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The Application of Garch Family Models to Some Agricultural Crop Products in Amhara National Regional State

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ABSTRACT
The price volatility of agricultural crop products has increased in the last decade. It 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. The aim of this thesis is to identify and analyze the determinant factors of average monthly price volatility of cereals (wheat and barley) and 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(1,0)-EGARCH(3,3) with GED for wheat, 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. The monthly price return series of barley exhibited no ARCH effects, and thus, was not modeled using (G)ARCH family models. From the results, exchange rate and general and food inflation rates were found to be an increasing effect on price volatility of wheat, 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 wheat and 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.
Key words: price volatility, crop products, ARMA, ARCH, GARCH family models

1. INTRODUCTION

According to the IMF (2013), Ethiopia was one of the fastest growing economies in the world, registering over 10% economic growth from 2004 through 2009. It was the fastest-growing non-oil-dependent African economy in the years 2007 and 2008. Growth has decelerated moderately in 2012 to 7% and is projected to be 6.5% in the future – reflecting weaker external demand and an increasingly constrained environment for private sector activity. Ethiopia's growth performance and considerable development gains has come under threat during 2008 and 2011 with the emergence of twin macroeconomic challenges of high inflation and a difficult balance of payments situation. Inflation surged to 40% in August 2011 because of loose monetary policy, large civil service wage increase in early 2011, and high food prices.

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).

It is crucial to examine the pattern of price volatility and identify its determinant on cereal crops. The differences between the variability in the prices among commodities are important for private investment decisions in farming and farm product marketing (Heifner& Randal, 1994). Another reason for the importance of identifying determinants for price volatility is the fact that negative price shocks have a greater negative impact on the economic growth of developing economies (Dehn, 2000). 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 cereal price instability and 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 the recent past, the price of general commodities has increased in Ethiopia as well as in the world.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. As one of the regional states of Ethiopia, the Amhara National Regional State is not immune from such negative impacts.
Therefore, this study has attempted to address the following problems:

- Is there volatility in the price of some selected agricultural crops products (cereal and pulse seed)?
- Which agricultural commodities under consideration have highly volatile prices?
- Which model is a good fit to data on price of agricultural crop products?

The main aim of this study is to identify and analyze the determinant factors of price volatilityof agricultural crop products in Amhara National Regional State using GARCH family models. Specifically, we are interested to address the following key issues.

- To fit and select an appropriate GARCH family models for the price volatility of cereal crops and pulse seed in Amhara State.
- To estimate and forecast the price volatility of cereals (wheat and barley) and pulses (pea and bean).

2. THEORETICALAND EMPIRICAL MODELS

The Box-Jenkins approach of time series models such as Autoregressive (AR), Moving Average (MA) and ARMA models are often very useful in modeling general time series. However, they all have the assumption of homoskedasticity or constant variance for the errors. The homoskedasticity assumption has the implication that uncertainty or volatility remains constant over time (Gebhard and Jurgenowolters, 2007).
One of the traditional and classical assumptions of conventional time series and econometric models is constant variance. The ARCH (Autoregressive Conditional Heteroskedastic) process introduced by Engle (1982) allowed the conditional variance to change over time as a function of past errors leaving the unconditional variance constant; it was the first model that provides a systematic form for volatility modeling.
After Engle proposed the ARCH model, it has been widely used in modeling economic phenomena and financial time series. However, some disadvantages of the ARCH model have been discovered, for example, the definition and modeling of the persistence of shocks and the problem of modeling asymmetries. In order to solve this, Bollerslev (1986) and Taylor (1986) proposed the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.
Extending the framework of Engle (1982), Bollerslev (1986) and Taylor (1986) generalized the ARCH(Q) model to GARCH(P, Q)in which they added P lags of past conditional variance into the equation. GARCH (P, Q) model allows for both autoregressive and moving average components in the heteroskedasticity variance. Empirical findings suggest that GARCH model is more parsimonious than ARCH model. A GARCH (0, 1) model is simply the first-order ARCH model. Although GARCH model has been the most popular volatility model, it has three main problems. Firstly, non-negativity constraint may be violated by the estimated models. Secondly, GARCH model does not take into account the leverage effect and not allow for feedback between the conditional variance and conditional mean.
After the introduction of simple GARCH models, a huge number of extensions and alternative specifications such as EGARCH (Nelson, 1991), Threshold GARCH (Glostenet al, 1993) have been proposed in an attempt to better capture the characteristics of return series.
Claessen and Mittnik (2002) investigated a range of alternative strategies for predicting volatility in financial markets applying GARCH model to daily returns on the DAX index, the major German stock index. They also examined whether or not the German DAX–index options market is informational efficient. Focusing on the problem of whether or not implied volatility information derived either from observed option prices or from time series models such as GARCH models are useful in predicting future return volatility, they concluded that implied volatility is a biased but highly informative predictor of future volatility. Moreover, implied volatilities are informational efficient relative to other historic volatility information sources.
Akpan&Umoren (2012) study on modeling the dynamic relationship between food crop output volatility and its determinants in Nigeria. Time series data derived from the FAO database for the period 1961 to 2010 was used in this study. Unit root test conducted on the specified time series shows that all the series were integrated of order one at the 1% probability level. The GARCH (1, 1) model was used to generate the food crop output volatility for the selected food crops (i.e. rice, maize, sorghum, cassava and yam). The short-run and long-run elasticities of food crop output volatility with respect to the specified explanatory variables were determined using co-integration and error correction model. The empirical results revealed that inflation rate, per capita real GDP, loan guaranteed by Agricultural Credit Guarantee Scheme Fund (ACGSF) in the food crop sub-sector, harvested area of land for food crop and liberalization policy era had mixed influence on food crop output volatility both in the short and long run periods. The result also

