Analysis of Energy and Agricultural Commodity Markets with the Policy Mandated: A Vine Copula-based ARMA-EGARCH Model

Kuan-Ju Chen
School of Economic Sciences
Washington State University
Pullman, WA 99164
E-mail: kuan718.chen@wsu.edu

Kuan-Heng Chen
Department of Financial Engineering
Stevens Institute of Technology
Hoboken, NJ 07030
E-mail: kchen3@stevens.edu

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Kuan-Ju Chen[a] and Kuan-Heng Chen[b]

a School of Economic Sciences, Washington State University, Pullman, WA 99164
b Department of Financial Engineering, Stevens Institute of Technology, Hoboken, NJ 07030

ABSTRACT

The Energy Independence and Security Act (EISA) of 2007 states an increase in ethanol production to 36 billion gallons per year by 2022. Biofuels mainly are produced from agricultural commodities, so that increasing demand of biofuels would have an impact on agricultural commodity prices. The linear relationships among crude oil prices and prices for agricultural commodities are well documented, but not appropriate to explain the asymmetric dependency. Vine copula modeling which is used in this study can be extended to higher dimensions easily and provide a flexible measurement to capture an asymmetric dependence among commodities. The purpose of this study is to analyze the degree and the dependence structure of commodities with the policy effect of EISA 2007 along the biofuel supply chain in the United States agricultural market. We employ vine copulas in order to better capture an asymmetric dependence among commodities using five U.S. agricultural commodities' and crude oil. The empirical results provide that vine Copula-based ARMA-EGARCH (1, 1) is an appropriate model with the skewed student t innovations to analyze returns dependency of crude oil and agricultural commodities before EISA 2007 (January 1st, 2003- January 17th, 2007) and after EISA 2007 (January 18th, 2007-December 31st, 2012). Our findings on the relationship among energy and agricultural commodities can provide policymakers and industry participants appropriate strategies for risk management, hedging strategies, and asset pricing.

JEL Classification: G13, Q11, Q13

Keywords: Agricultural commodity; Copula; Dependence; EISA 2007; Oil future; Time Series

1. INTRODUCTION

Petroleum reserves are limited natural resources and cannot be consumed forever. Over the last decade, there has been raised interest in the potential for biofuel as an alternative source in order to reduce consumption on fossil fuels and to improve environmentally friendly and renewable energy. The biomass based resource includes a wide variety of forestry and agricultural resources, industrial-process residues, and all plant and plant-derived materials (Perlack et al., 2005). Biofuels mainly are produced based on biomass that are generally from agricultural crops. The U.S. biofuel production has been increased in a rapid expansion because of high energy prices and government policies proposed to reduce the U.S. imported crude oil for energy needs (Tyner, 2008). In addition, the Energy Independence and Security Act of 2007 (EISA 2007) points that an increase in ethanol production to 36 billion gallons per year by 2022. Thus, an increase in demand of biofuels that are mainly composed of agricultural crops would have a certain impact on agricultural commodity prices.

The linear relationships among crude oil prices and agricultural commodities prices are well documented. Myers et al. (2014) indicated that the relationship between energy and agricultural feedstock prices will be less important in the long-run by running an econometric model in the short-run and long-run co-movements. Many studies have found that a significantly connection between agricultural feedstocks and oil prices from biofuel production since the biofuel boom in 2005-2006 (Harri et al., 2009; Frank and Garcia, 2010). Moreover, Serra and Zilberman (2013) mentioned that energy prices have driven long-run agricultural price levels and influenced food markets from instability in energy markets. Furthermore, Natanelov et al. (2011) concluded that the biofuel policy impacts the co-movement of crude oil and corn futures until the crude oil prices surpass in a certain threshold from a comprehensive study on the interaction between crude oil futures market and agricultural futures markets.

Jiang et al. (2015) investigated the new relationships among the U.S. crude oil, corn and plastics markets by using a vector error correction model (VECM), and concluded that plastics prices and corn futures prices have the strong co-movements and EISA 2007 has improved relationships between the corn futures and crude oil futures markets. Agricultural commodity prices have influenced by oil prices (Abbott et al., 2008; FAO, 2008; Mitchell, 2008; OECD, 2008; Piesse and Thirtle, 2009), especially after 2006, when raising biofuel production lifted the emerging demand for agricultural commodities (see, e.g., Chen et al., 2010).

The Energy Independence and Security Act of 2007 (EISA 2007) was signed into law in 2007 by President Bush, and his response “Twenty in Ten” challenge is to reduce gasoline consumption by 20% in 10 years (Bush, 2007). The idea of EISA 2007 is to promote different forms of alternative energy by moving the United States toward greater energy independence and security. In 2008, the United States has produced 9 billion gallons of ethanol fuel from an increase of more than 5000 percent since 1980 (Renewable Fuels Association, 2009). In addition, EISA 2007 followed another major energy legislation, the Energy Policy Act of 2005 (EPA 2005) that enhances economic security and stability by increasing the production and development of clean renewable fuels and materials, such as biofuels or bio-based products. The EPA 2005 has fortified the linkage between crude oil and agricultural commodity markets (Wu et al., 2011; McPhail, 2011). The environmental impacts of this mandate are unresolved and significant, such as net energy budget, effect on corn based commodities, greenhouse emissions, etc. (Food and Energy Security Act of 2007; Tilman et al., 2009).

