varepsilon^2_{t-i} + \sum_{i=1}^{Q}\lambda_i d_{t-i}\varepsilon^2_{t-i} + \sum_{j=1}^{P}\beta_j\sigma^2_{t-j}+ \boldsymbol{\gamma}'X_t. \qquad [11]$$

Assumptions of the Models

a. The expected value of the error term is zero, i.e. E[ε_t]=0
b. The variance of the error terms is conditionally hetroskedastic.
c. Error terms are independent having normal or student-t or GED distribution with mean zero and variance σ^2_t.
d. There is no serial autocorrelation among successive error terms.
e. No severe multicollinearity exists among explanatory variables.

Procedures for Model Building

Testing for the Presence of Unit Root

A test of stationarity (or non-stationarity) that has become widely popular over the past several years is the unit root test. There is a major problem with regression that involves non- stationary variables as the standard errors produced are biased. Due to such bias, conventional criteria used to judge whether there is a casual relationship between the variables are unreliable. Such a regression is what we call spurious regression. It is therefore very important to be able to detect the presence of unit roots in time series. For these tests, the null hypothesis is that the time series has a unit root. The widely used unit-root tests are Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) and Phillips Perron (PP) test (Phillips and Perron, 1987).

The Augmented Dickey Fuller (ADF) Test

The ADF test is comparable with the simple DF test, but is augmented by adding lagged values of the first difference of the dependent variable as additional repressors which are required to account for possible occurrence of autocorrelation. Consider the AR (p) model:

$$\nabla y_t = \mu + \alpha y_{t-1} + \sum_{i=2}^{p} \psi_i \nabla y_{t-p} + \varepsilon_t, \qquad [12]$$

where $\alpha = -(1-\sum_{i=2}^{p} \Phi_i)$ and $\psi_i = \sum_{j=i}^{p} \Phi_j$.

If the null hypothesis H_0: $\alpha = 0$ is not rejected, then we need to difference the data to make it stationary or we need to put a time trend in the regression model to correct for the variables' deterministic trend.

The Phillips and Perron (PP) Test

An important assumption of the DF test is that the error terms ε_t are independently and identically distributed. The ADF test adjusts the DF test to take care of possible serial correlation in the error terms by adding lagged difference terms of the dependent variable. Phillips and Perron use nonparametric statistical methods to take care of the serial correlation in the error terms without adding lagged difference terms. For details see Perron and Ng (1996) and Nabeya and Perron (1994).

Testing ARCH Effects

The Box-Jenkins (1976) approach is based on the assumption that the residuals are homoskedastic (remain constant over time) for ARMA or ARIMA model. But in financial data, ARCH effect is commonly found (Cotter and Stevenson, 2007, Asteriou and Hall, 2007). According to Tsay (2005), there are two available methods to test for ARCH effects.

(i) Ljung-Box Test:

It was developed by Box and Pierce (1970) and modified by Ljung and Box (1978) and tests the joint significances of serial correlation in the standardized and squared standardized residuals for the first k lags instead of testing individual significance. They suggested testing the hypothesis:

H_0: $\rho_1 = \rho_2 = \ldots\ldots = \rho_k = 0$

H_1: not all $\rho_j = 0$

where ρ_j is the ACF at lag j = 1, 2… k.

They suggested the statistic:

$$Q(k) = n(n+2) \sum_{j=1}^{k} \frac{d_j^2}{n-j},$$

where n denotes the length of the series after any differencing and d_j denotes the squared residual.

(ii) Lagrange Multiplier (LM) Test:

This test was suggested by Engle (1982) and used to test the significance of serial correlation in the squared residuals for the first q lags.

$$\hat{\varepsilon}_t^{\,2} = \gamma_0 + \gamma_1 \hat{\varepsilon}_{t-1}^{\,2} + \ldots + \gamma_q \hat{\varepsilon}_{t-q}^{\,2} \qquad [13]$$

The null hypothesis is that, $\gamma_0 = \gamma_1 = \ldots\ldots = \gamma_q = 0$.

The test statistic **n.R²** is distributed as chi-square with q degrees of freedom, where R^2 is the coefficient of determination from equation (13) and n is number of observations. The rejection of the null hypothesis indicates the presence of ARCH (Q) effects.

Test of Normality

When dealing with GARCH family models, the data is first tested for normality (i.e. whether the returns follow a normal distribution). The test is named after Jarque and Bera (1982).