showed that harvested area of land for the selected food crop was the most important factor that affects food crop volatility in the country. In addition, food crop volatility shows an average declining pattern in the liberalization policy period. Furthermore, agricultural policies in the liberalization policy package should be designed in the short term basis and used as a means for altering food crop output in Nigeria.

Jordaan et al. (2007) studied on measuring the price volatility of certain field crops in South Africa using the ARCH/GARCH approach. The conditional volatility in the daily spot prices of the crops traded on the South African Futures Exchange (yellow maize, white maize, wheat, sunflower seed and soybeans) is determined. The volatility in the prices of white maize, yellow maize and sunflower seed have been found to vary over time, suggesting the use of the GARCH approach in these cases. Using the GARCH approach, the conditional standard deviation is the measure of volatility, and distinguishes between the predictable and unpredictable elements in the price process. This leaves only the stochastic component and is hence a more accurate measure of the actual risk associated with the price of the crop. The volatility in the prices of wheat and soybeans was found to be constant over time; hence the standard error of the ARIMA process was used as the measure of volatility in the prices of these two crops. When comparing the medians of the conditional standard deviations in the prices of white maize, yellow maize and sunflower seed to the constant volatilities of wheat and soybeans, the price of white maize was found to be the most volatile, followed by yellow maize, sunflower seed, soybeans and wheat. These results suggest that the more risk-averse farmers will more likely produce wheat, sunflower seed and to a lesser extent soybeans, while maize producers are expected to utilize forward pricing methods, especially put options, at a high level to manage the higher volatility.

2.1. (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. But this may not be appropriate when dealing with some special characteristics of financial and agricultural price time series. This led to the introduction of Autoregressive Conditional Heteroskedasticity (ARCH) model which was proposed by Engle (1982).

After identifying the presence of ARCH effects, separate GARCH, TGARCH and EGARCH models have been employed in this study to investigate the pattern of price volatility and its determinants for cereal crops (wheat and barley) and pulse seeds (pea and bean) with joint estimation of a mean and a conditional variance equation.

2.2. Model Specification

Stationarity and Unit-Root Problem

Generally the concept of stationarity can be summarized by the followingconditions. 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 macroeconomicvariables. 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):

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

whereε_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 $\rho = 1$.

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.

A. The Mean Model

i.ARMA Model

In general, an Autoregressive moving average (ARMA)model is denoted by ARMA (p, q), where p and q are the orders of autoregressive and moving average components, respectively.

ARMA (p, q) mean model (Box-Jenkins, 1976) is given by:

$$y_t = \Phi_o + \Phi_1 y_{t-1} + \ldots\ldots + \Phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots\ldots - \theta_q \varepsilon_{t-q},$$

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

ii. ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) model was introduced byBox and Jenkins (hence also known as Box-Jenkins model) in 1960s forforecasting a variable. ARIMAmodels consist of unit-root non-stationary time series which can be madestationary by the order of integration 'd'. The general form of ARIMA (p, d, q) iswritten as:

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

where $\psi_p(B) = 1-\Phi_1B-\ldots\ldots-\Phi_pB^p$, $\Theta_q(B) = 1-\theta_1B-\ldots\ldots-\theta_qB^q$,$\Delta = 1-B$, d is the order of integration and B is the backward shift operator.