Even though the linear relationships among crude oil prices and agricultural commodities prices are well documented, the objective of this study is to analyze the degree and the dependence structure of along the biofuel supply chain in the United States agricultural market. There is extensive literature studying dependence structures of crude oil futures and agricultural futures markets. For examples, Reboredo (2011) examined several copula models to evaluate the dependence structure between crude oil benchmark prices and concluded crude oil prices are moving together with the same intensity in the global markets. Ahmed and Goodwin (2015) studied the dependence structure between commodity prices among international food grain markets by using copula-based modeling, and found that strong and significant dependence structures of most price pairs among global food grain markets.

In this study, we employ vine copula modeling which can be extended to higher dimensions and provide a flexible measurement to capture an asymmetric dependence among commodities. It is well known that the dependence structures of the returns of financial assets are non-Gaussian and exhibit volatility clustering. Sklar (1959) introduced the copula, which describes the dependence structure among variables. Patton (2002) extended Sklar’s theorem to the time series analysis. Cherubini et al. (2004) indicated descriptions and applications of a copulas methodology in the fields of mathematical finance and risk management.

Many studies showed that the agricultural commodities future market plays an important role in the agricultural and biofuel markets. Thus, this study investigates the dynamic relationship among agricultural commodities by studying the dependence structure of percentage changes of agricultural prices within the agriculture future market in the United States. Following Jiang et al. (2015), vine Copula-based ARMA-EGARCH (1, 1) with skewed student t innovations is used to analyze prices dependency of crude oil and agricultural commodities before EISA 2007 (January 1st, 2003- January 17th, 2007) and after EISA 2007 (January 18th, 2007-December 31st, 2012). This strong asymmetric dependence between crude oil and agricultural commodity markets might play a crucial role in the commodity price boom in 2007 and 2008. Our findings on the relationship among energy and agricultural commodities can provide policymakers and industry participants appropriate strategies for risk management, hedging strategies and asset pricing.

The paper is organized as follows. Section II describes the methodology. Section III shows the data collection and variable selection. Section IV presents the results and corresponding analysis. Finally, Section V draws conclusions and implications.

2. METHODOLOGY

Copula modeling has become a popular and frequently used tool in the fields of financial economics (Joe, 1997; Nelsen, 1999). In order to assess the degree and the structure of dependency among the percentage changes of the agricultural prices and crude oil prices in the United States, this study investigates the dynamic relationships among agricultural commodities and energy by using the vine Copula-based ARMA-EGARCH (1, 1) model within the agricultural and crude oil futures markets in the United States. This section is organized as follows: in Section 2.1, Univariate ARMA-EGARCH Model, in Section 2.2, Sklar’s Theory, in Section 2.3, Parametric Copulas, in Section 2.4, Vine Copulas, in Section 2.5, Estimation Method.

2.1 Univariate ARMA-EGARCH Model

In order to deal with the volatility clustering that usually referred to as conditional heteroscedasticity, Engle introduced the ARCH model. The volatility of prices today would result in a higher volatility of prices next day, so that the variance of returns series changes over time. Bollerslev (1986) extended the ARCH model to the generalized ARCH (GARCH) model, and Nelson (1991) proposed the exponential GARCH (EGARCH) model in handling asymmetric effects between positive and negative asset returns. In this study, we apply ARMA (p, q)-

EGARCH (1, 1) with the skewed student's *t* distributed innovations into the marginal to account for the time-varying volatility

$$r_t = \mu_t + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t,$$
$$\epsilon_t = \sigma_t z_t,$$
$$\log(\sigma_t^2) = \gamma_t + \alpha_t \frac{|\sigma_{t-1}\epsilon_{t-1}| + \xi_t \sigma_{t-1}\epsilon_{t-1}}{\sigma_{t-1}} + \beta_t \log(\sigma_{t-1}^2),$$

where r_t is the log return, μ_t is the drift term, ϵ_t is the error term, ξ_t captures leverage effect of ϵ_{t-1} and the innovation term z_t is the skewed student's *t* distribution (Lambert et al., 2001).

