

Volatility Modeling and Forecasting Efficiency of GARCH Models on Soy Oil Futures in India and The US

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Abstract
This paper attempts to fill the gap in volatility studies in the commodity markets by modeling the volatility of the soy oil futures in two interrelated markets of India and the US. The GARCH (1,1), TGARCH (1,1) and EGARCH (1,1) models are tested under the assumptions of normal distribution, Student's t distribution and general error distribution (GED). The results of our study indicate that there is high persistence of volatility in soy oil futures market and the volatility effect decays slowly with time. The half life for dissipation of volatility spikes in the US market is twice that of the half life in Indian market. The volatility models did not show leverage as the leverage term is found to be insignificant in all cases (p>0.05). A comparative analysis, based on Log Likelihood, AIC and SC criteria, of the three GARCH variants under three alternative distributions shows that refined soy oil returns in India are best modeled by GARCH (1,1) under GED while the bean oil returns in the US are best modeled by EGARCH (1,1). Forecasting efficiency of the GARCH models in the two markets is tested using the RMSE, MAE, MAPE and TIC. For soy oil in India, GARCH (1,1) under GED is best model by MAE and MAPE. For the bean oil in the US, EGARCH (1,1) under Gaussian distribution emerges as the best model based on RMSE and TIC criteria.
Keywords: Volatility, GARCH, Soy oil, Commodity, Forecasting

1. Introduction

Analysis of financial market volatility has occupied the focal point of interest of researchers as well as market participants across the world for the last two decades. Besides being the most important criteria for option valuations, volatility has many other financial applications. Volatility modeling provides a simple approach to calculating value at risk of a financial position. It also plays an important role in asset allocation under the mean variance framework. The volatility index (VIX), compiled by the Chicago Board of Trade, which has become a widely traded financial instrument, is proof that volatility is perhaps the all pervasive and important characteristic of financial markets.

Volatility for any given asset or commodity is given by the fluctuations in the standard deviations of daily returns. The volatility analysis is used as a risk management tool for hedging efficiency and selection of asset portfolios (Jondeau and Rockinger, 2003). Volatility also helps in hedging against adverse price movements. Excess volatility periods help day traders to gain nice profits using volatility strategies. Price limits and contract margins imposed by the exchanges depend on the volatility changes. In India, the commodity market regulator (Forward Markets Commission) decides additional margins on commodity contracts based on the increased volatilities. Volatility is an important factor in determining the pricing of option contracts. Volatility forecasts are important for option traders to predict the price over the life of the option contracts (Alexander, 2001).

Volatility estimates and forecasts are relatively less reported for the commodity markets. Prices of the agricultural commodities fluctuate between lows at harvest to the highs in between harvests, thereby causing volatility swings. Internationally linked commodity such as soy oil is also affected by any surprising crop report both in the US and India. These reports which vary from production to acreage to changes in inventory immediately cause shocks to the commodity prices. Understanding volatility behavior of an important agricultural commodity such as soy oil has implications for both farmers and other stake holders in the market such as hedgers and traders in managing their market exposures in times of high volatilities.

The volatility studies for commodity markets have focused more on the sources of volatility with less attention paid to the forecast of volatilities. This paper attempts to model and forecast the volatility of returns for soy oil in India (hereafter, RSO) and bean oil (hereafter, RBO) in the US [soy oil is traded as bean oil in the US]. In comparison to the matured RBO futures market in the US, RSO futures market in India is relatively under developed. A comparison therefore is likely to bring out salient differences in the two markets. This paper analyses the differences in the two markets using symmetrical and asymmetrical GARCH models such as GARCH (1,1), TGARCH (1,1) and EGARCH (1,1) for modeling the volatility of the two commodity futures. Also effects of fat tails are compared by assuming the error distributions as Gaussian, Student's t and General Error Distribution (GED). Further we have tested the forecasting efficiency of each model by using four different criteria of root mean square error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE), and Theil's inequality coefficient (TIC).

