

Thiyagarajan, S.; Naresh, G.; Mahalakshmi, S.

## Article

# Forecasting volatility in Indian agri-commodities market

Global Business & Finance Review (GBFR)

## Provided in Cooperation with:

People & Global Business Association (P&GBA), Seoul

*Suggested Citation:* Thiyagarajan, S.; Naresh, G.; Mahalakshmi, S. (2015) : Forecasting volatility in Indian agri-commodities market, Global Business & Finance Review (GBFR), ISSN 2384-1648, People & Global Business Association (P&GBA), Seoul, Vol. 20, Iss. 1, pp. 95-104, <https://doi.org/10.17549/gbfr.2015.20.1.95>

This Version is available at:

<https://hdl.handle.net/10419/224326>

### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

### Terms of use:

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc/4.0/>



# Forecasting Volatility In Indian Agri-Commodities Market

S. Thiagarajan<sup>a</sup>, G. Naresh<sup>b</sup> and S. Mahalakshmi<sup>c</sup>

<sup>a</sup>Assistant Professor, School of Management, Pondicherry University

<sup>b</sup>Assistant Professor, School of Management, Pondicherry University

<sup>c</sup>Assistant Professor, GITAM Institute of Management, GITAM University

### ABSTRACT

The market participants always wonder the use of agriculture futures markets to mitigate risk, as the trading in agricultural commodity not only leads to increasing exposure to external shocks but also raises the uncertainty about the future price movements. The farmers and the consumers generally disfavor the volatility in food markets and consider it as a serious concern; whereas the speculators favor such price fluctuations to profit by predicting which direction prices are headed. Generally such trading activity has an irrational component translated into prices. The unpredictability of food prices is a cause for concern because of the adverse effects it has on the producers as well as the consumers. The agricultural commodity prices all around the world have been substantially sensitive to the movements of macroeconomic indicators in this century. In India, the Dhaanya highlights the importance of agriculture and provides a reliable benchmark for the traded Agri-commodities. Today, the Investors all over the world consider Agri-commodities as one of the major asset class and the other indicators like Nifty market index and the Rupee Dollar (US) exchange rate have major influence on the prices of Dhaanya (Mahalakshmi, et.al., 2012 a, b & c). To gauge this volatility, GARCH class of models is the most appropriate model to estimate the volatility of the returns of groups of stocks with large number of observations. The analysis of ARCH and GARCH models and their many extensions catered many theories of asset pricing and portfolio analysis.

*Keywords: Volatility Forecasting, GARCH, GJR GARCH, Dhaanya*

## I. Introduction

The lessons from the great recession on derivatives as risky assets had not stopped the market participants to participate. The use of agricultural derivatives had increased globally over the past three decades and the shift in trading commodity derivatives as an alternative asset class aftermath of the 2008 crisis had exacerbated price volatility. Today most of the market players trading

in the agriculture commodity derivatives are interested in calculating the returns rather than the risk mitigation excepting the producers whose participation is too negligible. The price volatility in agri derivatives had not only distorted the prices but also in constructing risk management strategies for the producers concerned. The participation of such non-producers in agricultural commodity trading leads to increasing uncertainty about the future price movements. The developments of agricultural commodity exchanges in emerging economies may offer a fast and low cost mechanism for discovering prices and resolving contractual disputes (Habib, 2011).

In India, the Government has been gradually relaxing

† G. Naresh\* School of Management, Pondicherry University, India  
E-mail: [kgnaresh@gmail.com](mailto:kgnaresh@gmail.com)

the restrictions on derivatives trading by allowing new exchanges and also trading in previously banned instruments. As the Governments withdraw assistance, the markets grow more volatile whereby the producers and consumers would become more insecure.

The two major purposes of traders in the derivatives markets are hedging and speculation. In addition it also produce an important side effect known as a “future price” to guide market participants as they try to navigate the market’s uncertain future (Black, 1976). However, the “price discovery function” implies that futures prices are used as a benchmark for spot prices. This is confirmed by empirical analysis. In particular, Hernandez and Torero (2010) showed that futures and spot prices of main agricultural commodities are highly correlated, and that changes in futures prices tend to lead changes in spot prices. Agricultural products are more liquid with the wide trading in futures market, (Mahalakshmi, et.al. 2012 c) which ensures that new information is rapidly translated in to prices (Naresh et.al. 2013). In addition such trading creates speculative activity which has an irrational component translated into price fluctuations. Volatility in food markets is a cause for concern because of the adverse effects it has on both consumers and producers.

Agricultural economies all around the world have been substantially sensitive to the movements of macroeconomic indicators in this century. The commodity price spear that peaked in the early part of 2008 raised the spectre of high farm product prices which was not felt since 1970s, and the recession of 2007–2009 has proven to be the worst global downturn since the Great Depression of 1930s. One line of logic is that monetary policies played a pivotal role in each of these periods (Orden, 2010). Economists argue that macroeconomic effects on agriculture, particularly monetary policy felt through the exchange rate. Similarly the stock market index does play a role and is expected to capture systematic risk originating from macroeconomic factors.

In India, agriculture is the largest and most vital economic sector determining the prosperity of the country. However the inflationary expectations have added pressure on the food prices in addition to the speculative trading, crash in the equity market and the rupee sank to the dollar. The looming worries of food prices would be an obstacle for the policy makers to put the economy back on track. The Finance Minister, Arun Jaitley (2014) blames energy costs and speculative hoarding for a rise in whole sale

prices. However, the absence of efficient agri-commodity market also affects the producers recognizing the need for such trading environment/an instrument.