B. 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:

$\varepsilon_t = \sigma_t\upsilon_t$,

$\sigma^2_t = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \ldots\ldots.. + \alpha_q\varepsilon^2_{t-Q}$,or

$\sigma^2_t=\alpha_0+ \sum_{i=1}^{Q} \alpha_i\varepsilon^2_{t-i}$, [4]

where υ_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., $\sigma_t^2 =Var(\varepsilon_t|\varepsilon_{t-1}, \varepsilon_{t-2},\ldots.)$. This indicates that the current value of the variance of the errors possibly depend upon previous squared error terms. We impose the non-negativity constraints $\alpha_0,\alpha_i>0$ $i = 1, 2, \ldots., Q$.

C. 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:

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

$\varepsilon_t = \sigma_t \upsilon_t$,

$\sigma^2_t= \alpha_0+ \alpha_1\varepsilon^2_{t-1}+ \ldots. +\alpha_Q\varepsilon^2_{t-Q} + \beta_1\sigma^2_{t-1} + \beta_2\sigma^2_{t-2} +\ldots\ldots\ldots + \beta_P\sigma^2_{t-P}$, or

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

Restrictions: $\alpha_0>0$, $\alpha_i\geq 0$, $\beta_j \geq 0$ for i=1,2,…,Q and j=1,2,…,P.

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 EGARCHmodel. The ARMA(p,q)-EGARCH (P,Q) model is given as:

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

$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{Q} \alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{R} \lambda_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{P} \beta_j \ln(\sigma^2_{t-j})$.[6]

In contrast to the GARCH model, no restrictions need to be imposed on the model parameters since log-transformed conditional variance overcomes the positivity constraint of coefficients in EGARCH models. Note that the left hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic and that forecasts of the conditional variance are guaranteed to be non negative. 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 number of possible conditional volatility formulations is vast. The threshold GARCH, or TGARCH (P,Q), model is one of the widely used models introduced by Zakeian (1990) and Glosten et al. (1993). The TGARCH model with mean and conditional variance equations is given as:

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

$\sigma_t^2= \alpha_0+\sum_{i=1}^{Q} \alpha_i\varepsilon^2_{t-i}+\sum_{i=1}^{Q} \lambda_i d_{t-i}\varepsilon^2_{t-i}+ \sum_{j=1}^{P} \beta_j\sigma^2_{t-j}$, [7]

where$d_{t-i} = 1$ if $\varepsilon_{t-i}\geq 0$, and $d_{t-i} = 0$ otherwise. The TGARCH model allows a response of volatility to news with different coefficients for good and bad news. That is, depending on whether ε_{t-i} is above or below the threshold value of zero,ε^2_{t-i} has different effects on the conditional variance σ^2_t: when ε_{t-i} is positive, the total effects are given by $\alpha_i\ \varepsilon^2_{t-i}$; when $\varepsilon_{t-i}$is negative, the total effects are given by $(\alpha_i + \lambda_i)\ \varepsilon^2_{t-i}$. So, one would expect λ_i to be positive for bad news to have larger impacts. The presence of leverage effects can be tested by the hypothesis that $\lambda_i = 0$. The impact is asymmetric if $\lambda_i\neq 0$.

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:

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{Q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{P} \beta \sigma_{t-j}^2 + \gamma' X_t$ [8]

where $X_t = (x_{1t}, x_{2t}, .., x_{kt})'$ is a vector of explanatory variables and $\boldsymbol{\gamma} = (\gamma_1, \gamma_2, .., \gamma_k)'$ 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:

$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{Q} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{R} \lambda_i \left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{j=1}^{P} \beta_j \ln(\sigma^2_{t-j}) + \gamma' X_t$ [9]

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{Q} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{Q} \lambda_i d_{t-i} \varepsilon^2_{t-i} + \sum_{j=1}^{P} \beta_j \sigma^2_{t-j} + \gamma' X_t$ [10]

2.3. Assumptions of the Models

a. The expected value of the error term is zero, i.e. $E[\varepsilon_t] = 0$.
b. The variance of the error terms is conditionally hetroskedastic.
c. Error terms are independent having normal or student-t or GEDdistribution 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.

