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Forecasting Volatility of Returns for Corn using GARCH Models

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ABSTRACT

The purpose of this paper is to model and forecast volatility of returns for corn futures prices using GARCH models. Non-linear models from the GARCH family, specifically TGARCH and EGARCH are employed to assess the role of asymmetries and to analyze the time varying volatility of corn futures prices. The results reveal that the corn return series react differently to good and bad news. The presence of leverage effect would imply that the negative news has bigger impact on volatility than positive news of the same magnitude. The estimated volatility models were compared using symmetric measures for their forecasting accuracy. It is found that the EGARCH model provides the best out of sample forecasts for corn among all the GARCH specifications.

KEY WORDS: volatility, forecasting, GARCH models, corn futures

INTRODUCTION

Financial market volatility analysis has garnered the attention of academics as well as market participants across the world for the last two decades. Volatility can be defined as fluctuations in the standard deviation of daily returns for the selected asset or commodity. Volatility analysis is important as a risk management tool for hedging effectiveness, as well as, aiding in the selection and management of asset portfolios (Jondeau and Rockinger 2003).

Commodity prices fluctuate continuously throughout the year due to changes in the underlying supply and demand variables. Analyzing the volatility behavior of an agricultural commodity, like corn, has implications for both farmers and market participants. For example, market prices of agricultural commodities typically increase before harvest and fall after harvest, thereby causing volatility swings. Any surprising USDA crop reports, whether they be the condition of current crop progress or changes in the inventory of grain stocks (either surpluses or shortages), immediately put the commodity markets into an acceleration mode. Understanding volatility helps farmers in managing their production risks and making proper marketing decisions. This also helps

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farmers in minimizing their market exposure during periods of higher volatility. Volatility analysis can also be helpful in developing an effective hedge against adverse price movements. Market investors can also benefit from these studies in properly selecting and managing their investment portfolio. Periods of excess volatility help commodity traders, especially day traders, to gain significant profits through trading strategies tailored to volatilities. Knowledge about the source of price volatility can be useful to risk managers in making decisions about the timing of their decisions (Evans et al. 1992). Price limits and contract margins imposed by commodity exchanges, also in part, depend upon the volatility of corresponding commodities. Commodity traders who write options also need to forecast the volatility of the price process over the life time of the option (Alexander 2001). Volatility also has an important effect on the macro economy of a country. For example, increased volatility, beyond a certain threshold will increase the risk of losses to investors and raise concerns regarding the stability of a particular market and the overall economy (Pan and Zhang 2006).

Previous research on volatility analysis has been mostly concentrated on the financial indices. Volatility research in the commodity markets typically focused on understanding the sources of volatility and little attention has been paid to forecasting the volatilities. The purpose of the present paper is to model and forecast volatility of returns for corn using different types of GARCH models. We are also interested in examining whether positive and negative shocks have an asymmetric effect on return volatility and thereby provide evidence for any leverage effect in corn. The paper uses three different types of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) specifications: the standard GARCH, Exponential GARCH (EGARCH), and the Threshold GARCH (TGARCH) specifications to model and forecast the volatility (conditional variance). These models are known to capture the characteristics of financial time series such as time varying volatility, non-linearity dependence, and volatility clustering (See Pagan 1996; Enders 2004). The specifics of the ARCH model formulations are discussed in detail in the next section.

A quick review of recent literature shows various sources for volatility and its application in different areas. For example, Bernanke and Gertler (1999) discussed the role of volatility of financial markets and its effect on monetary policy. Crato and Ray (2000) studied the volatility of commodity markets and concluded that the volatility is more persistent for energy markets than the currency markets. Bajpai and Mohanty (2008) used EGARCH model with normal and non-normal errors to estimate the volatility of exchange rate. Their results indicate a negative relationship between exchange rate volatility and U.S. cotton exports to major countries. Brorsen and Irwin (1987) investigated if there is a significant relationship between the technical trading and increased volatility of ten different commodities. Their results show that technical trading is not a significant factor in contributing to the volatility of commodities. According to Irwin et al. (2008), recent surges in the volatility of agricultural commodities are due to structural changes in the markets and strong linkages with the energy complex. Crain and Lee (1996) suggested that the grain price volatility is influenced by changes in government programs and according to the authors, volatility typically transfers from futures markets to cash markets. With regard to the forecasting ability, Cao and Tsay (1992) point out that the TGARCH model produces better forecasts than GARCH, EGARCH, and ARMA models on the U.S. stock exchange. Balaban (2002) argues symmetric GARCH models provide relatively good forecasts of monthly exchange rate volatility in comparison with asymmetric models.