H_0: the observations come from a normal distribution. The test statistic is:

$$JB = \frac{n}{6} * \left(S^2 + \frac{(k-3)^2}{4}\right),$$

where n is the number of observations, S is the sample skewness and K is the sample kurtosis. Under the null hypothesis, the Jarque-Bera statistic is distributed as chi-square distribution with two degrees of freedom.

Model Order Selection in GARCH Family Model

A model selection criterion considers the "best approximating model" from a set of competing models.An important practical problem is the determination of the ARCH order Q and the GARCH order P for a particular series. Since GARCH models can be treated as ARMA models for squared residuals, traditional model selection criteria such as the Akaike information criterion (AIC) proposed by Akaike (1974) and the Schwartz Bayesian information criterion (SBIC) proposed by Schwartz (1989) can be employed to identify the optimal lag specification for the model. These criteria are computed using the log-likelihood estimates. Given the criterion values of two or more models, the model having minimum AIC or BIC is most representative of the true model and, on this account, may be interpreted as the best approximating model among those being considered (Dayton, 2003).

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

$$AIC = -2\ln(L) + 2K \qquad [14]$$

$$BIC = -2\ln(L) + K.\ln(n) \qquad [15]$$

where n = number of observations
K = number of parameters estimated
L = value of the likelihood function (log $L(\sigma_t^2)$)

The main reason for preferring the use of a model selection procedure such as BIC in comparison to traditional significance tests is the fact that a single holistic decision can be made concerning the model that is best supported by the data in contrast to what is usually a series of possibly conflicting significance tests.

Model Parameter Estimation

Under the presence of ARCH effects, the OLS estimation is not efficient since volatility models used are non-linear in conditional variance though linear in mean. As many studies indicated, the commonly used method known as the maximum likelihood estimation has been employed in GARCH family model. Financial time series data possess volatility clustering and leptokurtosis characteristics which lead to the use of different distributional assumptions for residuals such as: -

Normal, Student-t and GED. Thus, in this study the Gaussian (Normal), Student-t distribution and the GED were considered for GARCH family model parameter estimation and the appropriate distributions for the residuals were identified based on robust estimation. The estimation of conditional volatility models are typically performed by MLE procedures in Bollerselv and Wooldridge (1992).

Maximum likelihood method follows the following steps:

1. Specify the appropriate equations for the conditional mean and the variance.
2. Specify the log-likelihood function of the model to maximize.
3. Use regression to get initial guesses for the mean parameters from mean equation.
4. Choose some initial guesses for the conditional variance parameters.
5. Specify a convergence criterion.

Maximization of the likelihood function of the model analytically in terms of its parameter is impossible because of non-linearity of GARCH family models

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Model Adequacy Checking

After a GARCH family model has been fit to the data, the adequacy of the fit has been evaluated using a number of graphical and statistical diagnostics.

The followings are the methods for model adequacy checking that were used in this study:-

1. The ACFs of the residuals should be indicative of a white noise process.
2. The standardized residuals should be normally distributed. This was checked through Jarque-Bera test.
3. The Ljung-Box test is one of the widely used tests for the appropriateness of the fitted model; to test whether the model of the mean is appropriately specified and to test for the remaining ARCH effects
4. Evaluating the performance of different forecasting models: the most widely used statistical evaluation measures are MAE, RMSE, MAPE and Theils- U Inequality Coefficient (TU). These are applied to measure the forecasting accuracy of the ARCH-GARCH model in this study.

Prediction using GARCH Family Models

An important task of modeling conditional volatility is to generate forecasts for both the future value of a financial time series as well as its conditional volatility. Conditional variance forecasts from GARCH family models are obtained with similar approach to forecasts from ARMA models by iterating with the conditional expectations operator. In other words, when the estimation of the unknown parameters is done, estimates of the standard deviation series can be calculated recursively via the definition of the Conditional variance for the GARCH (P, Q) family process which helps to examine the past behavior of average monthly domestic price volatilities of the series under consideration.

Statistical Analysis

The return series were constructed for each of the prices to allow a market wide measure of volatility to be examined. The data analysis is carried out using EViews 7 and STATA 11 software.

RESULTS

Figure 1 is a plot of average monthly price trend of pulses. It can be observed that monthly prices show an increasing trend over the study period.