This paper is organized as follows: section 2 briefly traces the literature on volatility studies in the price series of equity and agricultural commodities; section 3 reviews the types of GARCH models used to model them;

section 4 details the methodology of volatility modeling and forecasting, section 5 presents the results and section 6 concludes.

2. Literature Survey

Autoregressive models are based on returns being affected both by exogeneous variables and also by their past values. The autoregressive models are extensively used in macroeconomics for money supply, inflation, exchange rates, rates, prices and gross domestic product. The autoregressive heteroscedastic (ARCH) models have been largely used in financial economics, such as asset pricing, options pricing, risk management and hedging. A number of studies abound in modeling the return on stocks as financial time series. Engle (1982) introduced the ARCH models for the time varying variance series and Bollerslev (1986) generalized the ARCH model (GARCH) for estimating stochastic volatility. Since then a number of studies have adopted ARCH and GARCH models to explain the volatility of stock market. It was observed that negative shocks have a much larger effect on stock pricing than positive shocks of the same magnitude. The negative shocks take much longer to dissipate questioning the wisdom of symmetric or normal distribution as a universally accepted reliable assumption. Time series based on equity stocks and indices have traditionally shown a tendency to show negative skewness and very high kurtosis values indicating fat tails and deviations from the normal Gaussian curves. Nelson (1991) used exponential distribution for the US stock markets. Hseih (1989), Theodossiou (1994)) and Koutmos and Theodossiou (1994) have applies exponential distribution in studying forex markets. Akgiray et al. (1991) have used exponential distribution for precious metal prices. Student's t distribution has been used as a better alternative to the Gaussian distribution by several researchers [Fernandez and Steel (1998), Bollerslev (1988), Bailie and Bollerslev (1989)]. Bernanke and Getler (1999) discuss the role of volatility in financial markets and its effect on monetary policy. Crato and Ray (2008) study the volatility of commodity markets and report that the volatility is more persistent for energy markets than currency markets. Bajpai and Mohanty (2008) use EGARCH model with both normal and non normal error distribution to estimate the volatility of exchange rate. Brorsen and Irwin (1987) analyse the relationship between the technical trading and increased volatility for ten commodities and conclude that technical trading does not contribute significantly to the volatility of commodities. Crain and Lee (1986) suggest that grain market volatility is affected by changes in government programmes. They further report that volatility gets transferred from futures markets to cash markets. Cao and Tsay (1992) find that TGARCH models perform better than GARCH, EGARCH, and ARMA models from their study on US stock exchange. Balaban (2002) finds that symmetric GARCH models perform better than asymmetric models for monthly exchange rate volatility.

Volatility studies in commodities space are less abundant. Agricultural commodities can be highly volatile and change over longer periods of time. Volatility in agricultural commodities originates mainly from supply disturbances. Gilbert (2010) attributes volatility of agricultural commodities to the arrival of information, hedging, speculation and physical availability of commodities. Donmez and Magrini (2013) use GARCH-MIDAS approach to estimate agricultural commodity volatility and determine its macro economic factors. Ovarian and Meade (2010) model the returns volatility for three commodities using GARCH (1,1) and report presence of seasonality and mean reversion. Musunuru, Yu and Larson (2013) test GARCH models to forecast volatility of returns for corn futures. Siddiqui and Siddiqui (2015) study volatility of metal, energy and agriculture indices in Indian market using GARCH models and report high persistence for metals and energy.

This study attempts to bring out the similarities and differences in the data generating process of soy oil futures in two related markets of India and US. Soy oil is one of the most important international commodity. Volatility models in agricultural commodities across two different markets are not attempted so far and this study undertakes to analyse the volatility models for the two cointegrated markets.

3. GARCH Class of Volatility Models

The analysis of volatility forecasting begins with the computation of continuously compounded daily returns for soy oil based on the following equation:

$$Rt = \ln [Pt/Pt\text{-}1] \qquad (1)$$

Where R_t is daily log return for soy oil, Pt and Pt-1 are daily prices of soy oil on t and t-1 days respectively.