Dhaanya is a Sanskrit word (an ancient language of India) meaning abundance of food grain and glares the prominent status of agriculture in India since civilization. Hence, National Commodity and Derivatives Exchange (NCDEX) formulated a sensitivity index ‘Dhaanya’ on traded agri-commodities which acts as a reliable benchmark. Dhaanya constitutes ten liquid traded Agri-commodity futures contracts from diverse sub sectors such as Oil Seeds (includes Soy Bean, Mustard Seed and Cotton Seed Cake), Grains/Pulses (consisting of Wheat and Chana), Spices (comprises Turmeric, Pepper and Jeera), and Others (include Guar Seed and Gur) account for nearly 70% of the trading. Dhaanya is initialized as a rolling index that is regularly the contracts are rolled over to consecutive months as the current month contracts expires. Thus the benchmark Dhaanya index, is an indicator of the movement in major agri commodities.

## II. Review Of Literature

The persisting food crises in the emerging economy like India have forced market participants and the economists to concentrate on the volatility of returns in agri-commodities. The speculative trading in Indian commodity futures creates several booms and busts in the market (Bose, 2007). Therefore, the commodities futures trading had obviously led to the spike in the prices of spot prices in India (Nath and Lingareddy, 2008). Producers have, at times, evinced fear that non producer participation in commodity markets infringes on their ability to mitigate risk. Even though, long term trading of producers is not sensitive to brief spikes in intraday volatility (Kauffman, 2013). But the growth in commodity futures leads to disadvantages to the economy in terms of significant increase in inflation (Sahi and Raizada, 2006).

The GARCH class of models has become the most appropriate model (Matei, 2009) to estimate the volatility of the returns of groups of stocks with large number of observations. The econometric models to test conditional volatility was initially tested on US market data and later these tests were applied on other stock markets like UK,

Japan, Singapore and Netherlands (Tse, 1991), (Tse and Tung, 1992) (Poon and Taylor, 1992) (de Jong *et al.*, 1992). With US stocks data, GARCH (1,1) model found to possess better forecasting power than the other old models of volatility (Akgiray, 1989). In another study using the US stock market data it was found that Threshold Autoregressive model like Exponential GARCH and ARMA models better forecasts than GARCH (Cao and Tsay, 1992). Whereas Exponentially Weighted Moving Average model was found to forecast better than GARCH (1, 1) model using Singapore stock market data which had non-stationary variance but standard GARCH model required stationarity (Tse and Tung, 1992).

In testing with the Australian market, the empirical evidence shows that advanced ARCH models and simple regression models were better at forecasting volatility but they choose GJR-GARCH (1, 1) as the best model for the Australian stock index. They also pointed out evaluation criteria is influential in the final choice of the model (Brailsford and Faff, 1995). However, Walsh and Tsou (1998) used the same Australian stock index data and rejected GARCH model and Brooks (1998) was not in a position to select the right model for DOW Jones. In forecasting the stock price volatility for Italy, Germany and Sweden with the following tests RW-GARCH, Q-GARCH & GJR-GARCH, it was found that Q-GARCH better forecasts stock price index volatility compared to the other tests (Franses and Van Dijk, 1996).

The volatility returns of the stock market index of Khartoum Stock Exchange, Sudan was modeled using GARCH (univariate Generalized Autoregressive Conditional Heteroscedastic) symmetric and asymmetric models. Symmetric models like GARCH (1,1), GARCH-M (1,1) and asymmetric models like exponential GARCH(1,1), Threshold GARCH(1,1) and Power GARCH(1,1) were applied. The test results have captured the volatility clustering and leverage effects on the stock market index returns (Ahmed & Suliman, 2011).

The volatility is high as the market declines, i.e., when volatility levels are high, stock returns exhibit negative correlation i.e., greater positive feedback trading follows a price decline than a price increase. This asymmetry is consistent with risk aversion and distress selling (Sentana and Wadhvani, 1992). Leverage effects generate smaller asymmetric volatility compared to the market shocks. All the stocks react severely during the market downturn, illustrating volatility feedback mechanism leading to

volatility asymmetry (Bekaert and Wu, 2000). Volatility feedback can be very large during volatile periods thus have greater effects in determining the return dynamics (Wu, 2001). The emerging markets exhibited high asymmetric volatility especially in sub-periods immediately following the Asian Financial Crisis (Jayasuriya and Rossiter, 2008). The 2008 financial crisis and their effect on developed and developing markets were discussed in several research papers. The asymmetric volatility of the G5 countries viz., UK, France, Germany, Japan and US revealed that the asymmetry coefficients of the EGARCH model were significant across the G5 countries. That is the volatility responds at a greater degree during market downturns (Sabbaghi, 2011). The asymmetric effects of stock market volatility transmission of Australia, Singapore, UK and US shows that negative shocks causes a larger increase in volatility and co-volatilities compared to positive shocks. In addition to significant volatility spillovers from the US market to the other markets. (Karunanayake and Valadkhani, 2011). The presence of asymmetric volatility was identified in the Indian Stock Market as well (Goudarzi and Ramanarayanan, 2011). However sometimes, unanticipated shocks cause asymmetric stock market returns and “good” news lead to more pronounced reactions than “bad” news (Entorf and Steiner, 2007). The Composite Commodity Derivative Index of Multi Commodity Exchange is influenced by its own past price movements using GARCH (1,1) model and the forecasting of commodity index will be futile without considering squared residual and conditional variance (Mahalakshmi, *et. al.*, 2012).