The structure of the paper is organized as follows: Section II describes the econometric methodology employed in the paper, Section III describes the data, Section IV discusses the results obtained from the analysis, and finally, the last section summarizes the paper.

METHODOLOGY

Our analysis of volatility forecasting begins with the calculation of continuously compounded daily returns for corn based on the following equation

$$r_t = \left[\ln\left(p_t / p_{t-1}\right)\right] \quad (1)$$

Where r_t represents the daily log returns for corn, p_t denotes the daily settlement price for the commodity, while p_{t-1} represents the settlement prices with one lag.

Random Walk Model. The behavior of asset prices relating to its random nature has attracted the attention of researchers worldwide. Proponents of Efficient Market Hypothesis (EMH) argue that the asset prices typically behave in a random fashion and any attempt to forecast future values based on its past values is futile (Fama 1965, 1970; Cooper 1982).

The basic model for estimating the volatility of returns using OLS is the naïve random walk (RW) model and is given by:

$$r_t = \mu + \varepsilon_t \quad (2)$$

Where μ is the mean value of returns, which is expected to be insignificantly different from zero under EMH, and ε_t is the error term.

The drawback of the above model is that it can be used only to characterize the mean returns. Traditional econometric models such as ordinary least squares are built upon the assumption of constant variance. The error variances may not be constant over time. The assumption of constant variance of the error term is inconsistent with financial time series where the variance is heteroskedastic and time-varying. In order to account for the time varying volatility which cannot be captured through linear models like OLS, this study uses GARCH models.

GARCH Specifications. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH), was developed independently by Bollerslev (1986) and Taylor (1986), was used in the present study to investigate the effect of volatility of corn futures prices. The appeal of the GARCH model is that it takes into consideration both mean and volatility in modeling the financial returns, and has an advantage over the traditional regression models. It also has the ability to capture volatility clustering, a characteristic of financial time series, where large returns are followed by large returns, small returns followed by small returns, leading to contiguous periods of volatility and stability (Mandelbrot 1963). Rarely, any higher order model than GARCH (1,1) is needed to capture volatility clustering (Alexander 2001; Brooks 2008).

The GARCH model is based on the assumption that forecasts of time varying variance depend upon the lagged variance of the asset. The analysis of the model involves estimation of two distinct specifications: one for the conditional mean and the other for conditional variance.

The basic GARCH (1,1) can be represented as:

$$r_t = \mu + \theta r_{t-1} + \varepsilon_t; \qquad \varepsilon_t \approx (0, h_t) \tag{3}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{4}$$

Where $\omega \succ 0, \alpha \geq 0, \beta \geq 0$ are required to ensure that the conditional variance is never negative. The variance (h_t) is a function of an intercept (ω), a shock from the prior period (ε_{t-1}) and the variance from the last period (h_{t-1}).

The ARCH terms indicates the short run persistence of shocks whereas the GARCH term represents the contribution of shocks to long run persistence. $(\alpha + \beta)$ is a measure of persistence of volatility clustering. If $(\alpha + \beta)$ is very close to 1, it shows high persistence in volatility clustering. The GARCH (1,1) is weak stationary if $(\alpha + \beta) < 1$.

The above GARCH model assumes a symmetric volatility response to market news. According to GARCH specification, positive and negative shocks have the same effect on volatility, as the unexpected return (ε_t) always enters the conditional variance as a square. It has been suggested in the financial literature that negative shocks in the market have a larger impact on volatility than positive shocks of the same magnitude (Asteriou and Hall 2011; Brooks 2008; Zivot 2008; Bollerslev et al. 1992; Engle and Ng 1993). As a result, Asymmetric GARCH models are more appropriate.