2.2 Sklar's Theory

Sklar's theorem (1959) states that given random variables $X_1, X_2, \dots, X_n$ with continuous distribution functions $F_1, F_2, \dots, F_n$ and joint distribution function H, and there exists a unique copula C such that for all $x = (x_1, x_2, \dots, x_n) \in R^n$

$$H(x) = C\big(F_1(x_1), F_2(x_2), \dots, F_n(x_n)\big)$$

Patton (2002) defined the conditional version of Sklar's theorem. Let $F_{1,t}$ and $F_{2,t}$ be the continuous conditional distriubtions of $X_1|\mathcal{F}_{t-1}$ and $X_2|\mathcal{F}_{t-1}$ given the conditioning set $\mathcal{F}_{t-1}$, and let H_t be the joint conditional bivariate distribution of $(X_1, X_2|\mathcal{F}_{t-1})$. Then, there exists a unique conditional copula C_t such that

$$H_t(x_1, x_2|\mathcal{F}_{t-1}) = C_t(F_{1,t}(x_1|\mathcal{F}_{t-1}), F_{2,t}(x_2|\mathcal{F}_{t-1})|\mathcal{F}_{t-1})$$

2.3 Parametric Copulas

Joe (1997) and Nelsen (1999) defined a comprehensive copula for each family.

(1) The bivariate Gaussian copula is defined as:

$$C(u_1, u_2; \rho) = \Phi_\rho\big(\Phi^{-1}(u_1), \Phi^{-1}(u_2)\big)$$

where Φ_ρ is the bivariate joint normal distribution with linear correlation coefficient ρ.

(2) The bivariate student's t copula is defined by the following:

$$C(u_1, u_2; \rho, \nu) = t_{\rho,\nu}\big(t_\nu^{-1}(u_1), t_\nu^{-1}(u_2)\big)$$

where ρ is the linear correlation coefficient and ν is the degree of freedom.

(3) The Clayton generator is given by $\varphi(u) = u^{-\theta} - 1$, its copula is defined by

$$C(u_1, u_2; \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}, \text{with } \theta \in (0, \infty)$$

(4) The Gumbel generator is given by $\varphi(u) = (-\ln u)^{\theta}$, and the bivariate Gumbel copula is given by

$$C(u_1, u_2; \theta) = \exp(-[(-\ln u_1)^{\theta} + \left(-\ln u_2)^{\theta}]^{\frac{1}{\theta}}\right), \text{with } \theta \in [1, \infty)$$

(5) The Frank generator is given by $\varphi(u) = ln(\frac{e^{-\theta u}-1}{e^{-\theta}-1})$, and the bivariate Frank copula is defined by

$$C(u_1, u_2; \theta) = -\frac{1}{\theta} log\left(1 + \frac{\left(e^{-\theta u_1} - 1\right)\left(e^{-\theta u_2} - 1\right)}{e^{-\theta} - 1}\right),$$

$$\text{with } \theta \in (-\infty, 0) \cup (0, \infty)$$

(6) The Joe generator is $\varphi(u) = u^{-\theta} - 1$, and the Joe copula is given by

$$C(u_1, u_2) = 1 - (\overline{u_1}^{\theta} + \overline{u_2}^{\theta} - \overline{u_1}^{\theta}\overline{u_2}^{\theta})^{\frac{1}{\theta}},$$

$$\text{with } \theta \in [1, \infty)$$

(7) The BB1 (Clayton-Gumbel) copula is given by

$$C(u_1, u_2; \theta, \delta) = (1 + [(u_1{}^{-\theta} - 1)^{\delta} + (u_2{}^{-\theta} - 1)^{\delta}]^{\frac{1}{\delta}})^{\frac{-1}{\theta}},$$

$$\text{with } \theta \in (0, \infty) \cap \delta \in [1, \infty)$$

(8) The BB6 (Joe-Gumbel) copula is

$$C(u_1, u_2; \theta, \delta) = 1 - (1 - \exp\{-[\left(-lo\,g\left(1 - \overline{u_1}^{\theta}\right)\right)^{\delta} + \left(-log(1 - \overline{u_2}^{\theta})\right)^{\delta}]^{\frac{1}{\delta}}\})^{\frac{1}{\theta}},$$

$$\text{with } \theta \in [1, \infty) \cap \delta \in [1, \infty)$$

(9) The BB7 (Joe-Clayton) copula is given by

$$C(u_1, u_2; \theta, \delta) = 1 - (1 - [(1 - \overline{u_1}^{\theta})^{-\delta} + (1 - \overline{u_2}^{\theta})^{-\delta} - 1]^{-\frac{1}{\delta}})^{\frac{1}{\theta}},$$

$$\text{with } \theta \in [1, \infty) \cap \delta \in [0, \infty)$$

(10) The BB8 (Frank-Joe) copula is

$$C(u_1, u_2; \theta, \delta) = \frac{1}{\delta}(1 - [1 - \frac{1}{1 - (1 - \delta)^{\theta}}(1 - \left(1 - \delta u_1\right)^{\theta}\right)\left(1 - \left(1 - \delta u_2\right)^{\theta}\right)]^{\frac{1}{\theta}}\right),$$