In the United States, the tight monetary policy increases rates of interest and induce capital inflows which cause the exchange rate to depreciate, hence, these circumstances ruin agricultural exports (Schuh, 1974). The effect of foreign exchange shortage on the price elasticity of supply has been examined in the context of rationed economies (Guillaumont and Bonjean, 1991). Therefore the exchange rates and interest rates were determined as significant factors affecting the US farm economy (Baek and Koo, 2008). In Malaysia, the agricultural commodity prices are highly sensitive to the exchange rates and have positive correlation, which indicates that the depreciation of the exchange rates will increase the agricultural commodity prices, whereas the other macroeconomic indicators are less significant to the price (Ali, *et.al.*, 2010). Market index does play a role and is expected to capture systematic risk originating from macroeconomic factors. Fama and

French (1989, 1993) studied the relationship between economic conditions and expected returns of financial assets on equity market. Previous literatures on commodity markets say that futures price is not only a function of expected spot price but also on other commodity markets signaling the presence of systematic risk (Bailey and Chan, 1993). The factors that potentially influence the volatility of crude oil prices and the possible linkage between this volatility and agricultural commodity markets had proved the presence of Volatility spillover effect after fall 2006 on crude oil, corn and wheat markets (Du et.al., 2011).

The Index funds do impact agricultural prices found obvious evidence that volatility of grains and livestock prices were influenced by index investment between 2006 and 2011. It is also clear that there is a strong correlation between variance of stock markets and commodity price changes (Gilbert and Pfuderer, 2012). The significant negative effect of the world price instability on the agricultural supply had further shown that poorly developed financial system exacerbates this effect (Subervie, 2008). The roll return (type of slope of the term structure of futures prices) is positive (negative) in the case where the term structure of commodity futures price is downward (upward) sloping. The commodity indexes which track the performance of crude oil futures markets are likely to yield a positive total return because these markets are usually in backwardation (Litzenberger and Rabinowitz, 1995). The nature of long and short run relationships between the spot and future prices of individual commodity indices indicates that the market participants build up their strategies either to hedge or speculate in the long term or short term in the commodity futures market to wield the futures risk (Naresh et.al., 2013). The shocks in food prices often have the issue of whether the idiosyncratic risk (commodity specific risk) factors driving commodity returns or the nature of the conditional volatility of returns. Henceforth this paper is an attempt to investigate for the evidence and its impact of speculation on volatility of agricultural prices (Dhaanya) in the context of Indian markets using class of GARCH models.

### III. Research Methodology

The paper aims at looking into the influence of Exchange

rate (Rupee to Dollar), NIFTY, Volatility and Conditional Variance on Dhaanya. The influence of volatility (Volatility is the Lag of the squared residuals, which is the spread of all likely outcomes of an uncertain variable widely measured as the sample standard deviation) is measured using ARCH Autoregressive Conditional Heteroskedasticity model proposed by Engle (1982) and Conditional Variance (Previous Period's Predicted Variance) using symmetric models where the conditional variance is often measured only on the magnitude ignoring the sign, like GARCH Generalized Autoregressive Conditional Heteroskedasticity model by Bollerslev (1986) and Taylor (1986) and asymmetric models like exponential GARCH (EGARCH) model of Nelson (1991), TGARCH Model Glosten, Jagannathan, & Runkle (1993) and Zakoian (1994) and PGARCH Ding, Granger and Engle (1993), which not only quantifies the magnitudinal effect of conditional variance but also the negative (bad news) and positive (good news) effects.

NIFTY is a bench mark index measuring the sensitivity of the equity market and Dhaanya is a composite index of agricultural commodities. The data used for the study were daily prices taken from January 2008 to September 2014. Dhaanya was taken from NCDEX, NIFTY was taken from NSE and Exchange rate from RBI website.

To explore the variables studied were stationary or not, the Augmented Dickey – Fuller (ADF) test, Dickey and Fuller (1981) and Phillips Perron Test (1988) were applied (Mahalakshmi et. al., 2011). “A time series is said to be stationary if its mean and variance are constant over time”. Moreover, the covariance between two time periods should not depend on the actual time at which it is computed, but should depend only on the distance or lag or gap between the two time periods (Gujarati & Sangeetha 2007). In simple terms, a stationary time series is time invariant which means that its variance, mean and auto covariance remain the same no matter at what point it has been measured. So, the time series tends to return to its mean and the variations around this mean will have constant magnitude (amplitude). But a non stationary time series which has a presence of unit root will have a time varying mean or variance or both.

Furthermore, a time series should not be non stationary, because the behavior of a non stationary time series can be studied only for that specific time period alone and it cannot be generalized. Thus a non stationary time series has no practical value for the purpose of forecasting. Since

Dhaanya, NIFTY and exchange rates are time series variables, they should actually be stationary in nature or else the results could not be generalized and forecasting the movements of Dhaanya. Moreover, at times the relationship between variables may tend to be spurious if both are non stationary in nature. Thus as a first step, the data used for the study i.e., Dhaanya, NIFTY and Exchange rates have been tested to verify the presence of unit root by applying Augmented Dickey Fuller Test.

$$\Delta Y_t = \alpha + \beta_t + \rho Y_{t-1} + \sum_{i=0}^m \sigma_i \Delta Y_{t-1} + \varepsilon_t$$

Null hypothesis :  $H_0 : \rho = 0$ ; There is a unit root; The time series is non stationary.  
 Alternate hypothesis :  $H_a : \rho \neq 0$ ; There is no unit root; The time series is stationary.