Two Asymmetric GARCH models (TGARCH and EGARCH) have been employed in the present paper to study the possible asymmetries typically attributed to leverage effects for corn futures returns. Asymmetry can be introduced in the ARCH models by weighing ε_{t-1}^2 differently for positive and negative residuals, thus,

$$r_t = \mu + \theta r_{t-1} + \varepsilon_t; \qquad \varepsilon_t \approx (0, h_t) \tag{5}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma I_{t-1}\varepsilon_{t-1}^2 \tag{6}$$

This model is called TGARCH , following the works of Zakoian (1994) and Glosten et al. (1993) where α, β, and γ are constant parameters and I_t is an indicator dummy variable that takes the value of 1 if $\varepsilon_{t-1} < 0$ and zero otherwise. When ε_{t-1} is positive, the total contribution to volatility is $\alpha\varepsilon_{t-1}^2$ and when ε_{t-1} is negative, the total contribution to the volatility is $(\alpha + \gamma)\varepsilon_{t-1}^2$. The TGARCH (1,1) model is asymmetric as long as $\gamma \neq 0$.

The TGARCH models can be extended to higher order specifications by including more lagged terms. The TGARCH *(p,q)* model is defined by adding p terms to the right side of equation (6), so that

$$h_t = \omega + \sum_{i=1}^{p}(\alpha_i + \gamma_i I_{t-1})\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j h_{t-j} \tag{7}$$

The parameters in the model usually constrained by $\omega \geq 0, \alpha \geq 0, \beta \geq 0$ and $\alpha + \gamma > 0$.

The EGARCH specification of conditional volatility due to Nelson (1991) may be expressed as:

$$r_t = \mu + \theta r_{t-1} + \varepsilon_t ; \qquad \varepsilon_t \approx \left(0, h_t\right) \tag{8}$$

$$\ln\left(h_t\right) = \omega + \beta \ln\left(h_{t-1}\right) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{\left|\varepsilon_{t-1}\right|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] \tag{9}$$

As the name indicates, EGARCH assumes conditional variance as exponential, whereas TGARCH treats conditional variance as quadratic. The above model has several advantages over the traditional GARCH specification. As h_t is modeled in log form, even if the parameters are negative, h_t becomes positive. Another advantage is allowance of asymmetries in the EGARCH model formulation. In EGARCH, γ captures the asymmetrical effect and therefore any non-zero values shows the impact of any external event being asymmetric. For detailed information on GARCH models readers may refer to Bollerslev et al. (1992, 1994).

Forecasting Methodology. The random walk and GARCH models are evaluated in terms of their ability to forecast future returns. The forecasting performance of each model is evaluated by using standard symmetric measures: the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percent error (MAPE), and the Theil inequality coefficient (TIC). The forecasting statistics are given as follows:

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (\hat{\sigma}_t^2 - \sigma_t^2)^2} \tag{10}$$

Where $\hat{\sigma}_t^2$ is one step ahead volatility forecast, σ_t^2 is the actual volatility and T is the number of forecasts.

$$MAE = \frac{1}{T} \sum_{t=1}^{T} \left| \hat{\sigma}_t^2 - \sigma_t^2 \right| \tag{11}$$

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \frac{\left| \hat{\sigma}_t^2 - \sigma_t^2 \right|}{\left| \sigma_t^2 \right|} \tag{12}$$

$$TIC = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^{T} (\hat{\sigma}_t^2 - \sigma_t^2)^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} (\hat{\sigma}_t^2)^2} \sqrt{\frac{1}{T} \sum_{t=1}^{T} (\sigma_t^2)^2}} \tag{13}$$

The Theil inequality coefficient is the scaled measure that always lies between 0 and 1 where zero indicates a perfect fit. The best model for forecasting is the one with the smallest value for that measure.

The data used in the present paper is the daily settlement prices for corn, covering the period of January 3, 1995 to June 16, 2012, excluding public holidays. In order to eliminate price distortions caused by price gaps located between expiring contracts and subsequent futures contracts, this study used continuous corn futures contract developed from the settlement prices. The total sample comprises 3954 observations spanning approximately seventeen years of daily data. Corn is traded on the Chicago Board of Trade (CBOT) and is the most actively traded (liquid) contract among all the agricultural commodities. As of June 2012, the average daily volume for December 2012 corn is 137,332 contracts with an open interest of 420,282. In order to make forecasts, the full sample is divided into two parts: an in sample of 3954 observations (January 03, 1995 to September 16, 2010) and an out of sample of 439 observations (September 17, 2010 to June 16, 2012). The last 10% of observations are reserved for forecasting purposes.