GARCH Specification: the Generalized Autoregressive Conditional Heteroscedascticity (GARCH), was developed independently by Bollerslev (1986) and Taylor, is used in the present study to investigate the effect of volatility of soy oil prices. It has the ability to capture volatility cluster or contiguous periods of stability followed by volatility (Mandelbrot, 1963).

The GARCH(p,q) model is given by equation (2) depicts the conditional variance of a price

$$h_t^2 = \delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}^2 \qquad (2)$$

series to depend on a constant (δ), past news about volatility (i.e. the ε_{t-i}^2 terms) and the past forecast variance (the h_{t-i}^2 terms). A simpler form of equation (2) is the GARCH (1,1) model specified as follows:

$$h_t^2 = \delta + \alpha\varepsilon_{t-i}^2 + \beta h_{t-1}^2 \qquad (3)$$

Equation (3) offers the benefit of fewer coefficient restrictions. The only requirement for the well defined variance

and covariance function of the model is the coefficients to lie inside a unit circle such that- $\delta, \alpha > 0; \beta \geq 0$ and $\alpha + \beta < 1$. persistence of volatility is measured by the sum of α and β.
In financial markets, it is observed that the downward price changes are often followed by higher volatility than upward price movements of the same magnitude [Asteriou and Hall (2011), Zivot (2008), Bollerslev et al. (1992)]. This asymmetry or the leverage effect in the variance can be captured by two variants of the GARCH family, namely, the Threshold GARCH (TGARCH) [Zakonian (1994), Glosten et al. (1994)] and Exponential GARCH (EGARCH) [Nelson (1991)]. The conditional variance of a TGARCH model is given by (4).

$$h_t^2 = \delta + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \qquad (4)$$

Where d_t=1 if $\varepsilon_t < 0$ and $d_t = 0$ otherwise. Adverse market conditions and unfavourable news ($\varepsilon_{t-1}^2 < 0$)such as drought, bad monsoon, political unrest has an impact of $\alpha + \gamma$.
EGARCH models differ from the TGARCH model in that the effect of recent residuals is exponential in place of quadratic. The variance equation of this model is given by equation (5).

$$\ln(h_t^2)=\delta + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}^2}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}^2} + \beta \ln(h_{t-1}^2) \qquad (5)$$

Asymmetry is introduced for $\gamma \neq 0$. the impact of good news is captured by $(\alpha + \gamma)/\sqrt{h_{t-1}^2}$ and the impact of bad news is given by $(\alpha - \gamma)/\sqrt{h_{t-1}^2}$. A negative and significant γ supports evidence of asymmetry and greater impact of negative shocks.

4. Methodology

The GARCH models not only provide the forecasting properties of a traditional time series but also extend them to the conditional variance (Holt and Aradhyula, 1990). The GARCH models are evaluated on the basis of their ability to forecast future returns. The forecasting performance of each model is evaluated by using standard symmetric measures such as Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient (TIC) besides the Akaike Information Criteria (AIC) and log likelihood functions.

4.1 Data Sources

The present study uses daily closing prices of refined soy oil on National Commodity and Derivatives Exchange (NCDEX). NCDEX is the largest agricultural commodity exchange of India. Refined soy oil or RSO is the single largest agricultural commodity traded on three of the six national commodity exchanges in India. It forms upto a third of the daily turnover of the NCDEX. Effective April 2014, soy oil has been recognized as an internationally linked commodity by the commodity market regulator in India (FMC, 2014). Soy oil is also a global commodity with a very wide footprint. It accounts for over 10% share in the agricultural commodities on the three largest commodity exchanges, namely, Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT) and Dalian Commodity Exchange (DCE).