The results of the unit root test are in (Table: 1) from which it can be understood that Dhaanya, NIFTY and Exchange rates are non stationary in nature. Thus in order to make the series stationary, the entire data have been transformed by way of first differencing ( $\Delta Y_t = Y_t - Y_{t-1}$ ; where,  $\Delta$  is the first difference operator,  $Y_t$  is the current period value and  $Y_{t-1}$  is the previous period value) which means differences of the successive values of the variables. The first difference transformation will make the non stationary time series stationary by stabilizing its variance and mean by eliminating the seasonality, trend and changes. The autoregressive moving-average ARMA (1,1) models which is a combination of AR and MA proposed by Box, Jenkins and Reinsel (1994) was first applied on the data and the residuals were tested for ARCH effect by applying Lagrange Multiplier (LM) test. Based on the results of LM test ARCH (1,1), symmetric GARCH (1,1) model and asymmetric EGARCH (1,1) TGARCH/ GJR GARCH (1,1) and PGARCH (1,1) were applied to capturing the incidents.

#### A. ARMA (1, 1)

ARMA Autoregressive moving-average developed by Box, Jenkins and Reinsel (1994) is a mixture of AR and MA in a single model aimed at predicting Y (Dependent

variable Dhaanya) incorporating the effect Y lag i.e.,  $DH_{t-1}$  (previous performance) and its moving average i.e.,  $\varepsilon_t$  and  $\varepsilon_{t-1}$ . Autoregressive model can predict Y lead ( $Y_{t+1}$ ) by integrating  $Y_t$  and the error term  $\varepsilon_t$ . The basic form of ARMA (1,1) is given below where  $DH$  is Dhaanya,  $EX$  is Exchange rate and  $NF$  is NIFTY,  $DH_{t-1}$  is the lag of the dependent variable and  $\varepsilon_t$  and  $\varepsilon_{t-1}$  are the moving average terms.

$$DH_t = \alpha + \beta DH_{t-1} + \gamma EX_t + \zeta NF_t + \varphi \varepsilon_t + \tau \varepsilon_{t-1}$$

#### B. ARCH (1, 1)

ARCH Autoregressive Conditional Heteroskedasticity, Engle (1982) is the basic model that takes care of clotted error and nonlinearities. One characteristic of ARCH models is the “random coefficient problem”: the power of forecast changes from one period to another (Chris Brooks, 2008). The drawback of the model is positive and negative shocks (good and bad news) have same effect on volatility, as it the square of the error or previous shock ( $\chi \varepsilon_{t-1}^2$ ).

$$\varepsilon_t^2 = \alpha + \gamma EX_t + \zeta NF_t + \chi \varepsilon_{t-1}^2 + e_t$$

#### C. GARCH (1, 1)

Generalized Autoregressive Conditional Heteroskedastic Model (GARCH) by Bollerslev (1986) and Taylor (1986) allows for any number of squared roots to influence the current conditional variance. GARCH is simpler than ARCH model and has more practical use. ARCH only incorporates the feature of autocorrelation in volatility whereas GARCH also includes a more general feature of conditional heteroskedasticity (conditional variance). ( $\chi \varepsilon_{t-1}^2$ ) is the ARCH term and ( $\vartheta \sigma_{t-1}^2$ ) is the GARCH term,  $EX$  is the exchange rate and  $NF$  is NIFTY.

$$\sigma_t^2 = \alpha + \gamma EX_t + \zeta NF_t + \chi \varepsilon_{t-1}^2 + \vartheta \sigma_{t-1}^2$$

## D. EGARCH (1, 1)

Asymmetric GARCH modeling has the advantage of incorporating the positive and negative conditional variance, which is to see the effect of Good News and bad News on volatility. The tendency for volatility to decline when returns rise and to rise when the returns fall is often called the leverage effect Enders W. (2004). This model captures asymmetric responses of the time-varying variance to shocks and, at the same time, ensures that the variance is always positive and it was developed by Nelson (1991) where  $v$  is the asymmetric response parameter or leverage parameter. If the sign is negative it implies negative shock increases future volatility or uncertainty while a positive shock relieves the effect on future uncertainty (Kalu O. 2010)

$$\log(\sigma_t^2) = \alpha + \gamma EX_t + \zeta NF_t + w(|Z_{t-1}| - E(|Z_{t-1}|)) + vZ_{t-1} + \Psi \log \sigma_{t-1}^2$$

## E. GJR GARCH (1, 1)

Another volatility model commonly used to handle leverage effects is the threshold GJR GARCH (or TGARCH) model by Glosten, Jagannathan, & Runkle (1993) and Zakoian (1994). In the GJR GARCH is closely related to TGARCH model proposed by Zakoian (1994) and asymmetric GARCH or AGARCH models of Engel (1990). The estimate of the GJR Model  $\vartheta$  is significant and positive the negative shocks have a larger effect than positive shock.

$$\sigma_t^2 = \alpha + \gamma EX_t + \zeta NF_t + \Omega \varepsilon_{t-1}^2 + \vartheta \varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \theta \sigma_{t-1}^2$$