$$\text{with } \theta \in [1, \infty) \cap \delta \in (0,1]$$

2.4 Vine Copulas

It is limited to capture the dependence structure with one or two parameters by multivariate Archimedean copulas. Therefore, vine copula method that is a more flexible measure to capture the dependence structure among assets allows a joint distribution to be established based on bivariate and conditional bivariate copulas arranged together according to the graphical structure of a regular vine. Bedford and Cooke (2002) introduced canonical vine copulas, in which one variable plays a pivotal role. Kurowicka and Joe (2011) summarized vine copulas, and the general n-dimensional canonical vine copula can be written as

$$c(x_1, \dots, x_n) = \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{i,i+j|1,\dots,i-1}(F(x_i|x_1, \dots, x_{i-1}), F\big(x_{i+j}|x_1, \dots, x_{i-1}\big))$$

Similarly, D-vines are also constructed by choosing a specific order for the variables. The general n-dimensional D-vine copula can be written as

$$c(x_1, \dots, x_n) = \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{j,j+i|j+1,\dots,j+i-1}(F\big(x_j|x_{j+1}, \dots, x_{j+i-1}\big), F\big(x_{j+i}|x_{j+1}, \dots, x_{j+i-1}\big))$$

Table 1 presented that the automated algorithm for searching an appropriate R-vine tree structure, the pair-copula families, and the parameter values of the chosen pair-copula families based on AIC criterion (Dissmann et al., 2013).

TABLE 1

SEQUENTIAL METHOD TO SELECT AN R-VINE MODEL

Algorithm. Sequential method to select an R-Vine model
1. Calculate the empirical Kendall's tau for all possible variable pairs.
2. Select the tree that maximizes the sum of absolute values of Kendall's taus.
3. Select a copula for each pair and fit the corresponding parameters based on AIC.
4. Transform the observations using the copula and parameters from Step 3. To obtain the transformed values.
5. Use transformed observations to calculate empirical Kendall's taus for all possible pairs.
6. Proceed with Step 2. Repeat until the R-Vine is fully specified.

2.5 Estimation Method

Joe (1997) proposed the two-step separation procedure to estimate the parameters by maximum log-likelihood, where marginal distributions and copulas are estimated separately.

$$\log f(x) = \sum_{i=1}^{n} log f_i(x_i) + log c(F_1(x_1), \dots, F_n(x_n))$$

3. DATA

We use the daily future data on Bloomberg[1] from January 1st, 2003 until December 31st, 2012 for a total of 2,512 observations to evaluate the dependence relationship for the crude oil future price[2] and agricultural commodity prices - corn futures[3], soybean futures[4], soybean meal futures[5], rice futures[6], and wheat futures[7] in the United States. Corn, soybean, rice, and wheat are mainly used in biofuels or biodiesel in the transportation sector, and they compete with the derived demand for alternative energy production, especially when oil prices are high. Thus, this is why we focus on those abovementioned prices. In addition, the initial version of H.R. 6 - EISA 2007 passed the House of Representatives on January 18, 2007. Thus, we would like to investigate the effect of Energy Independence and Security Act (EISA) of 2007 on the spillover parameters. Therefore, we separate our sample into two time windows, the prior to EISA 2007 is from January 1st, 2003 to January 17th, 2007 (1,011 observations) and the after EISA 2007 is from January 18th, 2007 to December 31st, 2012 (1,501 observations). Table 3 presents all variables and abbreviations used with a short description through the entire paper. The summary statistics for price returns of six commodities before EISA 2007 presented in table 4, which shows that the standard deviation of crude oil returns is higher than those of other commodities returns, consistent with the similar results in previous studies that commodities have higher volatilities. The skewness statistics of crude oil, soybean, soybean meal, and rice are negative and significant, which means that those commodities returns are significantly skewed to the left and with a greater probability of large

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[1] Bloomberg: http://www.bloomberg.com/markets/commodities.

[2] Crude oil future contract is continuous contract number 1, and crude oil future price (cent/ bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[3] Corn future contract is continuous contract number 1, and corn future price (cent/ bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[4] Soybean future contract is continuous contract number 1, and soybean future price (cent/ bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[5] Soybean meal future contract is continuous contract number 1, and soybean meal future price (cent/ bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[6] Rice future contract is continuous contract number 1, and rice future price (cent/hundredweight) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[7] Wheat future contract is continuous contract number 1, and wheat future price (cent/ bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

decreases in returns. However, the skewness statistics of corn and wheat are positive and significant, which means that their returns are significantly skewed to the right. Moreover, the values of the excess kurtosis statistics for all commodities are significantly positive, which implies that the distribution of returns has larger, thicker tails than the normal distribution.

Table 5 reports the summary statistics for price returns of six commodities after EISA 2007, and the standard deviation of wheat returns become the highest value among those of other commodities returns. The skewness statistics of all commodities become negative and significant, which indicates that all commodities returns are significantly skewed to the left. Furthermore, the values of the excess kurtosis statistics for all commodities are still significantly positive, which implies that the distribution of returns has larger, thicker tails than the normal distribution.