The data used in the present study is the daily settlement price of soy oil on the NCDEX (www.ncdex.com). NCDEX is the largest agricultural commodity exchange of India. Of the 23 agricultural commodities traded on the NCDEX, four have been identified as commodities with international linkage (FMC, 2014). Soy oil is the most prominent of these commodities and forms approximately 24% of the daily exchange turnover on NCDEX. Bean oil futures prices have been obtained from the CME (www.cme.com). The GARCH models not only provide the forecasting properties of a traditional time series but also extend them to the conditional variance (Holt and Aradhyula, 1990). The GARCH models are evaluated on the basis of their ability to forecast future returns. The forecasting performance of each model is evaluated by using standard symmetric measures such as Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient (TIC) besides the Akaike Information Criteria (AIC) and log likelihood functions.

The data sample comprises 1020 observations from 5 December 2008 to 20 March 2013. For forecasting purpose, we have split the data into two parts: The first part comprises an in sample of 778 observations (5 December 2008 to 20 March 2012) whereas the second part consists of an out of sample of 242 observations (21 March 2012 to 20 March 2013).

5. Results

Figure 1 represents the time series of daily returns (equation 1) for soy oil (RRSO) and bean oil (RRBO) futures. The figure shows constant means and changing variances over time. Soy oil exhibits clusters of high and low volatility.

Table 1 depicts the statistical characteristics for the daily return series for soy oil. The returns on refined soy oil in India are depicted as RRSO and returns on bean oil in US are depicted as RRBO. Total number of observations in both series is 1020. Matching datasets were obtained for both RRSO and RRBO. The Jarque Bera test ($p<0.05$) indicates rejection of normal distribution. The return series for soy oil (RRSO) is negatively skewed while that for bean oil (RRBO) is positively skewed. The Kurtosis for soy oil (RRSO) is 16.08 which indicates very highly leptokurtic and presence of fat tails. The daily mean returns and standard deviation on soy oil are lower than those of bean oil.

The standard deviation of RRSO daily series is 1.23%, which is equivalent to an annualised volatility of 21.70%. The standard deviation of RRBO daily series is 1.52% or an annualised volatility of 24.13% which indicates a higher volatility than RRSO. (Note: Indian commodity markets operated six days of a week during the period under study).

Table 2 shows the results of the volatility models for refined soy oil (RRSO) in India. The table presents results for GARCH (1,1), TGARCH (1,1) and EGARCH (1,1). As we know the distribution differs from normal distribution, we analyse the models for Normal distribution, Student's t distribution and also for the Generalized Error Distribution (GED).

The sum of (alpha and beta) is lowest (0.923163) for the GARCH (1,1) under normal distribution while it is highest (0.971209) the TGARCH (1,1) under the Student's t distribution. The leverage coefficient (gamma) is negative but not significant ($p>0.05$) for all distributions for both TGARCH and EGARCH indicating lack of leverage effect for the soy oil in India. TheLB10 and LB210 tests are all insignificant ($p>0.05$).

The models are evaluated on the Log Likelihood, AIC and SC. GARCH (1,1) model under Student's t distribution is the best with largest Log Likelihood value and lowest value of Schwarz Criteria. The half life of the variance shock is 23.3 days for RRSO.

Table 3 shows the results of the volatility models for bean oil (RRBO) in India. For bean oil we analyse the GARCH (1,1), TGARCH (1,1) and EGARCH (1,1) models assuming Normal distribution, Student's t distribution and also for the Generalized Error Distribution (GED).

The sum of (alpha and beta) is lowest (0.981908) for the TGARCH (1,1) under GED while it is highest (0.986263) for the GARCH (1,1) under the Normal distribution. The leverage coefficient (gamma) is not significant for any model indicating lack of leverage effect for the soy oil in US. The LB10 and LB210 tests are all insignificant ($p>0.05$).

The models are evaluated on the Log Likelihood, AIC and SC. GARCH (1,1) model under GED distribution is the best with a large Log Likelihood value and lowest value of Schwarz Criteria. The half life of the variance shock is 47.7 days for RRBO.

The half life of volatility shocks for US bean oil is slightly over twice that of the half life of volatility shocks for refined soy oil in India.