RESULTS

Figure 1 represents the price index for corn (panel a) and the time series of daily returns calculated from the settlement prices (panel b) for the study period. Visual inspection of the return series shows that the mean returns are constant but the variances change over time. The commodity exhibits volatility clustering property indicating periods of high volatility (turbulence) and low volatility (tranquility). From the figure, it is evident that the volatility of corn had increased significantly during the recent times when compared to the initial periods. Periods of high volatility show large positive and negative returns when compared to the low volatility periods. The bottom part of figure 1 consists of histogram of returns (panel c) and a Gaussian QQ plot (panel d). The distribution of returns is characterized by a high peak at the center, which is considered to be a stylized fact of financial time series. For a detailed discussion of stylized facts, please see Taylor (2005) and Kovacic (2008). The QQ plot plots the quantiles of two distributions: the empirical distribution of corn returns and the hypothesized Gaussian distribution. The QQ plot clearly shows that the distribution tails for corn are heavier than the tails of the Gaussian distribution.

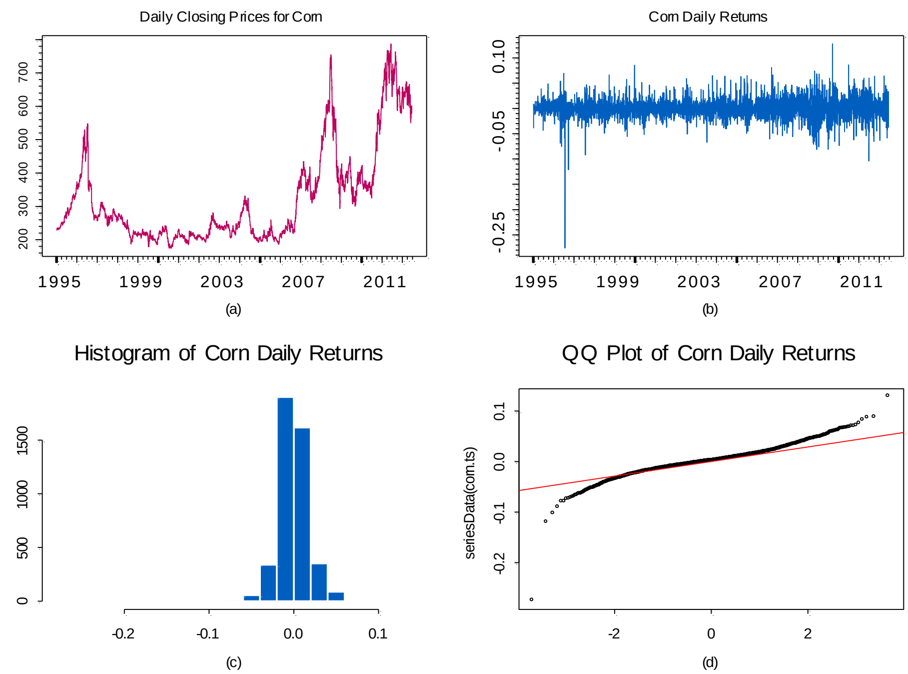

Figure 1. Corn Daily Returns and Tail Distribution.

The descriptive statistics for the time series of daily returns for corn are presented in Table 1. This table includes minimum, maximum, average daily returns, standard deviation, skewness, kurtosis, and Jarque-Bera statistics of the returns. As expected of financial time series, the mean of returns is close to zero. Positive mean returns show that the price series of corn has increased through time. The standard deviation of the daily returns is 1.847% which is equivalent to an annualized volatility of 29.32%. Corn shows high standard deviation and therefore considered to be a volatile commodity. The statistics also show a substantial difference between maximum and minimum returns for this commodity. The presence of slight negative skewness indicates that the lower tail of the distribution was thicker than the upper tail and decline in returns are more common than its increases. The kurtosis for the time series is 17, which is above the normal value of 3, and is considered as leptokurtic in nature. Generally, either a very high or very low kurtosis value indicates leptokurtic or platykurtic distribution of the sample data. The Jarque-Bera statistics indicate that the return series is non-normal and significant as evidenced by its p-value. These findings are consistent with earlier discussion related to the histogram of returns and QQ plot.