## F. PGARCH (1, 1)

Power GARCH was introduced by Ding, Granger and Engle (1993) specialized to deal with asymmetry. In this model the standard deviation is modeled as against variance in other models. In Power GARCH an optional parameter  $\Omega$  can be added to account for asymmetry in modeling up to order  $n$ . The model also offers one the opportunity to estimate the power parameter  $\vartheta$  instead of imposing it on the model Ocran and Biekets (2007).

$$\sigma_t^\vartheta = \alpha + \gamma EX_t + \zeta NF_t + \sum_{j=1}^q \varphi_j \sigma_{t-1}^\vartheta + \sum_{i=1}^p \vartheta_i (|u_{t-i}| - \Omega_i u_{t-1})^\vartheta$$

Where  $\vartheta > 0$ ,  $|\Omega_i| \leq 1$  for  $i = 1, 2, \dots, n$ ,  $\Omega_i = 0$  for all  $i > n$  and  $n \leq p$

From the insignificant test statistics results of Augmented Dickey-Fuller (ADF) test and Philips Perron tests (Table: 1), it can be said that all the variables selected for the study are non-stationary at levels NIFTY, Exchange rate and Dhaanya, as the presence of unit root cannot be rejected for all the variables at their levels. (Nelson, C.R., Plosser, C.R., 1982 and Libânio, G.A., 2009, Malakshmi et. al., 2012). Therefore, to make the variables stationary for further analysis first difference ( $\Delta Y_t = Y_t - Y_{t-1}$ ) transformation was done for all the variables and were tested for stationarity again. The results (Table 1) of ADF and PP tests clearly indicate that all the variables are stationary after first difference paving the way for the rejection of the presence of unit root. First differenced variables have been taken for further analysis to examine the effect of Squared residuals and Conditional variance in Dhaanya.

Table 1. Test for Stationarity

Variables	Augmented Dickey Fuller Test		Phillips Perron Test	
	Tau ( $\tau$ ) Statistics		Adjusted T Statistics	
	Levels	First Difference	Levels	First Difference
NIFTY	-1.899	-40.095***	-1.746	-39.997***
Exchange Rate	-2.335	-32.437***	-2.443	-42.916***
Dhaanya.	-1.530	-21.448***	-1.731	-42.503***

\*, \*\*, \*\*\* Level of significance at 10%, 5%, 1% respectively.

**Table 2.** Effect of Volatility and Conditional Variance

Variables	OLS	ARMA (1, 1)	ARCH (1, 1)	GARCH (1, 1)	EGARCH (1, 1)	GJR GARCH (1, 1)	PGARCH (1, 1)
Constant	0.948***	0.921	0.439*	0.492**	0.676***	0.659***	0.660***
NIFTY	0.007	0.007	0.012***	0.014***	0.014***	0.015***	0.015***
Exchange Rate (Rupee to dollar)	3.641***	3.421***	3.442***	0.651	0.213	0.501	0.450
AR		0.937***					
MA		-0.880***					
Constant			119.116***	0.721***	-0.059***	0.232**	0.163
Squared Residuals (ARCH)			0.499***	0.077***	0.110***	0.074***	0.045***
Conditional Variance (GARCH)				0.922***	0.995***	0.955***	0.955***
Leverage Effect					0.045***	-0.055***	-0.349***
Power							1.777***
BG - LM Test (F)	12.022***	0.006					
LM Test	114.570***	119.801***	3.374*	0.215	1.505	1.245	1.076

\*, \*\*, \*\*\* Level of significance at 10%, 5%, 1% respectively.

Results of OLS, ARMA, ARCH and GARCHs are in table 2. In Column 2 of table 2 OLS (Ordinary Least Square) regression analysis are presented. Nifty and Exchange rate are significant (at 1%) in influencing and predicting Dhaanya but as one moves down the column, the results of BG LM (Breusch-Godfrey Serial Correlation LM Test) statistics states there is a significant effect of serial correlation and LM (Lagrange multiplier test presence of Volatility clustering in Dhaanya returns. LM test indicates that there no more ARCH effect (Heteroskedasticity problem) in the equation.

To explore the existence of leverage effect in Dhaanya returns asymmetric EGARCH (1, 1), GJR GARCH (1, 1) and PGARCH(1,1) models were applied and the results are in column 6, 7 and 8 of table 2. EGARCH (1, 1) results are on line with the previous results where Nifty, ARCH and GARCH terms were significant influencers. The key component of EGARCH model, the asymmetric leverage effect is also significant in the model with a positive sign, which is interesting, implying that past Positive shocks or Good news lead to a higher next period volatility (conditional variance) than Negative shocks or Bad news. LM test is insignificant, signaling no ARCH effect left in the equation. The results of GJR GARCH (1, 1) (column7) are on line with the previous model with the significant (at 1 %) asymmetric effect and the coefficient of the Leverage effect term is negative, implying a positive shocks or good news seem to have larger effect on volatility (conditional variance) than negative shocks

or bad news. LM test is insignificant indicating no more ARCH effect left in the model. PGARCH (1, 1) results also state the same with the significant leverage coefficient confirming the asymmetric effect and this model also says positive shocks or good news will lead to a higher next period conditional variance (volatility) than negative shocks with insignificant LM statistics confirming, no ARCH effect. To summarize, the best model for the data would GARCH (1, 1) and for the asymmetric modeling P GARCH (1, 1) as they explain volatility better in their categories.