The empirical result shows that the average monthly price for bean and pea are 4.4577 and 5.1270 with standard deviation 3.2850 and 3.4921, respective of their order (Table 1). In the case of log return series, the coefficients of kurtosis exceed three, indicating that the log return series are peaked relative to the normal distribution (that is, leptokurtic). Moreover, the series exhibit positive skewness. The Jarque-Bera test of normality rejects the normality of all the series under consideration.

Table 2 displays summary statistics for each of the explanatory variables. The sample mean (SD) was estimated to be about 10.901 (3.186) for exchange rate in birr, 3.5906 (0.7596) for saving interest rate, 11.161 (0.744) for lending interest rate. Moreover, mean (SD) was estimated to be about 15.82 (14.87) for general inflation rate, 19.21 (21.04) for food inflation rate, 11.914 (9.089) for non-food inflation rate, 18.394 (1.4249) for average monthly temperature and 3.0393 (3.3705) for average monthly rain fall.

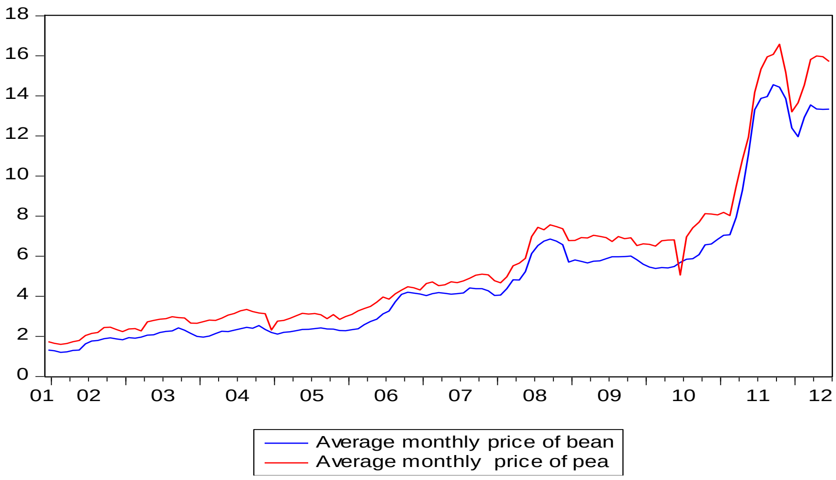

Figure 1: Average monthly price trend of Bean and Pea

Table 1: Summary results for average monthly price and Log-return series for Bean and Pea

Statistics	Average monthly price		Log-return series	
	bean	pea	bean	pea
Mean	4.4577	5.1270	0.0203	0.0176
Median	3.8211	4.1277	0.0137	0.0171
Maximum	13.4914	16.6800	0.3694	0.4694
Minimum	0.9214	1.3566	-0.1168	-0.2758
Std. Dev.	3.2850	3.4921	0.0677	0.1172
skewness	1.4803	1.4810	1.3859	0.5334
kurtosis	4.3961	4.5415	7.7633	5.3852
Jarque-Bera	56.7036	59.0032	159.4429	35.8467
P-value	0.0000	0.0000	0.0000	0.0000

Table 2: Summary results for covariates

statistics	Exchange rate	Saving Interest rate	Lending interest rate	General inflation rate	Food inflation rate	Non-food inflation rate	Temperature (in ^{0}c)	Rain fall (in mm)
Mean	10.901	3.5906	11.161	15.815	19.21	11.914	18.394	3.039
Median	8.931	3.00	10.75	12.20	14.10	12.00	18.30	1.50
Minimum	8.645	3.00	10.500	-7.30	-14.00	-2.200	13.6099	0.00
Maximum	17.846	6.00	12.75	64.20	91.70	29.50	21.7620	13.873
St. dev.	3.186	0.7596	0.744	14.867	21.035	9.0885	1.4249	3.3705

Tests of Stationarity

Before considering volatility models, the first logical step is to check the stationarity of the average monthly price using ADF test and PP unit root test. In ADF test, the null hypothesis of unit root is rejected if the test statistic is less than the critical value or the *P*-value is less than the level of significance (α=0.05). As can be seen from the table 3, the null hypothesis of unit root would not be rejected, that is, there is a unit root problem in each of the series indicating that each average monthly price series is non-stationary.