2.4. Procedures for Model Building

2.4.1. Testing for the Presence of 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). Once the presence of unit root (non-stationarity) is confirmed, the series needs to be differenced to achieve stationarity.

The Dickey Fuller (DF) Test

The simplest form of the DF (Dickey fuller, 1979) test amounts to estimating

$y_t = \rho y_{t-1} + \varepsilon_t$.

One could use a t- test to test the hypothesis $\rho = 1$ (unit root) against $\rho < 1$. Alternatively, one can rearrange the model as follows:

$y_t - y_{t-1} = \Delta y_t = (\rho - 1) y_{t-1} + \varepsilon_t$,

$\Delta y_t = \alpha y_{t-1} + \varepsilon_t$, [11]

where $\varepsilon_t \sim$ IID $(0, \sigma^2)$ with $\alpha = \rho - 1$. The null and alternative hypotheses for unit root test are:

$H_0: \alpha = 0$

$H_1: \alpha < 0$.

The test statistic is the conventional t-ratio:

$t_\alpha = \frac{\hat{\alpha}}{s.e(\hat{\alpha})}$, [12]

where $\hat{\alpha}$ is the OLS estimate of α and $s.e(\hat{\alpha})$ is the coefficient standard error. Dickey and Fuller (1979) show that under the null hypothesis of a unit root, this statistic does not follow the conventional Student's *t*-distribution, and they derive asymptotic results and simulate critical values for various sample sizes. More recently, MacKinnon(1991, 1996) implements a much larger set of simulations than those tabulated by Dickeyand Fuller. In addition, MacKinnon estimates response surfaces for the simulation results,permitting the calculation of Dickey-Fuller critical values and p-values for arbitrary samplesizes.

The simple Dickey-Fuller unit root test described above is valid only if the series is an AR(1)process. If the series is correlated at higher order lags, the assumption of white noise disturbancesis violated. The Augmented Dickey-Fuller (ADF) test constructs a parametric correction for higher order correlation by assuming that the series follows an AR(p) processand adding lagged difference terms of the dependent variable to the right-hand side of the test regression.

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 regressors which are required to account for possible occurrence of autocorrelation. Consider the AR (p) model:

$y_t = \mu + \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t$, [13]

We can write equation [13] as:

$\nabla y_t = \mu + \alpha y_{t-1} + \sum_{i=2}^{p} \psi_i \nabla y_{t-p} + \varepsilon_t$, [14]

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

The presence of a unit root is tested in a similar manner as described above. 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 methodsto 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).

Examining ACF and PACF

Examining AC patterns within a time series is an important step in many statistical analyses. The autocorrelation coefficient is the correlation between y_t and y_{t-k} (separated by k periods apart) and the formal expression at time lag k is:

$$\rho_k = \frac{Cov(y_t,\ y_{t-k})}{\sqrt{Var(y_t)Var(y_{t-k})}} = \frac{Cov(y_t,\ y_{t-k})}{Var(y_t)},$$

wherecov (y_t, y_{t-k}) is the autocovariance between $y_t$and y_{t-k} for k= 0, 1, 2 … The ACF is a listing or graph of the sample autocorrelations at lag k = 0, 1, 2… The partial autocorrelation at lag k is the correlation between yt and y_{t-k} after removing the effect of $y_{t-1}, \ldots y_{y-k+1}$ and the formal expression is given as:

$$\gamma_k = \frac{Cov(y_t, y_{t-k}|y_{t-1}, \ldots, y_{t-k+1})}{\sqrt{Var(y_t|y_{t-1} \ldots\ )Var(y_{t-1}|\ y_{t-k+1})}},$$

where$cov(y_t, y_{t-k}|y_{t-1}, \ldots, y_{t-k+1})$ is the auto covariance between$y_t$and y_{t-k} after removing the effect of $y_{t-1}, \ldots, y_{t-k+1}$ for k =0, 1, 2… However, for GARCH family models the autocorrelation and partial autocorrelation coefficients are computed for squared returns of the process. Thus, the autocorrelation coefficient at lag k is given as:

$$\rho_k = \frac{cov(y_t^2, y_{t-k}^2)}{\sqrt{var(y_t^2)var(y_{t-k}^2)}},$$

wherecov(y^2_t, y^2_{t-k}) is the auto covariance between y^2_t and y^2_{t-k} for k= 0, 1, 2 ….