The market index (Nifty) and the exchange rate (USDINR) are considered to be the major macroeconomic indicators which capture the systematic risk associated with the agricultural commodity index (Dhaanya), having a significant impact. However the exchange rate influence has been replaced when the conditional variance has been measured. The increase in volatility for derivative instruments increases the hedgers and speculators demand equally (Bush, 2013). Therefore volatility is considered to be the foundation for the existence of derivatives. In the agricultural futures markets, the good news leads to higher future volatility i.e., “good” news lead to more pronounced reactions than “bad” news (Litzenberger and Rabinowitz, 1995, Entorf and Darmstadt, 2007) i.e., increase in long only speculative positions was equaled or surpassed by an increase in short hedging. Thus, the agriculture market (Dhaanya) reacts positively to good fortune / surplus supply (i.e., good news) whereby the



speculators allegedly increase the futures prices (the market rises). Indeed the speculators are needed in the futures market for good news providing liquidity for the smooth functioning. But the consumers are whined about the speculators aggravating influence on rising prices. The producers and consumers participate more in the market for hedging whereby the speculators raise the margin level of the futures contract to meet out the demands of the hedgers leading to higher volatility / increase in prices. Thus the track on conditional volatility could guide market players with their trading strategies. To summarize, the best model for the Indian data would GARCH (1, 1) and for the asymmetric modeling P GARCH (1, 1) as they explain volatility better in their category as the calculated LM test values are least for them signaling that these models are better in capturing the effect of volatility, than others, in the Indian Agricultural market.

#### IV. Conclusion

“Excessive speculation is distorting prices, increasing volatility, undermining the commodity markets and hurting the economic recovery” stated the US Senator, Carl Levin (2011). The instability in the economy generally refers to a situation of inordinate fluctuations of economic variables which has been accelerated by trade shocks. The traders in the agricultural derivatives continue to make wild speculation despite producers raised their concern during the times of surplus and consumers during the short supplies. However curbing speculation may well be counter-productive in terms of price levels or market volatility. Such food price volatility wreaks havoc on the farmers and consumers. Volatile agricultural commodity prices have been and continue to be a cause for concern among the policy makers, market participants, agriculturalists and the consumers. As volatility rises, demand for derivative instruments increases by the hedgers and speculators alike (Bush, 2013). Dhaanya an agri-commodity index acts as a barometer for the farmers and other stake holders. Therefore, an understanding for long term trends in agricultural commodity return volatility is essential as the results offer insights in to regulatory bodies to curb excessive volatility, fund managers incorporate to formulate profitable trading and investment

strategies and firms incorporate for hedging strategies. The agricultural commodity market reacts more to positive news like good monsoon, cheap energy costs, soaring equity market and strengthening of Indian rupees to a dollar rate rather than negative news where speculative hoarding takes place. The speculators would like to profit in the market when they have a good fortune influencing the producers / farmers to hedge for their produce from fall in prices which in turn creates a high volatility even during surplus supply. That is speculators in agri-commodities markets are to be blamed for the rises in prices in spite of providing liquidity needed for the functioning of the markets. Therefore, forecasting future volatility for Dhannya, a sensitivity index for agriculture commodities help market participants in the agriculture market to edge over market fortune whenever there is good news / bad news and gives a signal for the producers, consumers and other policy makers.

#### Reference:

- Ahmed, A.E.M. and Suliman, Z. (2011). Modelling Stock Market Volatility using GARCH models evidence from Sudan. *International Journal of Business and Social Science*, Vol. 2, No. 23, pp 114-128.
- Agkiry, V. (1989). Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts. *Journal of Business*, Vol. 62, pp 55-80.
- Ali, R., Ali, A.K., Fatah, F.A. and Ariff, E.E.E. (2010). Linkages of macroeconomic indicators and agricultural variables in Malaysia. *Economic and Technology Management Review*, Vol. 5, pp 1-9.
- Andersen, T. G. and Bollerslev, T. (1998a). Answering the skeptics: Yes, Standard Volatility models do provide Accurate Forecasts. *International Economic Review*, Vol. 39, No. 4, pp 885-905.
- Baek, J. and Koo, W.W. (2007). Identifying macroeconomic linkages of U.S. Agricultural Trade Balance. *Canadian Journal of Agricultural Economics*, Vol. 56, No. 1, pp 63-77.
- Bailey, W. & Chan, K. C. (1993). Macroeconomic influences and the variability of the commodity futures basis. *The Journal of Finance*, Vol. 48, No.2, pp 555-573.
- Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *Review of Financial Studies*, Vol. 13, No. 1, pp 1-42.
- Black, F. (1976). The pricing of commodity contracts. *Journal of financial economics*, Vol. 3, No. 1, pp 167-179.
- Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, Vol. 31, pp 307-327.