The table 4 shows that all the t-statistics are less than the critical values. These indicate that the null hypothesis of unit root would be rejected in all of the four cases. Hence the log return series are stationary.

All the variables except saving interest rate are non-stationary at level. However, except saving interest rate all the variables are stationary after first difference as shown in Table 5, implying that all explanatory variables are integrated of order one.

Table 3: ADF unit root test at level for average monthly prices

Prices	Test Statistics	1% critical value	5% critical value	10% critical value	P-value
Bean	-0.0103	-3.4833	-2.8846	-2.5791	0.9552
Pea	0.3528	-3.4833	-2.8846	-2.5791	0.9801

Table 4: ADF unit root test at level for average monthly price of log-return series

Log-returns	Test Statistics	1% critical value	5% critical value	10% critical value	P-value
Bean	-8.0807	-3.4833	-2.8846	-2.5791	0.0000*
Pea	-16.22092	-3.4833	-2.8846	-2.5791	0.0000*

*Statistically significant

Table 5: ADF unit root test of the first difference of explanatory variables

Explanatory variable	ADF test statistic	1% critical value	5% critical value	10% critical value	p-value
Exchange rate	-10.4595	-3.4833	-2.8846	-2.5791	0.0000*
Lending interest rate	-20.0609	-3.4833	-2.8846	-2.5791	0.0000*
General inflation rate	-5.8561	-3.4833	-2.8846	-2.5791	0.0000*
Food inflation rate	-5.7294	-3.4833	-2.8846	-2.5791	0.0000*
N-food inflation rate	-5.7294	-3.4833	-2.8846	-2.5791	0.0000*
Temperature	-10.2286	-3.4880	-2.8867	-2.5802	0.0000*
Rain fall	-21.0537	-3.4880	-2.8867	-2.5802	0.0000*

*Statistically significant

Estimation of Mean Equation

In the specification of the mean equation, lower order ARMA models are often considered, say, the twenty five combinations of AR (0-4) and MA (0-4). Optimal lag length was selected based on the minimum BIC provided that no serial autocorrelation exists in the residuals from the specified mean model. The presence of autocorrelation in the residuals was tasted using the Lagrange Multiplier (LM) test for each of the mean equations considered. Only models with no remaining serial correlations are considered as candidate models.

Among the candidate mean models for the price return series of bean, ARMA (4, 4) has the smallest BIC and exhibits no serial autocorrelation.

Similarly, ARMA (1, 0) has found to have the smallest BIC for the return series of pea. The fitted mean equations are shown in Tables 6 and 7.

Table 6: ARMA (4, 4) mean equation for average monthly price return series of Bean

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019799	0.006370	3.108349	0.0024
AR(1)	0.306711	0.067574	4.538884	0.0000
AR(2)	0.718954	0.071917	9.996980	0.0000
AR(3)	-0.157235	0.068252	-2.303762	0.0231
AR(4)	-0.692221	0.064204	-10.78162	0.0000
MA(1)	-0.046703	0.026910	-1.735490	0.0854
MA(2)	-0.854187	0.033694	-25.35109	0.0000
MA(3)	-0.059356	0.025937	-2.288484	0.0240
MA(4)	0.958533	0.021534	44.51244	0.0000

Table 7: ARMA (1, 0) mean equation for average monthly price return series of Pea

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.017884	0.007229	2.473819	0.0147
AR(1)	-0.362475	0.083995	-4.315441	0.0000

Testing for ARCH Effects

The ARCH LM test helps to test the hypothesis that there is no ARCH effect up to lag Q. Table 8 shows the results of ARCH LM test for lags 1, 2 and 3 for monthly price return series. The test for the null hypothesis of no ARCH effects using Engle LM test and F-test confirmed the presence of ARCH (1) effects in the residuals from mean equations for bean and pea average monthly price returns. These results indicate that the respective log return series are volatile and need to be modeled using GARCH family models.

Optimal Order Selection and Parameter Estimation of GARCH Family Model

The optimal lag for GARCH family models has to be determined prior to the construction of the final model to investigate the determinants of monthly price volatility. Since there is a consensus that GARCH(1,1) family model is the most convenient specification in the financial literature (Bollerslev *et al*., 1992 and Lee and Hansen, 1994), the GARCH(1,1) model is compared to various higher-order models of volatilities based on the minimum AIC and BIC.