The partial autocorrelation coefficient at lag k can be computed as:

$$\gamma_k = \frac{Cov(y_t^2, y_{t-k}^2|y_{t-1}^2, \ldots, y_{t-k+1}^2)}{Var(y_t^2|y_{t-1}^2, \ldots, y_{t-k+1}^2)},$$

wherecov(y^2_t, $y^2_{t-k}|y^2_{t-1}$, …. , y^2_{t-k+1}) is the auto covariance between y^2_t and y^2_{t-k} after removing the effect of y^2_{t-1}, …y^2_{t-k+1}fot k = 0, 1, 2, …. The plot of the autocorrelation and partial autocorrelation functions of the ordinary and standardized residuals at time lag k = 0, 1, 2….can be used for checking the presence of ARCH effects in the residuals from mean equation. In case of ARCH effects, ACFs of squared residuals should dies down slowly (i.e. ACFs of squared residuals should not be white noise).

The ACFs are also used for checking model adequacy in fitted GARCH (P,Q) family process, i.e. the ACFs of standardized residuals should be indicative of a white noise process if the model is adequate.

2.4.2. Testing ARCH Effects

The presence of ARCH effect (whether or not volatility varies over time) has to be tested through the squared residuals of the series (Tsay, 2005). According to Tsay, 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: $\rho_1 = \rho_2 = \ldots\ldots = \rho_k = 0$ (the ACF for the first k lags of the squared residuals series is zero)

H_1: not all $\rho_j = 0$

whereρ_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 from equation (2). They showed that under the null hypothesis Q(k) is asymptotically distributed as chi-square with (k-p-q) degree of freedom, where k is the maximum lag considered, p and q are the order of the AR and MA from equation (2), respectively.

(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. The steps to derive the test statistic for LM test are:

- Estimate the mean equation ε, $\hat{\varepsilon}$
- Obtain the residuals

- Then regress current squared residual on lagged squared residuals and a constant:

$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1\hat{\varepsilon}_{t-1}^2 + \ldots + \gamma_q\hat{\varepsilon}_{t-q}^2$ [15]

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

The test statistic $\mathbf{n.R^2}$ is distributed as chi-square with q degrees of freedom, where R^2 is the coefficient of determination from equation (15) and n is number of observations. The rejection of the null hypothesis indicates the presence of ARCH (Q) effects.

It is important to apply the LM test on the residuals from the mean equation (ARMA) model (not GARCH model). Also one does not test directly for GARCH effects; if ARCH effect exists, GARCH model can also be considered.

2.4.3. 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). In statistics, the JB test is a test of departure from normality based on the sample kurtosis and skewness. The test is named after Jarque and Bera (1982). The null hypothesis states that the observations come from a normal distribution. The test statistic is:

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

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

2.4.4. 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.

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

$$AIC = -2\ln(L) + 2K \quad [16]$$

$$BIC = -2\ln(L) + K.\ln(n) \quad [17]$$

where n = number of observations

K = number of parameters estimated

L = value of the likelihood function (log $L(\sigma_t^2)$)

2.4.5. 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. In maximum-likelihood estimation the distributional assumption on the residuals is the core point.Financial time series data possess volatility clustering and leptokurtosis characteristics which lead to the use of different distributional assumptions for residuals such as: - 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. As suggested by Bollerslev (1986) and Tsay (2005), initial values of both the conditional mean equation and past conditional variances are needed in estimating the parameters of the model and then the conditional maximum- likelihood estimates can be obtained by maximizing the conditional log-likelihood. The estimation of conditional volatility models are typically performed by MLE procedures in Bollerselv and Wooldridge (1992).

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

2.4.6. 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.

2.4.7. 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.

2.5. Source and Type of Data

To assess the average monthly price volatility and its determinants on certain cereal crops (wheat and barley) and pulse seeds (pea and beans) in Amhara National Regional State, the data for the study were obtained from Central Statistical Agency (CSA), National Bank of Ethiopia (NBE) and National Metrological

Agency of Ethiopia, Bahir Dar district onmonthly basis from December 2001 to June 2012 G.C.
The variables of interest in this study arethe average monthly prices of different agricultural crop product categories, that is, the price of cereal crop (wheat and barley) and price of pulse seed (bean and pea) are 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. Also seasonal dummies are used since the data are not seasonally adjuste

3. STATISTICAL DATA ANALYSIS

3.1 Descriptive Statistics

The data analysis is carried out using EViews 7 and STATA 11 software.