Forecasting efficiency is measured using the four measures namely RMSE, MAE, MAPE and TIC. For soy oil in India, GARCH (1,1) under GED is best model by MAE and MAPE. RMSE is not able to differentiate among models. For the bean oil in US, EGARCH (1,1) under Gaussian distribution emerges as the best model based on RMSE and TIC criteria.

6. Conclusions

While volatility studies abound for stock exchanges, they are rare as far as commodities are concerned. This paper contributes to the sparse literature on volatility in commodity markets by analyzing the volatility in soy oil futures, which is the most voluminous and liquid commodity contract in agricultural commodity markets both in India and the US. The paper also analyses the alternative models of GARCH family under assumptions of three return distributions namely Gaussian, Student's t and GED.

The results of our study indicate that there is high persistence of volatility in soy oil futures market and the volatility effect decays slowly with time. The half life for dissipation of volatility spikes in the US market is twice that of the half life in Indian market. The volatility models did not show leverage as the leverage term is found to be insignificant in all cases ($p>0.05$). A comparative analysis, based on Log Likelihood, AIC and SC criteria, of the three GARCH variants under three alternative distributions shows that refined soy oil returns in India are best modeled by GARCH (1,1) under GED while the bean oil returns in the US are best modeled by EGARCH (1,1).

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Table 1. Statistical characteristics of soy oil (RRSO) and bean oil (RRBO)

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
RRSO	0.000422	0.000286	0.069956	-0.125146	0.012287	-0.747283	16.08517	7371.849	0.0000	1020
RRBO	0.000523	0.00000	0.068447	-0.065672	0.015200	0.233359	4.718653	134.7927	0.0000	1020

Source: Author's data

Table 2: Volatility models for RRSO (p value in brackets)

	GAUSSIAN DISTRIBUTION			STUDENTS t DISTRIBUTION			GED		
PARAMETER	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)
MEAN EQUATION									
φ_0	0.000425 (0.2979)	0.000433 (0.2967)	0.000466 (0.2721)	0.000276 (.3648)	0.000278 (.3612)	0.000263 (.3856)	0.000215 (.4427)	0.00022 (.4320)	0.000215 (.4407)
φ_1	-8.75E-05 (0.9982)	0.000736 (0.9851)	-0.019483 (0.5948)	-1.39E-02 .6462	-0.0139 (.6460)	-0.01465 (.6152)	-0.03581 (.1829)	-0.03572 (.1867)	-0.03671 (.1627)
VARIANCE EQUATION									
δ	1.12E-05 (0.0014)	1.09E-05 (0.0015)	-0.527376 (0.0006)	3.67E-06 .0171	3.66E-06 (.0174)	-0.29492 (.0088)	4.73E-06 (.0313)	4.62E-06 (.0317)	-0.32546 (.0194)
α	0.024679 (0.0006)	0.028457 (0.0063)	0.071811 (0.0000)	.03448 .0031	0.03495 (.0191)	0.101469 (.0002)	0.031831 (.0114)	0.034973 (.0364)	0.09409 (.0007)
β	0.898484 (0.0000)	0.899448 (0.0000)	0.946079 (0.0000)	.9362 .0000	0.93626 (.0000)	0.975423 (.0000)	0.931734 (.0000)	0.931971 (.0000)	0.971284 (.0000)
$\alpha + \beta$	0.923163	0.927905	**1.01789**	0.970721	0.971209	**1.076892**	0.963565	.966944	**1.065375**
γ		-0.005336 (0.6432)	-0.006886 (0.4624)		-0.00089 (.9601)	-0.00842 (.6380)		-0.00553 (.7717)	-0.00449 (.8047)
LB10	8.8133 (0.5500)	8.3729 (0.5920)	9.3262 (0.5010)	8.3729 (0.5920)	8.3903 (0.5910)	9.1587 (0.517)	9.3262 (0.5010)	9.4544 (0.4900)	10.319 (0.413)
$LB^2 10$	3.7652 (0.9570)	1.671 (0.9980)	1.671 (0.998)	1.671 (0.998)	1.6842 (0.998)	2.742 (0.987)	2.0621 (0.996)	2..1858 (0.995)	3.8913 (0.952)
ARCH LM Test	0.083735 (0.7724)	0.1398 (0.7086)	0.1398 (0.6780)	0.1398 (0.7086)	0.1381 (0.7103)	0.0338 (0.8540)	0.1724 (0.6780)	0.1596 (0.6896)	0.0402 (0.8411)
AIC	-5.987646	-5.985787	-5.977800	-6.196104	-6.194144	-6.192270	-6.163225	-6.161350	-6.159862
SC	-5.963472	-5.956779	-5.948792	-6.167096	-6.160301	-6.158427	-6.134217	-6.127507	-6.126019
Log Likelihood	3055.706	3055.758	3051.689	3162.915	3162.916	3161.962	3146.163	3146.208	3145.45
Half Life	8.7	9.3		23.3	23.7		18.7	20.6	