After testing for different orders of P and Q of GARCH family, it was found that EGARCH(1,3) under Normal distributional assumption for residuals, EGARCH(2,1) under Student-t distributional assumption for residuals and EGARCH(2,3) under GED distributional assumption for residuals for the price volatility of bean and EGARCH(1,1) under Normal distributional assumption for residuals, EGARCH(1,2) under Student-t distributional assumption for residuals and EGARCH(2,1) under GED distributional assumptions for residual for the price volatility of pea were found to be the best models to describe the data as they possess minimum BIC. The summary results are displayed in Table 9.

Moreover, to select the appropriate error distribution for selected asymmetric GARCH class models among normal, Student-t and GED distributions, the four forecast accuracy statistics: RMSE, MAE, MAPE and Theil Inequality coefficient were applied using in-sample forecast. The results show that ARMA(4,4)-EGARCH (2,3) model with GED for residuals and ARMA(1,0)-EGARCH (1,2) model with student-t for residuals for bean and pea, respectively perform best as compared to others as they possess the smallest forecast error measures in the majority of the statistics considered. The parameters in the mean and variance equations are estimated using the maximum likelihood (ML) method. The results are shown in Table 10.

Table 8: ARCH LM test summary statistics

Item	ARCH(Q)	X^2 statistic	p-value	F-statistic	p-value	BIC
Bean	ARCH(1)	9.4601	0.0021	10.0709	0.0019	-7.6773
	ARCH(2)	2.1749	0.0371	1.0793	0.0343	-7.5575
	ARCH(3)	2.1551	0.5408	0.7070	0.5497	-7.5093
Pea	ARCH(1)	13.5135	0.0032	14.9091	0.0002	-4.7987
	ARCH(2)	3.2218	0.1997	1.6138	0.2034	-4.7549
	ARCH(3)	3.4957	0.3213	1.1602	0.3280	-4.7117

Table 9: Optimal lag selected based on BIC under different distributional assumptions of residuals

Variable	Model	Error Distribution	BIC	Asymmetric term (α=5%)
bean	ARMA(4,4)-EGARCH(1,3)	Normal	-2.2486	significant
	ARMA(4,4)-EGARCH(2,1)	Student-t	-2.2141	Not significant
	ARMA(4,4)-EGARCH(2,3)	GED	-2.4844	significant
pea	ARMA(1,0)-EGARCH(2,2)	Normal	-1.0630	Significant
	ARMA(1,0)-EGARCH(1,2)	Student-t	-1.0828	significant
	ARMA(1,0)-EGARCH(2,1)	GED	-1.0683	Not significant

Table 10: ML parameter estimates of the volatility models for Wheat, Bean and Pea

Parameter	Bean		Pea	
	Mean (*P*-value)	**Variance (*P*-value)**	**Mean (*P*-value)**	**Variance (*P*-value)**
Constant	0.0167 (0.000)**	5.0892(0.000)**	0.0685(0.000)**	-3.0820(0.0017)**
AR(1)	0.1578(0.0001)**		-0.1602(0.028)*	
AR(2)	0.3737(0.0009)**			
AR(3)	0.0712(0.0074)**			
AR(4)	0.0132(0.0000)**			
MA(1)	-0.208(0.0031)**			
MA(2)	-0.283(0.3621)			
MA(3)	0.2721(0.0010)**			
MA(4)	0.1080(0.0064)**			
ARCH (-1)		0.9621(0.000)**		0.4030(0.0019)**
ARCH (-2)		0.3435(0.003)**		
Asymmetric (-1)		1.3167(0.001)**		0.6067(0.0000)**
Asymmetric (-2)		0.8162(0.000)**		
EGARCH (-1)		0.5174(0.0182)*		-0.5212(0.0405)*
EGARCH (-2)		0.8380(0.000)**		0.4121(0.0294)*
EGARCH (-3)		0.2110(0.000)**		
Exchange rate		1.9877(0.0351)*		1.3425(0.000)**
Saving interest rate		-0.3054(0.0326)*		-0.6216(0.2262)
Lending interest rate		-2.6011(0.0502)		2.6144(0.2586)
General inflation rate		0.3076(0.002)**		0.2480(0.0282)*
Food inflation rate		0.1213(0.007)**		0.2899(0.0000)**
N-Food inflation rate		0.4922(0.0421)*		0.0544(0.9250)
Temperature		-0.4824(0.6472)		0.2673(0.0038)**
Rain fall		-0.1314(0.0359)*		-0.5914(0.0135)*
February		0.4076(0.0108)*		-0.9004(0.0033)**
March		-0.2121(0.006)**		-1.1125(0.0020)**
April		-0.5478(0.001)**		0.3230(0.8362)
May		-0.5190(0.4479)		0.5762(0.7251)
June		1.0782(0.1562)		2.2574(0.1407)
July		4.4911(0.000)**		2.3735(0.0000)**
August		0.7770(0.0291)*		1.7715(0.0100)*
September		0.0913(0.9399)		2.2717(0.0070)**
October		-0.6234(0.002)**		2.1119(0.2272)
November		0.6394(0.4920)		2.5899(0.1374)
December		1.7450(0.0816)		1.4327(0.0067)**