- Bollerslev, T., Engle, R. F. and Nelson, D. B. (1994). ARCH Models. *Handbook of Econometrics*, Amsterdam: Elsevier Science B. V.
- Bose, S. (2007). Understanding the Volatility Characteristics and Transmission Effects in the Indian Stock Index and Index Futures Market. *Money and Finance, ICR4 Bulletin*, 139-162.
- Box, G. E. P., Jenkins, G. M. and Reinsel G. C. (1994). *Time Series Analysis: Forecasting and Control*, New Jersey: Prentice Hall, Inc.
- Brailsford, T. J., & Faff, R. W. (1996). An Evaluation of Volatility Forecasting Techniques. *Journal of Banking & Finance*, Vol. 20, No. 3, pp 419-438.
- Brooks, C. (1998). Predicting stock index volatility: can market volume help? *Journal of Forecasting*, Vol. 17, pp 59-80.
- Brooks, C. (2008). *Introductory econometrics for finance*. Cambridge University Press.
- Bush, S.B. (2013). Risky Business – Derivatives and Global Agriculture, *Dollars & Sense*, Vol.50, No.8, pp 14-18.
- Cao, C. Q., & Tsay, R. S. (1992). Nonlinear time-series analysis of stock volatilities. *Journal of Applied Econometrics*, Vol. 7, No. 1, pp 165-185.
- Carter, R. H, William, E., & Lim, C. (2007). Principles of Econometrics, 3rd Edition, New York. John Wiley and Sons, Inc
- De Jong, F., Kemna, A. and Kloek, T. (1992). A contribution to event study methodology with an application to the Dutch stock market. *Journal of Banking and Finance*, Vol. 16, pp 11-36.
- Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: Journal of the Econometric Society*, Vol. 49, No. 4, pp 1057-1072.
- Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical finance*, Vol. 1, No. 1, pp 83-106.
- Du, X., Yu, C.L. and Hayes, D. J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis. *Energy Economics*, Vol. 33, pp 497-503.
- Dunis, C. L., Laws, J., & Chauvin, S. (2001). The use of market data and model combination to improve forecast accuracy. *Development in Forecasts Combination and Portfolio Choice (Wiley, Oxford)*.
- Enders, W. (2004). Applied Econometric Time Series, by Walter, *Technometrics*, Vol. 46, No.2.
- Enders, W. (2004). Applied Econometric Time Series, 2nd Edition, Wiley Series in Probability and Statistics.
- Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with estimates of the variance of United Kingdom Inflation, *Econometrica*, Vol. 50, No. 4, pp 987-1007.
- Engle, R. F. (2004). Risk and volatility: Econometric models and financial practice. *The American Economic Review*, Vol. 94, pp 405- 420.
- Entorf, V. H., and Darmstadt, C. S. (2007). Announcement of Business Cycle Forecasts and the reaction of the German Stock Market. Yearbooks of Economics and Statistics, Lucius & Lucius, Stuttgart publisher, Vol. 227, No.1, pp. 1-26.
- Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of financial economics*, Vol. 25, No.1, pp 23-49.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, Vol. 33, No. 1, pp 3-56.
- Fostel, A. and Geanakoplos, J. (2012). Why does bad news increase volatility and decrease leverage? *Journal of Economic Theory*, Vol. 147, pp 501-525.
- Franses, P. H., & Dijk, D. V. (1996). Forecasting Stock Market Volatility using (nonlinear) GARCH Models. *Journal of Forecasting*, pp 229-235.
- Gilbert, C. L., & Pfuderer, S. (2012). Index Funds Do Impact Agricultural Prices. In *Money, Macro and Finance Study Group workshop on commodity markets, London, Bank of England*, Vol. 25, No. 5, pp 1-15.
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, Vol. 48, No. 5, pp 1779-1801.
- Goudarzi, H. & Ramanarayanan, C.S. (2011). Modeling Asymmetric Volatility in the Indian Stock Market. *International Journal of Business and Management*, Vol. 6, No. 3, pp 221-230.
- Guillaumont, P. and Bonjean, C. (1991). Effects on agricultural supply of producer price level and stability with and without goods scarcity. *Journal of International Development*, Vol. 3, pp. 115-133.
- Gujarati, D.N. & Sangeetha. (2007). Basic Econometrics, 4<sup>th</sup> Edition, Tata McGraw-Hill, New Delhi. Page No.816, 834 & 836
- Habib, Shah Md. Ashan. (2011). Prospect of Developing an effective Agricultural Commodity in Bangladesh. *International Journal of Economic Perspectives*, Vol. 5, No. 3, pp 293-302.
- Hernandez, M. and Torero, M. (2010). Examining the Dynamic Relationship between Spot and Future Prices of Agricultural Commodities, *IFPRI Discussion Paper*, n.988.
- Heynen, R. C. (1995). *Essays on Derivatives Pricing Theory* (No. 94). Amsterdam: Thesis Publishers.
- Jaitley, A. (2014). Finance Minister Arun Jaitley vows action on Inflation, warns Hoarders. Reuters, June 17.
- Jayasuriya, S.A. & Rossiter, R. (2008). Asymmetric Volatility in Asian Equity Markets. *Journal of International Finance and Economics*, Vol. 8, No. 4, pp 11-21.
- Kalu O. (2010). Modelling Stock Returns Volatility in Nigeria Using GARCH Models. Munich Personal RePEc Archive, MPRA Paper No. 22723.
- Karunanayake, I. & Valadkhani, A. (2011). Asymmetric Dynamics in Stock Market Volatility. *Economic Papers*, Vol. 30, No. 2, pp 279-287.
- Levine, C. (2011). Opening Statement at PSI Hearing on Excessive Speculation and Compliance with the Dodd-Frank Act - See more at: <http://www.levin.senate.gov/newsroom/press/release/opening-statement-at-psi-hearing-on-excessive-speculation-and-compliance-with-the-dodd-frank-act#sthash.JnrQNOa3.dpuf>
- Libânio, G. A. (2009). Aggregate demand and the endogeneity of the natural rate of growth: evidence from Latin American economies. *Cambridge Journal of Economics*, Vol. 33, No. 5, pp 967-984.