Source: Author's own construct based on data from www.ncdex.com

Table3: Volatility models for RRBO (p value in brackets)

	GAUSSIAN DISTRIBUTION			STUDENTS t DISTRIBUTION			GED		
PARAMETER	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)
MEAN EQUATION									
φ_0	0.000344 (0.4186)	0.000303 (0.4970)	0.000315 (0.4764)	0.000278 (0.5126)	0.000261 (0.5479)	0.000227 (0.5955)	0.000169 (0.6840)	0.000141 (0.7382)	0.000137 (0.7448)
φ_1	.004525 (0.8896)	0.004608 (0.8886)	0.000426 (0.8961)	-0.00406 (0.8989)	-0.00367 (0.9089)	-0.00199 (0.9507)	-0.01079 (0.7307)	-0.01041 (0.7407)	-0.00896 (0.7759)
VARIANCE EQUATION									
δ	2.48E-06 (0.0088)	2.45E-06 (0.0152)	-0.14753 (0.0002)	250E-06 (0..0131)	250E-06 (0..0230)	-0.14382 (0.0033)	2.55E-06 (0.0228)	250E-06 (0.0361)	-0.14922 (0.0037)
α	0.029625 (0.0002)	0.027476 (0.0051)	0.083178 (0.0000)	0.017848 (0.0237)	0.017146 (0.0975)	0.066257 (0.0028)	0.022408 (0.0141)	0.020946 (0.0662)	0.074269 (0.0018)
β	0.956638 (0.0000)	0.954987 (0.0000)	0.99038 (0.0000)	0.968052 (0.0000)	0.966631 (0.0000)	0.98924 (0.0000)	0.963177 (0.0000)	0.960962 (0.0000)	0.989345 (0.0000)
$\alpha + \beta$	0.986263	0.982463		0.985900	0.983777		0.985585	0.981908	
γ		0.008487 (0.5413)	-0.00678 (0.5052)		0.004525 (0.7760)	-0.01173 (0.3637)		0.007938 (0.6357)	-0.01052 (0.4195)
LB10	9.9823 (0.4420)	9.9487 (0.4450)	10.5120 (0.3970)	10.613 (.3880)	10.541 (0.3940)	10.508 (0.3970)	10.512 (0.3970)	10.414 (0.4050)	10.471 (0.4000)
$LB^2 10$	8.9974 (0.5320)	8.7694 (0.5540)	9.9078 (0.4490)	11.497 (0..3200)	11.150 (0..3460)	10.046 (0.4370)	9.9078 (0..4490)	9.5301 (0.4830)	8.8976 (0.5420)
ARCH LM Test	0.809878 (0.3684)	0.8092 (0.3686)	0.7497 (0.3868)	0.61326 (0.4337)	0.6221 (0.4304)	0.8817 (0.3479)	0.7497 (0.3868)	0..75385 (0.3855)	1.0429 (0.3073)
AIC	-5.625596	-5.62389	-5.62389	-5.63926	-5.63736	-5.6387	-5.6411	-5.63933	-5.64112
SC	-5.601423	-5.59489	-5.59489	-5.61025	-5.60352	-5.60485	-5.61209	-5.60548	-5.60728
Log Likelihood	2871.241	2871.374	2871.374	2879.202	2879.234	2879.916	2880.141	2880.236	2881.151
Half Life	50.1	39.2		48.8	42.3		47.7	37.9	