Table 1. Descriptive Statistics of Daily Returns for Corn.

Mean	0.000219	Skewness	-0.72694
Maximum	0.12757	Kurtosis	17.0095
Minimum	-0.2762	Jarque-Bera	36303.98
Std. Deviation	0.01847	Probability	0.00000

Table 2 shows the estimation results for the mean and variance equations for random walk (RW), GARCH, TGARCH, and EGARCH models of volatility for corn. The z statistics are also reported in the parentheses for each model. The results for RW model suggest that the mean of the return series is not significantly different from zero, which is consistent with the random walk hypothesis. The Ljung-Box Q statistics of the standard residuals (19.91), squared residuals (40.58) and ARCH-LM tests (5.99) are significant and show the presence of significant ARCH effects in the model. Since the OLS estimate of RW is an inadequate model to capture the financial return characteristics such as time varying volatility and volatility clustering, GARCH models were further used to understand the nature of commodity data. The model rankings also suggest that the RW model is the least preferred model among all the specifications. Columns 3, 4, and 5 in Table 2 show the mean returns and variance equation of the GARCH (1,1), TGARCH (1,1), and EGARCH (1,1) models respectively for the volatility estimation. Preliminary analysis suggests that the conditional mean equation for corn was best modeled as an autoregressive process, especially, an AR (1). The recent literature also suggests the inclusion of AR (1) is useful in order to remove any serial correlation in the returns which may be caused by non-synchronous trading (Lo and MacKinlay 1988; Campbell et al. 1997; Tsay 2002). Thus the mean equation in all the GARCH specifications includes an AR (1) term for this study. The z statistics indicate the significance of the intercept and coefficients at 5% significance level.

The mean daily returns range from 0.0387% to 0.0534% for all the GARCH specifications, whereas only GARCH (1,1) coefficient proved to be significant at 5% level. From the mean equation in the GARCH models, we also observe that the lagged value (θ) is significant for corn for all the specifications indicating that the returns of this commodity exhibit serial correlation and reflects inefficiency during the period of study. The coefficients of the conditional variance equation, α and β, are positive and significant for all the GARCH models suggesting strong support for ARCH and GARCH effects. The GARCH coefficient (β) can be used to understand the impact of past volatility on current volatility. The GARCH coefficient is significant at 5% level suggesting that the current volatility is affected by past volatility for corn. As typical of GARCH models for financial returns, the sum of the coefficients on lagged squared error (α) and lagged conditional variance (β) is very close to one implying that shocks to the conditional variance will be highly persistent for corn. A high persistence indicates that the shocks are likely to die slowly. If there is a new price shock, it will have implication on returns for a longer period. The only exception here is EGARCH model where sum of both α and β coefficients are greater than one and parameters are overestimated.

The asymmetric (leverage) coefficient γ captures the impact of negative versus positive shocks on volatility. Leverage coefficient (γ) when greater than zero under the TGARCH model, indicates that the negative shocks cause more volatility than positive shocks. Accordingly, γ is positive and significant for corn suggesting the presence of leverage effect. For this commodity, negative shocks tend to cause more volatility than positive news. Under EGARCH model, when the leverage coefficient is less than zero, then the positive shocks (good news) generate less volatility than negative shocks (bad news). Accordingly, with a negative and significant γ, the results indicate that negative news caused more volatility for corn confirming the earlier results of TGARCH model.

Table 2. Volatility Models and their Corresponding Results.