- Litzenberger, R.H. and Rabinowitz, N. (1995). Backwardation in Oil Futures Markets: Theory and Empirical Evidence. *The Journal of Finance*, Vol. 50, No.5, pp 1517-1545.
- Mahalakshmi, S., Thiagarajan, S. and Naresh, G. (2011a). Influence of Macroeconomic Indicators on Foreign Direct Investments in India, *Banking Finance*, Vol. 24, No.8, pp 16-22.
- Mahalakshmi, S., Thiagarajan, S. and Naresh, G. (2012b). Commodity Derivatives Behaviour in Indian market using ARCH/GARCH. *JIMS 8M: The Journal of Indian Management & Strategy*, Vol. 17, No. 2, pp 60-64.
- Mahalakshmi, S., Thiagarajan, S. and Naresh, G. (2012c). Agricultural Commodity Derivatives. *Arthshastra: Indian Journal of Economics & Research*, Vol. 1, No. 1, pp
- Matei, M. (2009). Assessing Volatility Forecasting Models: Why GARCH Models take the lead. *Romanian Journal of Economic Forecasting*, Vol. 4, pp 42-65.
- Naresh, G., Thiagarajan, S., Mahalakshmi, S., and Shanthi, P. (2013). Testing the nature of Long and Short run relationships between Spot and Future Commodity prices in India. *Prajnan: Journal of Social and Management Sciences*, Vol. XLII, No. 2, pp
- Nath, C. G. and Lingareddy, T. (2008). Commodity Derivative Market and its Impact on Spot Market, available at <http://ssrn.com>
- Nelson, C. R. & Plosser, C. R. (1982). Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of monetary economics*, Vol. 10, No. 2, pp 139-162.
- Nelson, D.B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, Vol. 59, No. 2, pp 347-370.
- Ocran, M., & Biekets, N. (2007). Forecasting Volatility in Sub-Saharan Africa's Commodity Markets. *Investment Management and Financial Innovations*, Vol. 4, No. 2, pp 91-102.
- Orden, D. (2010). Recent Macroeconomic Dynamics and Agriculture in Historical Perspective, *Journal of Agricultural and Applied Economics*, Vol. 42, No. 3, pp 467-476
- Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, Vol. 75, No. 2, pp 335-346.
- Poon, S. H. and Taylor, S. J. (1992). Stock returns and volatility: An empirical study of the UK stock market. *Journal of Banking and Finance*, Vol. 16, pp 37-59.
- Retrieved from <http://stat.duke.edu/research/BEST/BEST2011-12/Yuan.pdf>
- Sabbaghi, O. (2011). Asymmetric Volatility and Trading Volume: The G5 Evidence. *Global Finance Journal*, Vol. 22, No. 2, pp 169-181.
- Sahi, Gurpreet S. and Raizada, Gaurav (2006), Commodity Futures Market Efficiency in India and Effect on Inflation, available at <http://ssrn.com>
- Schuh, G.E. (1974). The Exchange rate and U.S. Agriculture. *American Journal of Agricultural Economics*, Vol. 56, No. 1, pp 1-13.
- Schwert, G.M. (1989). Why Does Stock Market Volatility Change Over Time?. *The Journal of Finance*, Vol. 44, No. 5, pp 1115-1153.
- Sentana, E. & Wadhwani, S. (1992). Feedback Traders and Stock return Autocorrelations: Evidence from a Century of Daily Data. *The Economic Journal*, Vol. 102, No. 4, pp 415-425.
- Subervie, J. (2008). The variable response of agricultural supply to world price instability in developing countries. *Journal of Agricultural Economics*, Vol. 59, No. 1, pp 72-92.
- Taylor, S.J., (1986). *Modelling Financial Time Series*, Wiley, New York.
- Tsay, R. (2010). *Analysis of Financial Time Series*. Hoboken: Wiley.
- Tse, Y. K. (1991). Stock return volatility in the Tokyo stock exchange. *Japan and the World Economy*, Vol. 3, pp 285-298.
- Tse, Y. K. and Tung, S. H. (1992). Forecasting volatility in the Singapore stock market. *Asia Pacific Journal of Management*, Vol. 9, pp 1-13.
- Walsh, D. M., & Tsou, G. Y. G. (1998). Forecasting index volatility: Sampling interval and non-trading effects. *Applied Financial Economics*, Vol. 8, No. 5, pp 477-485.
- Wu, G. (2001). The Determinants of Asymmetric Volatility. *The Review of Financial Studies*, Vol. 14, No. 3, pp 837-859.
- Yu, J. (2002). Forecasting volatility in the New Zealand stock market. *Applied Financial Economics*, Vol. 12, No. 3, pp 193-202.
- Yuan, K. (2012). Persistence, Leverage Effects, Jumps and Heavy Tails in International Equity Markets. (Thesis, Duke University, Durham, USA).
- Zakoian, J.M. (1994). Threshold Heteroskedasticity Models. *Journal of Economic Dynamics and Control*, Vol. 15, pp 931-955.
- Zlatko, K., (2007). Forecasting volatility: Evidence from the Macedonian stock exchange. MPRA Paper 5319, University Library of Munich, Germany.