* Significance at the 5% level and ** significance at the 1% level.

DISCUSSION

Monthly Price Return Series for Bean

From the results, exchange rate, general inflation, food inflation and non-food inflation have positive and significant effect on the price volatility of bean. An increase in exchange rate, general inflation, food inflation and non-food inflation leads to increase in the volatility of average monthly price of bean. In contrast, saving interest rate and average rainfall had significant negative effect. The rainfall result is in line with the findings by Alisher (2012). From the observed results of seasonal dummies, prices in February, July and August have an increasing significant effect, while March, April and October have decreasing effect.

The results indicate that EGARCH (-1), EGARCH (-2) and EGARCH (-3) terms are positive and statistically significant at the 5% level. The positive coefficient of the EGARCH(-1), EGARCH(-2) and EGARCH(-3) terms show that the 1-, 2- and 3- month lagged price volatility of bean leads to an increase in current month volatility. Also, 1- and 2- month lagged shocks (ARCH (-1) and ARCH (-2) terms) of the average monthly price of bean have statistically significant effect. Similarly, the asymmetric term was positive and statistically significant at the 1% level of significance. Thus, bad news had larger impact on the price volatility than good news.

Monthly Price Return Series for Pea

The results of pea also indicate that exchange rate, general inflation, food inflation and temperature are positively significant, while rainfall negatively affects price volatility of pea. The prices in July, August, September and December have a positive significant effect. On the other hand, prices in February and March affect the price volatility of pea negatively.

The EGARCH (-1) term has a negative effect on the current price volatility of pea. This result is not in line with the findings by Greene (2003). And 1- month lagged shock (ARCH (-1) term) of the average price of pea had a positive significant effect. Likewise, the asymmetric (-1) term was positively significant at the 1% level.

Checking Adequacy of Fitted Models

Various diagnostic tests were performed to check the appropriateness of the fitted models. The Ljung-Box Q(k) test indicates that autocorrelations in the standardized residuals are not significantly different from zero for the first 32 lags for bean and pea return series, indicating that the residuals are uncorrelated (white noise).

The tests for the remaining ARCH effect at time lag 1, 2 and 3of squared residuals shows no remaining ARCH effect as the p-values from both chi-square and F tests are greater than 5%.

The results reveal that the coefficients of skewness were 0.2988 and 0.0865 and the coefficients of kurtosis were 2.6791 and 2.7501 for bean and pea, respectively. The Jarque-Bera test statistics were insignificant in all cases implying that the residuals were approximately normally distributed. Thus, the volatility models fitted for average monthly prices were good fit for the data.

In-sample Forecast of Average Monthly Price Volatility Using EGARCH Fitted Models

Using the fitted volatility models for average monthly price of wheat, bean and pea, the volatility of prices (using variance as a volatility measure) was forecasted. The dynamic in-sample forecasts are presented in Figure 2 and Figure 3.

It can be observed that high price volatility was observed during 2008-2012 for bean. Also high price volatility values were observed during the year 2008 and 2011- 2012 for pea. Moreover, it can be seen that the average monthly price of pea shows more volatility (in particular around 2008) as compared to the other monthly price series.