We use the augmented Dickey-Fuller (ADF) test to examine stationarity for each of these commodity price return series (Banerjee et al., 1993). The test statistics for all commodities shows that the null hypothesis of a unit root can be rejected at the 5% significant level, which confirmed stationarity. Moreover, the Jarque-Bera (J-B) test to examine normality for each commodity price return series, and the test statistics shows that the null hypothesis can be rejected at the 5% significant level, whereby indicating price return series of all commodities are not normally distributed. Similarly, the autoregressive conditional heteroscedasticity – Lagrange multiplier (ARCH) test to examine heteroscedasticity for all commodities price return series (Engle, 1982), conducted using ten lags. The test statistics indicates that the null hypothesis can be rejected at the 5% significant level, whereby implying the data are not independently distributed so that ARCH effects are most likely to be found in all price return series. Thus, we apply the EGARCH model to deal with the volatility clustering effect.

Table 6 and table 7 show the Pearson linear correlations for all commodities prices return pairs before and after EISA 2007, respectively. The positive and high correlation values demonstrate that two markets move together toward the same direction. The soybean and soybean meal pairs have the strongest positive linear dependence before and after EISA 2007. The weakest dependences are for the wheat and crude oil return pair with the positive correlation before EISA 2007 and the soybean and crude oil pair with the negative correlation after EISA 2007.

Figure 1 shows the trends of crude oil and agricultural futures prices, and we can see that all trends are similar over time. The relationship among oil and agricultural commodity prices remains weak before 2007, when oil prices are below 80 US dollars. However, this relationship becomes stronger when oil prices started to move up from 2007. In addition, all of commodity price series have increasing trends after the policy mandated until the financial crisis between 2008 and 2009. After the financial crisis, they all follow the similar path with an upward movement and reach another price spikes in 2011. Figure 2 illustrates prices returns of crude oil and agricultural futures prices, and we can find that volatility in price series are somewhat clustered for each commodity markets which imply that large changes in prices followed by large change. However, wheat futures returns are more volatile than other commodities and rice future returns seem to be smooth.

Table 3: Descriptions of the Variables

Predictor	Short description
C1	Corn future contract with continuous contract number 1
S1	Soybean future contract with continuous contract number 1
SM1	Soybean meal future contract with continuous contract number 1
CL1	Crude oil future contract with continuous contract number 1
RR1	Rice future contract with continuous contract number 1
W1	Wheat future contract with continuous contract number 1

Table 4: Descriptive statistics before EISA 2007 (Jan. 1st, 2003 – Jan. 17th, 2007)

Before	**1 (C1)**	**2 (S1)**	**3 (SM1)**	**4 (CL1)**	**5 (RR1)**	**6 (W1)**
Mean	0.00054	0.00021	0.00022	0.00048	0.00098	0.00037
Std. Dev.	0.01631	0.01738	0.01869	0.02108	0.01919	0.01829
Skewness	0.57974	-1.07116	-0.78070	-0.13648	-1.73299	0.44692
Kurtosis	5.08853	12.52763	11.22256	3.47959	35.05021	4.04583
Obs. Num.	1011	1011	1011	1011	1011	1011
ADF test	1	1	1	1	1	1
J-B test	1	1	1	1	1	1
ARCH test	1	1	1	1	1	1

Table 5: Descriptive statistics after EISA 2007 (Jan. 18th, 2007 – Dec. 31st, 2012)

After	**1 (C1)**	**2 (S1)**	**3 (SM1)**	**4 (CL1)**	**5 (RR1)**	**6 (W1)**
Mean	0.00035	0.00045	0.00046	0.00038	0.00023	0.00033
Std. Dev.	0.02238	0.01825	0.02041	0.02504	0.01677	0.02504
Skewness	-0.03197	-0.61947	-0.74838	-0.02817	-0.27956	-0.03560
Kurtosis	4.56260	6.06343	6.70432	6.99344	5.82116	4.06132
Obs. Num.	1501	1501	1501	1501	1501	1501
ADF test	1	1	1	1	1	1
J-B test	1	1	1	1	1	1
ARCH test	1	1	1	1	1	1

Table 6: Pearson correlation before EISA 2007 (Jan. 1st, 2003 – Jan. 17th, 2007)

Before	1 (C1)	2 (S1)	3 (SM1)	4 (CL1)	5 (RR1)	6 (W1)
1 (C1)	1	0.533027	0.457651	0.033531	0.157231	0.625248
2 (S1)	0.533027	1	0.883107	0.035683	0.184391	0.363982
3 (SM1)	0.457652	0.883107	1	0.046295	0.197504	0.301078
4 (CL1)	0.033531	0.035683	0.046295	1	-0.04317	0.030905
5 (RR1)	0.157231	0.184391	0.197504	-0.04317	1	0.117788
6 (W1)	0.625248	0.363982	0.301078	0.030905	0.117788	1