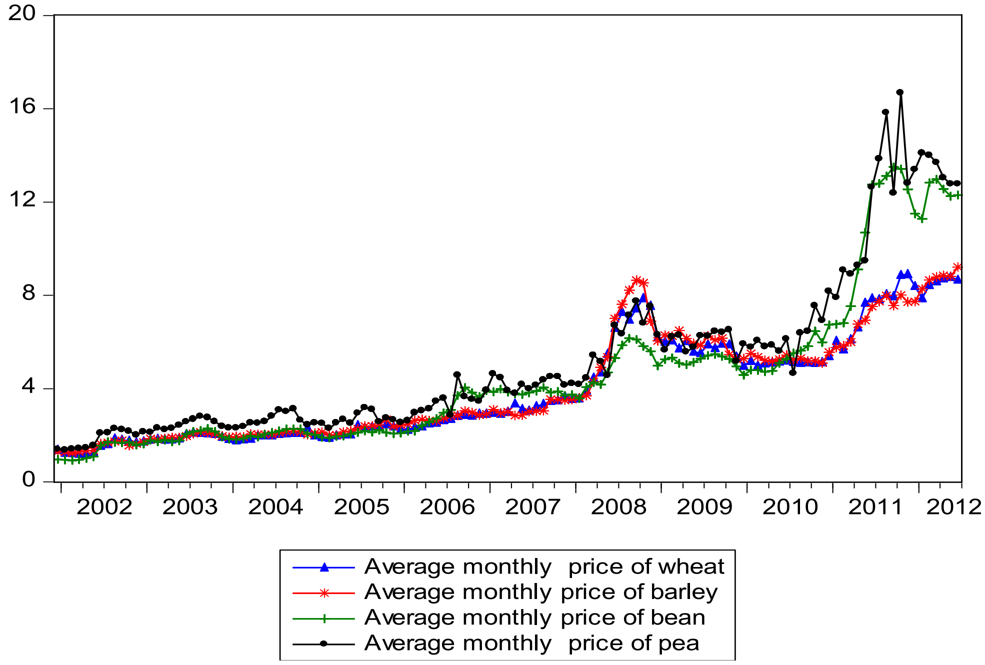

Fig 3.1: Average Monthly Price Trend of Wheat, Barley, Bean and Pea

Table 3.1:Summary Results for Average Monthly Price and Log-Return Series for Wheat, Barley, Bean and Pea

Statistics	Average monthly price				Log-return series			
	Wheat	Barley	bean	pea	wheat	barley	bean	pea
Mean	3.9909	4.0452	4.4577	5.1270	0.0146	0.0156	0.0203	0.0176
Median	2.9994	3.0034	3.8211	4.1277	0.0083	0.0170	0.0137	0.0171
Maximum	8.8968	9.2148	13.4914	16.6800	0.2029	0.2685	0.3694	0.4694
Minimum	1.1896	1.2215	0.9214	1.3566	-0.1996	-0.2141	-0.1168	-0.2758
Std. Dev.	2.2895	2.3034	3.2850	3.4921	0.0608	0.0593	0.0677	0.1172
skewness	0.6741	0.6572	1.4803	1.4810	0.2776	0.2311	1.3859	0.5334
kurtosis	2.1537	2.1005	4.3961	4.5415	4.8290	7.2263	7.7633	5.3852
Jarque-Bera	13.4097	13.4243	56.7036	59.0032	19.1813	94.8970	159.4429	35.8467
P-value	0.0012	0.0012	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3.2 displays summary statistics for each of the explanatory variables.

Table 3.2: 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

3.2 Tests of Stationarity

As can be seen fromthe table, 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

Table 3.3:ADF Unit Root Test at Level for Average Monthly Prices

Prices	Test Statistics	1% critical value	5% critical value	10% critical value	P-value
Wheat	-0.2316	-3.4833	-2.8846	-2.5791	0.9302
Barley	-0.2046	-3.4833	-2.8846	-2.5791	0.9337
Bean	-0.0103	-3.4833	-2.8846	-2.5791	0.9552
Pea	0.3528	-3.4833	-2.8846	-2.5791	0.9801

Table 3.4 summarizes the ADF unit root test of the log return series for wheat, barley, bean and pea. The table 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.