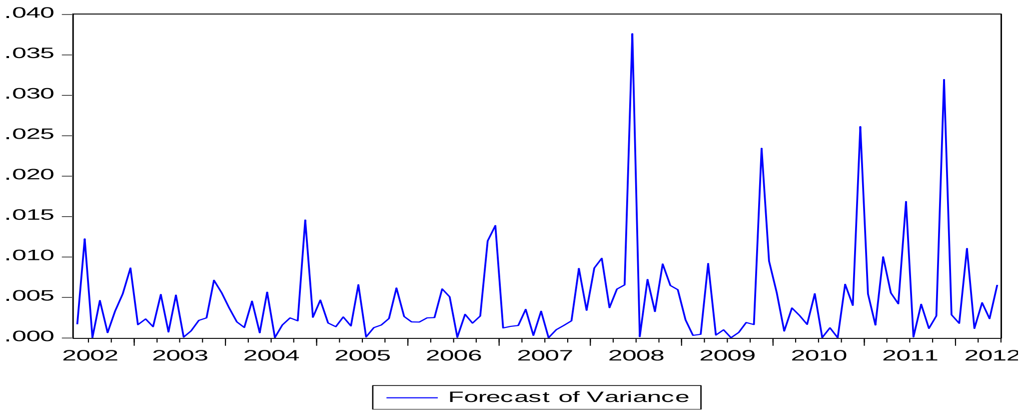

Figure 2: In sample forecast of average monthly price volatility for Bean

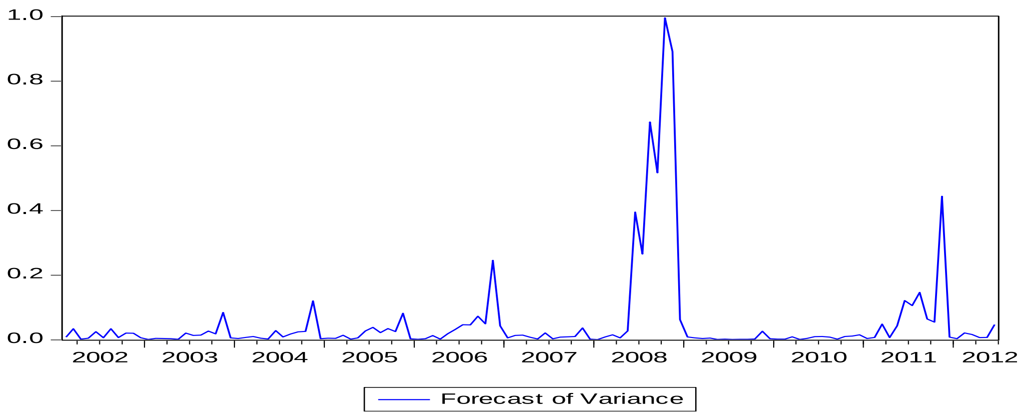

Figure 3: In sample forecast of average monthly price volatility for Pea

CONCLUSIONS

This study considered the average monthly price volatility and its determinants pulse (bean and pea) from December 2001 to June 2012 G.C in Amhara National Regional State (ANRS). From the empirical results, it can be concluded that average price return series of, bean and pea show the characteristics of financial time series such as volatility clustering, leptokurtic distributions and asymmetric effect. This justifies the use of the GARCH family models.

The forecast performances of the models were evaluated using the MAE, MAPE, RMSE and Theil inequality coefficient. Asymmetric EGARCH model with GED and Student–t distributional assumption for residuals was found to be the best fit model. That is, ARMA(4,4)-EGARCH(2,3) model with GED for bean and ARMA(1,0)-EGARCH(1,2) model with student-t for pea were found to be the best fit models for average monthly price of log return series.

Monthly average price volatility of bean had a significant positive relationship with exchange rate, general inflation and food inflation rate. Thus, an increase in exchange rate, general inflation rate and food inflation rate push up the average price volatility of bean. Also inflation of non-food items had a positive significant effect on the average price volatility of bean. On the other hand, price volatility of bean had a negative relationship with saving interest rate and rainfall. The volatility in the average price of pea had a significant positive relationship with exchange rate, general inflation, food inflation and temperature. Rainfall was negatively affecting the volatility of average price of pea.

Some of the monthly dummies were found to be significant. This indicates that price volatility has seasonal pattern.

In all the series considered, the asymmetric term (s) was (were) found to be positive and significant. This is an indication that unanticipated increase in prices had larger impact on price volatility than unanticipated decrease of the same. Moreover, the EGARCH terms were significant in all volatility models considered. This is a strong evidence of the presence of volatility spillover from one period (month in our case) to another.

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