Table 7: Pearson correlation after EISA 2007 (Jan. 18th, 2007 – Dec. 31st, 2012)

After	1 (C1)	2 (S1)	3 (SM1)	4 (CL1)	5 (RR1)	6 (W1)
1 (C1)	1	0.627218	0.537464	-0.02281	0.301967	0.659937
2 (S1)	0.627218	1	0.894134	-0.00948	0.350928	0.500912
3 (SM1)	0.537464	0.894134	1	0.010359	0.285491	0.416561
4 (CL1)	-0.02281	-0.00948	0.010359	1	-0.04623	-0.02642
5 (RR1)	0.301967	0.350928	0.285491	-0.04623	1	0.322004
6 (W1)	0.659937	0.500912	0.416561	-0.02642	0.322004	1

Figure 1: Crude oil and agricultural futures prices

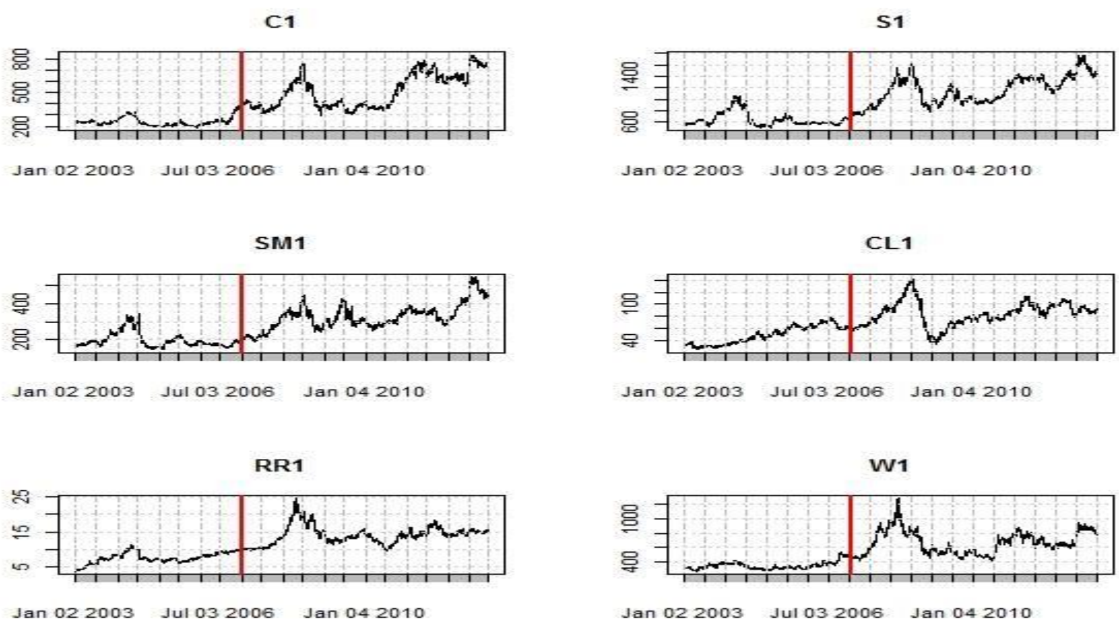
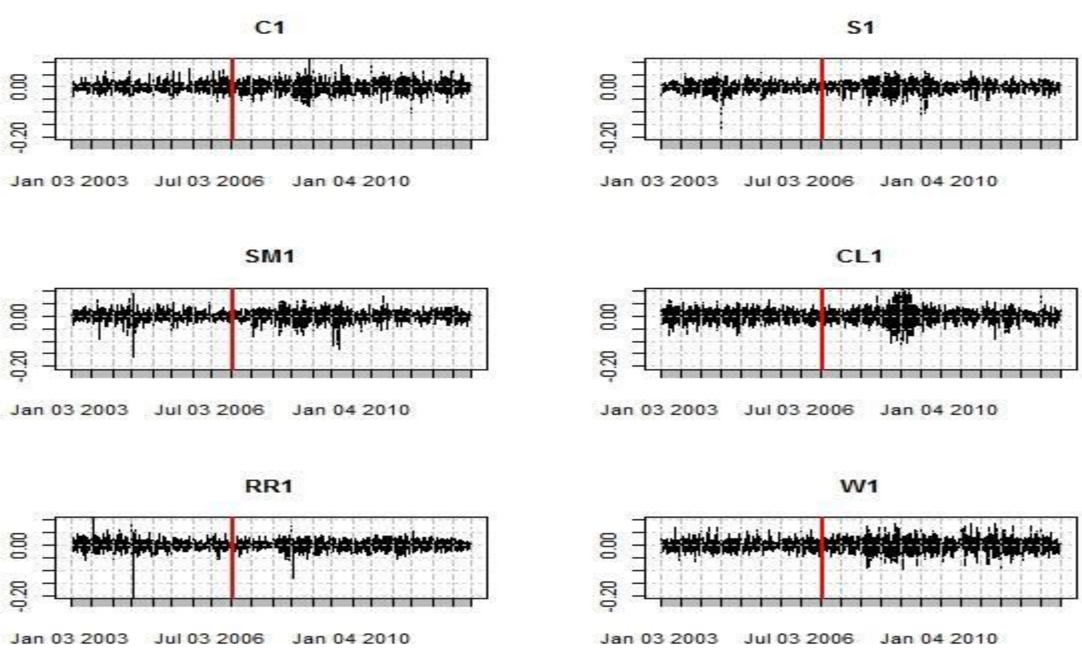