Table 3.4: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
Wheat	-9.3948	-3.4833	-2.8846	-2.5791	0.0000*
Barley	-8.9575	-3.4833	-2.8846	-2.5791	0.0000*
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 3.5 and 3.6 (and Table A_3 and Table A_4 in appendix I) show the results ofADF and PP tests for the predictors. The results from Table 4.5 and Table A_3 reveal that 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 4.6 and Table A_4, implying that all explanatory variables are integrated of order one.

Table 3.5: ADF Unit Root Test of Explanatory Variables at Level

Explanatory variable	test statistic	1% critical value	5% critical value	10% critical value	p-value
Exchange rate	1.8107	-3.4828	-2.8844	-2.5790	0.9997
Saving interest rate	-3.0749	-3.4828	-2.8844	-2.5790	0.0310
Lending interest rate	-2.2139	-3.4828	-2.8844	-2.5790	0.2025
General inflation rate	-1.6499	-3.4885	-2.8869	-2.5804	0.4539
Food inflation rate	-1.9933	-3.4885	-2.8869	-2.5804	0.2895
N-food inflation rate	-0.9160	-3.4885	-2.8869	-2.5804	0.7800
Temperature	-2.0333	-3.4880	-2.8867	-2.5802	0.2724
Rain fall	-2.3178	-3.4880	-2.8867	-2.5802	0.1682

Table 3.6: 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*

3.3. 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). Table A_5 – Table A_8 in appendix I presents AIC and BIC for optimal order selection from each combination of the mean models across a range of lag specifications 0, 1, 2, 3 and 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. The results are shown in Tables A_5 to A_8 (appendix I).

Among the candidate mean models for the price return series of wheat, ARMA (1, 0) has the smallest BIC and exhibits no serial autocorrelation. Similarly, ARMA (0, 1), ARMA (4, 4) and ARMA (1, 0) were found to have the smallest BIC for the return series of barley, bean and pea, respectively.

3.4. Testing for ARCH Effects

The ARCH LM test helps to test the hypothesis that there is no ARCH effect up to lag Q. Table 4.11 shows the results of ARCH LM test for lags 1, 2 and 3 for the four average 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 wheat, 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. But in the case of barley, there is no evidence to reject the null hypothesis of no ARCH effect at the 5% level of significance. Thus, there is no need to proceed with GARCH family models for the return series of barley.

Table 3.11: ARCH LM Test Summary Statistics

Item	ARCH(Q)	X^2 statistic	p-value	F-statistic	p-value	BIC
Wheat	ARCH(1)	9.7880	0.0018	10.4496	0.0016	-7.0680
	ARCH(2)	0.5576	0.7567	0.2732	0.7614	-7.0215
	ARCH(3)	0.6932	0.0218	0.2247	0.0090	-7.0641
Barley	ARCH(1)	0.0054	0.9413	0.0053	0.9419	-6.6613
	ARCH(2)	0.0729	0.9642	0.0356	0.9650	-6.6144
	ARCH(3)	0.2902	0.9619	0.0938	0.9633	-6.5686
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

3.5. Optimal Order Selection and Parameter Estimation of GARCH Family Model

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 SW &Hansen BE. 1994), the GARCH(1,1) model is compared to various higher-order models of volatilities based on the minimum AIC and BIC. The summary of empirical results of GARCH, TGARCH and EGARCH model specifications and information criteria for order selection are displayed in Table A_{12} – Table A_{20} for price return series of wheat, bean and pea (Appendix III).

After testing for different orders of P and Q of GARCH family, it was found that EGARCH(1,1) under Normal distributional assumption for residuals, EGARCH(1,1) under Student-t distributional assumption for residuals and EGARCH(3,3) under GED distributional assumption for residuals for the price volatility of wheat; 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.

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 summary results are presented in Table A_{21}- Table A_{23} (Appendix IV).The results show that ARMA(1,0)-EGARCH(3,3) model with GED for residuals, ARMA(4,4)-EGARCH(2,3) model with GED for residuals and ARMA(1,0)-EGARCH(1,2) model with student-t for residuals perform best as compared to others as they possess the smallest forecast error measures in the majority of the statistics considered.