Parameter	RW	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
		Mean Equation		
μ	0.000205 (0.71)	0.000534* (2.24)	0.000410 (1.64)	0.000387 (1.53)
θ		0.036* (2.16)	0.040* (2.38)	0.044* (2.74)
		Variance Equation		
ω		3.44E-06* (9.27)	3.77E-06* (8.40)	-0.27324* (-14.68)
α		0.069* (27.26)	0.055* (12.58)	0.161* (26.42)
β		0.924* (380.87)	0.919* (358.66)	0.981* (482.37)
γ			0.038* (5.06)	-0.014* (-2.41)
LB 10	19.91* (0.03)	8.28 (0.50)	8.33 (0.50)	7.74 (0.56)
LB^2 10	40.58* (0.00)	3.25 (0.95)	3.43 (0.94)	3.25 (0.95)
ARCH-LM Test	5.99* (0.01)	0.007 (0.93)	0.0004 (0.98)	0.015 (0.90)
AIC	-5.18^{4}	-5.36^{3}	-5.37^{2}	-5.38^{1}
LL	10251.03^{4}	10615.13^{3}	10621.09^{2}	10651.32^{1}

θ is AR(1) coefficient; *denotes significance at 5% level. Numbers in parentheses below coefficient estimates are z statistics. AIC, LL are Akaike information criteria, and log likelihood respectively. LB 10 and $LB^2$10 are the Ljung-Box statistics for the standardized and squared standardized residuals using 10 lag, respectively. Numbers in parentheses below the LB statistics and arch coefficients are the p-values. Superscript denotes the rank of model.

Finally, to determine which GARCH model provides a reasonable explanation of behavior of commodity returns, some diagnostic tests are performed. The diagnostic tests results show that the GARCH models are correctly specified and there are no remaining ARCH effects in all the estimated GARCH models. The Ljung-Box Q statistics for the standard residuals and squared residuals are insignificant, suggesting that all the GARCH models are correctly specified (Table 2). Overall, using the minimum AIC, maximum log likelihood values as model selection criteria (Alagidede and Panagiotidis 2006) for the GARCH specifications, the model rankings indicate that the

EGARCH (1,1) is the preferred model for corn and captures most of the time series characteristics of the returns during the study period.

The models were also evaluated in terms of their ability to forecast volatility of future returns. The measures of forecast evaluation used in the present study include root mean square error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE) and Theil's inequality coefficient (TIC). Table 3 reports the forecast performance values and the corresponding ranking for all the GARCH models. The results indicate that the relative differences among forecasting performance measures are quite small and the largest relative difference between the best and worst performing models for out of sample data using TIC is approximately 4%. Figure 2 presents the out of sample volatility forecast and variance forecast of the corn returns. The forecasting results show that EGARCH (1,1) model is the most preferred among all the models and the naïve RW model performed worse in forecasting the volatility of returns for corn. Thus the EGARCH model was found to be the best model to study the volatility behavior and the corresponding forecasting of returns.

Table 3. Forecast Performance of the Estimated GARCH Models.

Forecast Criteria	RW	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
Root Mean Square Error (RMSE)	0.021796^{4}	0.021609^{3}	0.021606^{2}	0.021412^{1}
Mean Absolute Error (MAE)	0.015993^{4}	0.015515^{3}	0.015219^{2}	0.015024^{1}
Mean Absolute % Error (MAPE)	111.49^{1}	143.42^{4}	135.48^{3}	135.03^{2}
Theil Inequality Coefficient (TIC)	0.9905^{4}	0.9584^{3}	0.9577^{2}	0.9545^{1}
Overall Rank	4	3	2	1

Forecast sample: September 17, 2010 to June 16, 2012; superscript indicates the rank of the model