Source: Author's own construct based on data from www.cme.com

Table 4: Forecast efficiency for Soy Oil and Bean Oil

RRBO	GAUSSIAN			t Distribution			GED		
	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
RMSE	0.015831	0.015831	0.015831	0.015831	0.015832	0.015833	0.015835	0.015836	0.015836
MAE	0.011718	0.011717	0.011717	0.011716	0.011716	0.011716	**0.011715**	0.011715	0.011716
MAPE	99.57454	99.27133	99.36239	99.07066	98.95243	98.76355	**98.54364**	98.55069	98.55162
TIC	**0.977813**	0.980401	0.979617	0.982031	0.983071	0.985236	0.988898	0.990729	0.990958

RRSO	GAUSSIAN			t Distribution			GED		
	GARCH (1,1)	TGARCH 1,1	EGARCH 1,1	GARCH (1,1)	TGARCH 1,1	EGARCH 1,1	GARCH (1,1)	TGARCH 1,1	EGARCH 1,1
RMSE	0.011677	0.011677	**0.011675**	0.011681	0.011681	0.011682	0.011683	0.011683	0.011683
MAE	0.008492	0.008492	0.008499	0.008489	0.008489	0.008489	0.008488	0.008488	0.008488
MAPE	102.7833	102.8848	105.6435	101.1068	101.1218	101.0062	100.6259	100.6634	**100.6251**
TIC	0.963641	0.962975	**0.94929**	0.976197	0.976026	0.977348	0.981679	0.981243	0.981685

Source: Author's own construct

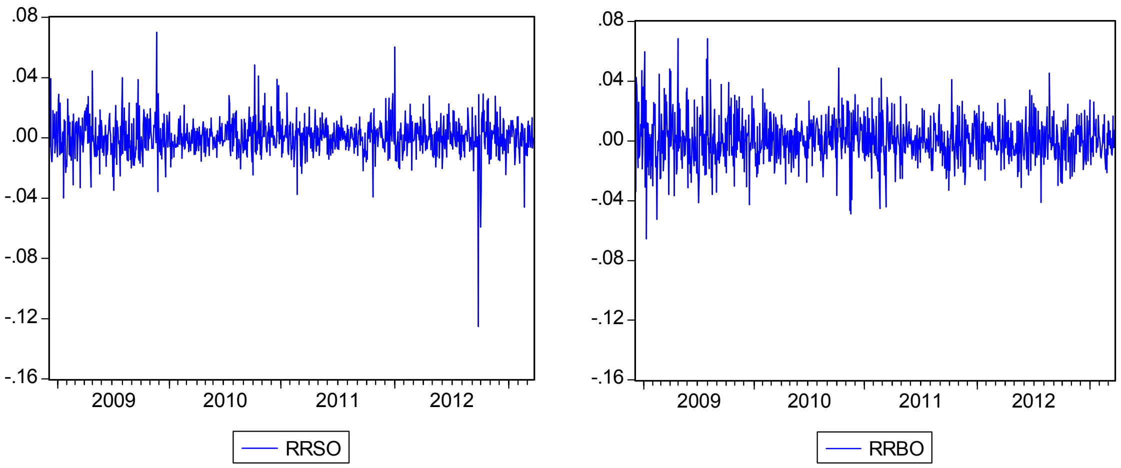

Figure 1. Volatility Clustering in Refined Soy Oil (RRSO) and Bean Oil (RRBO)
Source: Author's own data.

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