Figure 2: Returns of crude oil and agricultural futures prices



4. EMPIRICAL RESULTS

Table 8 and table 9 present the ARMA-EGARCH (1, 1) results and parameter estimations for crude oil, corn, soybean, soybean meal, rice, and wheat before and after EISA 2007, respectively. We use the Ljung-Box Q test to examine each commodity price return serial correlation in the model residuals, computed with 10 lags (Ljung and Box, 1978; Hamilton, 1994). The test statistics for all commodities shows that the null hypothesis of the serial correlation in the volatility of the commodity prices return series is independent distributed can be rejected at the 5% significant level, which confirmed autocorrelation (Elyasiani et al., 2011). Then, we select a copula family from forty copulas based on AIC model-fitting criterion that capture asymmetries for a multivariate analysis of six different prices return series. Finally, the ARMA-EGARCH (1, 1) with the skewed student t innovation is an appropriate model for the appropriate marginal distributions. We evaluate different combinations of the parameters for the lags of autoregressive and moving average terms ranging from zero up to a maximum lag of ten, with the most suitable model selected according to AIC values. We also consider that the characteristics of price returns are usually non-normal and skewed. Therefore, the parameter estimates are shown in table 8 and table 9.

From figure 3 and figure 4, we can see that the skewed student's t distribution fit better than normal distribution for each commodity's residuals before and after EISA 2007. This result is consistent with the evidence reported in table 4 and table 5. Ahmed and Goodwin (2015) also found that the skewness coefficients, that capture asymmetry in the distribution, are significant for each series which justify the rationale of using the skewed student t innovation and EGARCH model. On the other side, there are not every joint distributions follow multivariate normal distributions based on residual plots in figure 5 and figure 6.

Taking the characteristics of non-normal and skewed price changes into consideration, we employ the ARMA-EGARCH (1, 1) model with the skewed student t innovation to capture the asymmetry in the distribution and to fit the marginal distributions for the copula model. Following the ARMA-EGARCH model, the cumulative distributions of standardized residuals are formed to plug into copula model.

In Figure 7, we can see crude oil, rice, and wheat prices return series are more volatile after the policy changed than other prices return series. Corn, soybean, and soybean meal are stable and smooth over time.

Table 8: ARMA-EGARCH (1, 1) Results and Parameter Estimates (Before EISA 2007)

Before	1 (C1)	2 (S1)	3 (SM1)	4 (CL1)	5 (RR1)	6 (W1)
P	8	8	10	9	8	10
q	7	10	8	10	9	10
μ	0.0004265687	0.0009404608	0.0004347039	7.317087e-05	0.001545908	0.000320729
φ_1	-0.5826011764	-0.2104289683	-0.9603089937	-3.904272e-01	-0.185706956	0.027774537
φ_2	-0.6090476599	-0.3921743920	0.2682299054	-1.427517e+00	-0.279168905	-1.501880087
φ_3	-0.4482085240	-0.8766508310	0.8195893881	-1.781563e-01	-1.042461122	-0.168621433
φ_4	-0.4509241807	-0.2153982431	0.3168902341	-1.289594e+00	0.175810417	-0.984061938
φ_5	-0.5962593011	0.3535320407	0.6091294094	-7.426339e-02	-0.857739166	-0.018085582
φ_6	-0.6298437302	0.1111454183	0.1292583834	-4.237565e-01	-0.554232309	0.509905349
φ_7	-0.9376832040	-0.0311425015	-0.8268063298	3.904573e-01	-0.046137096	0.136585799
φ_8	0.0100163393	0.7201934004	-0.7828077654	-2.915472e-02	-0.645780208	0.742063172
φ_9	*	*	0.0142431204	1.793996e-02	*	0.246749723
φ_{10}	*	*	-0.0049947966	*	*	0.436157538
θ_1	0.6099473263	0.1566925868	1.0072202622	2.558288e-01	0.217546427	-0.037923764
θ_2	0.6707076737	0.2827149851	-0.2783044131	1.482649e+00	0.170660499	1.520908952
θ_3	0.4756441607	0.9226570718	-0.8264233080	2.474217e-03	1.038941181	0.177525851
θ_4	0.4904050950	0.2157460681	-0.2216768758	1.390929e+00	-0.178766937	0.938431912
θ_5	0.6109074783	-0.4621813068	-0.6172422533	-1.640053e-01	0.781668698	0.033791441
θ_6	0.6371931843	-0.0669347806	-0.2232406665	4.767390e-01	0.655574935	-0.726322907
θ_7	1.0050907265	0.1405547957	0.8494284955	-5.579882e-01	-0.005050825	-0.127745375
θ_8	*	-0.7658165921	0.9104568491	6.424045e-02	0.607543292	-0.969553426
θ_9	*	0.0443849583	*	-1.141783e-01	0.074447024	-0.281908654
θ_{10}	*	0.0843972733	*	-1.015538e-02	*	-0.537257564
γ	-0.2684593087	-0.1057662351	-0.2481236186	-2.355105e+00	-0.001254839	-0.609762775
α	0.0461966023	0.0377448723	0.0742702744	-2.169837e-01	0.020440315	0.045506301
β	0.9676943476	0.9873005319	0.9695878490	6.982784e-01	0.999809287	0.924575541
ξ	0.1408081864	0.1440664222	0.1585968674	-3.096027e-02	-0.023036339	0.020488385
η	1.1643003184	0.9966480666	1.0630150726	9.214036e-01	1.102913683	1.184878953
ν	5.8899085648	6.5944098231	5.1689062897	2.496524e+01	4.648123149	8.963658642
Log-likelihood	2833.982	2809.523	2747.484	2527.227	2765.384	2680.982
AIC	-5562.774	-5508.453	-5385.724	-4948.025	-5423.114	-5250.211
Ljung-Box Q (10)	0.5386	0.1699	0.8497	0.2458	0.672	0.4673