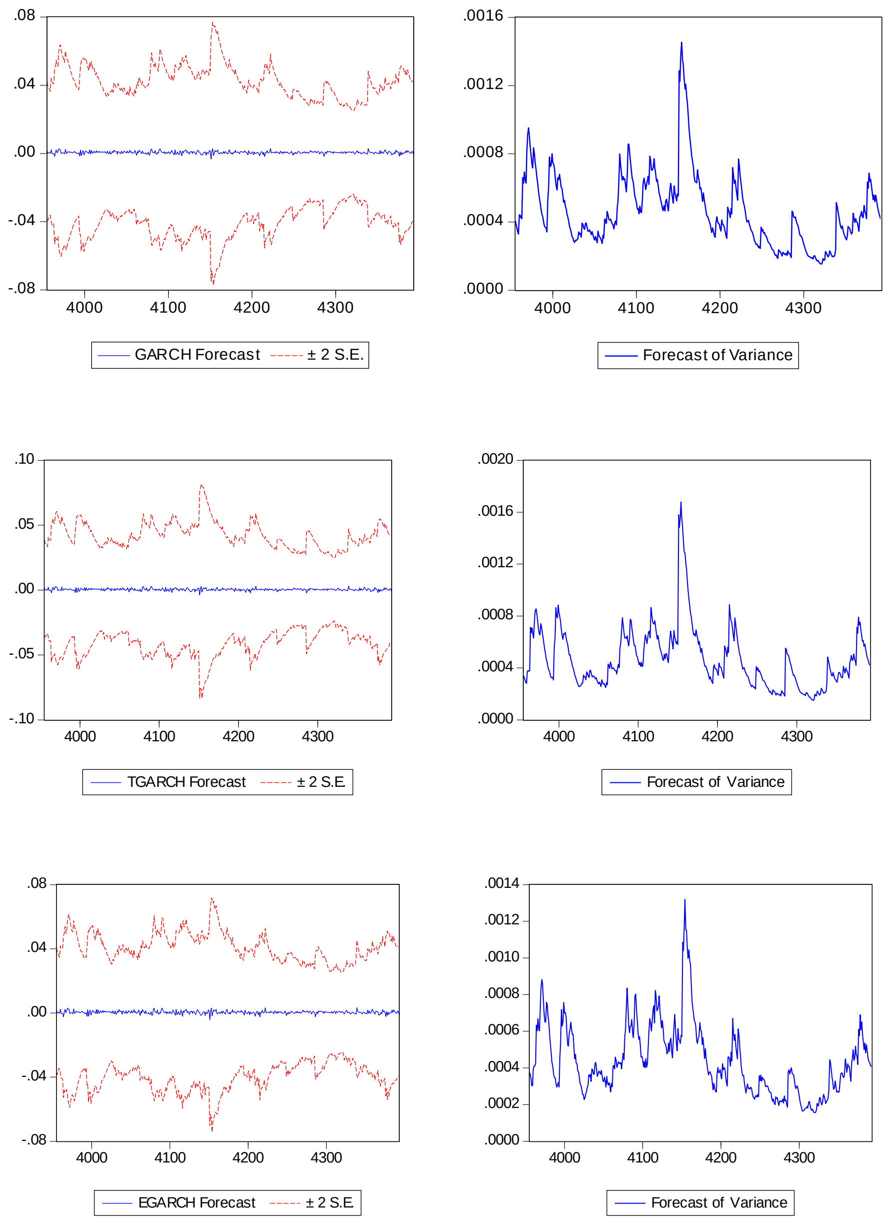

Figure 2. Volatility Forecast and Forecast of Variance Graphs.

CONCLUSIONS

This paper contributes to the existing body of literature in two aspects: first, most of the volatility studies seen in the financial literature are focused on stock exchanges and agricultural commodities were not explored in detail. By focusing on the most liquid member of agricultural commodity group, this study attempts to understand the volatility behavior for corn. Second, we analyzed alternative group of GARCH models in order to find the best model that can be used to understand and forecast the commodity returns. The significance has been tested using a traditional OLS model, a non-linear symmetric GARCH (1,1) model, and two non-linear asymmetric models, TGARCH (1,1) and EGARCH (1,1).

Under GARCH models, the results indicated that the sum of the coefficients on the lagged squared error and lagged conditional variance is close to unity for corn indicating that the shocks to the conditional variance will be highly persistent. The leverage effect term in both the TGARCH and EGARCH specifications for corn is statistically significant indicating negative shocks imply a higher next period variance than positive shocks of the same magnitude. From the overall results, it is evident that the EGARCH model performs well with the dataset and seems to capture the dynamics of the corn market including time varying volatility.

Agricultural commodities typically exhibit periods of high volatility stemming from both positive and negative shocks of new information. Market participants adjust to volatilities caused by new information as quickly as possible and try to profit from such inefficiencies. The empirical results of this paper suggest, that by properly analyzing the volatility of agricultural commodities, market participants, whether they be farmers or investors, are better prepared for shifts in market momentum and in managing their market decisions.

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