Finally an analysis of the determinants of monthly average price volatility was conducted. The parameters in the mean and variance equations are estimated using the maximum likelihood (ML) method. The results are shown in Table 4.13.

3.6. Discussion

3.6.1 Monthly Price Return Series for Wheat

Accordingly to the results, the coefficient estimate of exchange rate (dollar versus birr) is positive and statistically significant at the 5% level. Thus, an increase in exchange rate leads to an increase in the current month volatility of the average monthly price of wheat. The link between exchange rate and increase in average monthly price volatility at current month was likely to be through the impact that exchange rate has on the purchasing power of money. This result was consistent with findings by Loening et al. (2009), Gilbert (1989), Chambers (1984) and Sarris and Morrison (2009).The coefficient of saving interest rate was negative and statistically significant at the 1% level, that is, the impact of saving interest rate on the conditional variance of monthly average price of wheat was stabilizing. Hondroyiannisand Papapetrou

(1998) showed that money supply changes can affect agriculturalprices through the mechanism of interestrate.

General and food inflation rates have positive and significant influence on the monthly average price volatility. The positive coefficients indicate that a rise in general and food inflation rates move up current month price volatility of wheat. This result concurred with the finding of Akpan&Umoren (2012).The coefficient of rainfall in the variance equation for wheat was negative and statistically significant at the 5% level of significance. A unit increase in rainfall leads to a decrease in the average monthly price volatility of wheat. This may be due to an increase in agricultural crop production.

Among the candidate explanatory variables, the impact of lending interest rate, inflation for non- food item and temperature on the price volatility of wheat were insignificant.

Among the seasonal dummies, price in February, March, June and December have an increasing effect on the current month variability of average price of wheat. On the contrary, price in September and October have a decreasing effect. The link between those months and monthly average price volatility was likely to be through the seasonal pattern of wheat price. Jordan et al.(2007) showed that prices are characterized to be lower at harvest and higher in the other seasons.

From the results we can see that EGARCH(-1), EGARCH(-2) and EGARCH(-3) terms are positive and statistically significant at the 1% level. This is a strong evidence of price volatility spillover in the average monthly price of wheat. The positive coefficients of the EGARCH(-1), EGARCH(-2) and EGARCH(-3) terms indicate that the 1-, 2- and 3- month lagged price volatility of wheat causes an increase in current month volatility. This result was consistent with the findings by Demisew and Yegnanew (2012).

Likewise, 1-, 2- and 3- month lagged shocks (ARCH (-1), ARCH (-2) and ARCH (-3) terms) of the average monthly price of wheat have statistically significant effect on the current month price volatility. This is an indication that current price volatility is sensitive to price movements in the past. This result was consistent with the findingsby Anteneh (2012).

Moreover, the coefficient of the asymmetric term was positive and statistically significant at the 1% level of significance. Thus, bad news (an expected increase in average monthly price) had larger impact on the price volatility than good news (an expected decrease in average monthly price). The significance of the asymmetric term in the variance equation also suggests that the EGARCH model could be a suitable model than a symmetric GARCH model. Thisresult was consistent with the findings by Greene (2003).

3.6.2 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 newshad larger impact on the price volatility than good news.

3.6.3 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.

3.7. Checking Adequacy of Fitted Models

Various diagnostic tests were performed to checkthe appropriateness of the fitted models. From TableA_{27} - Table A_{29}(Appendix V), 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 wheat, bean and pea return series, indicating that the residuals are uncorrelated (white noise).

From Table A_{30} (Appendix V), 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%.
Figure 2, 3 and 4 (Appendix V) show summary of descriptive statistics for standardized residuals. The results reveal that the coefficients of skewness were 0.1985, 0.2988 and 0.0865 and the coefficients of kurtosis were 2.8896, 2.6791 and 2.7501 for wheat, bean and pea, respectively. The Jarque-Bera test statisticswere 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.

4. CONCLUSIONS

This study considered the average monthly price volatility and its determinants on cereals (wheat and barley) and pulse (bean and pea) from December 2001 to June 2012 GCin Amhara National Regional State (ANRS).From the empirical results, it can be concluded that average price return series of wheat, 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(1,0)-EGARCH(3,3) model with GED for wheat, 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 wheat and 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 wheat and 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 wheat and 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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