* Parameters not present in a lag

Table 9: ARMA-EGARCH (1, 1) Results and Parameter Estimates (After EISA 2007)

After	1 (C1)	2 (S1)	3 (SM1)	4 (CL1)	5 (RR1)	6 (W1)
P	9	9	4	9	9	10
Q	10	4	5	8	10	7
μ	0.0001938312	0.0009952867	0.0002748034	0.0006380165	0.0005417257	0.000992924
φ_1	1.6073252286	1.1139331072	-1.9094502496	-0.9530309081	0.9778186917	-1.674768562
φ_2	-2.6074894528	-2.1567504537	-1.9897254626	0.6934357681	-0.5861881362	-2.390846236
φ_3	3.0788446525	1.1654659055	-0.9293541586	1.1605057135	0.2591891117	-2.604808920
φ_4	-3.0677805400	-1.0592150142	-0.3221310004	0.1147961748	-0.4149097899	-2.234515875
φ_5	3.1147056611	0.0529046702	*	-1.0659856432	0.2414643421	-1.67730884
φ_6	-2.8022109377	-0.0283244200	*	-0.8733372117	-0.4611353545	-0.469454724
φ_7	1.8570125245	-0.0138830663	*	0.7737992233	0.8728575629	0.010381795
φ_8	-1.1686327097	0.0033480795	*	1.0464282479	-1.0676274089	0.163039119
φ_9	0.2212914134	-0.0023346705	*	0.1145603120	0.1256106718	0.125162314
φ_{10}	*	*	*	*	*	0.070757271
θ_1	-1.4965391756	-1.1005792592	1.9613558207	0.8473305968	-0.8932970342	1.662106705
θ_2	2.4137473582	2.1283371776	2.1117679912	-0.7763729725	0.4950474040	2.418642615
θ_3	-2.7818399334	-1.1061740203	1.0553943884	-1.0971681690	-0.2308645038	2.632313656
θ_4	2.7204107588	0.9866932423	0.3847584208	0.0017341923	0.4276734837	2.313454117
θ_5	-2.7939969161	*	0.0131207205	1.0920943331	-0.2437816003	1.843169955
θ_6	2.4622356211	*	*	0.7737372324	0.4924499207	0.650686131
θ_7	-1.5601938040	*	*	-0.8951549127	-0.8995962397	0.190678281
θ_8	0.9317097025	*	*	-0.9871284280	1.0567615493	*
θ_9	-0.0638837270	*	*	*	-0.0501190134	*
θ_{10}	-0.0220971341	*	*	*	0.0040858151	*
γ	-0.2103548293	-0.0956713252	-0.1902339933	-0.0835465513	-0.0530740221	-0.099678684
α	-0.0541879596	-0.0083188071	-0.0176586934	-0.0622241433	0.0009350205	0.034634873
β	0.9727006239	0.9882647479	0.9758562202	0.9889731076	0.9936791254	0.986642943
ξ	0.1230037988	0.1299258569	0.1337529398	0.1169392620	0.0895314169	0.098457916
η	0.9835184461	0.8943444812	0.8842152117	0.8670271412	1.0962430373	1.057106818
ν	7.5518792499	5.6405013293	6.9397662811	12.5454836609	9.3053085591	8.371462399
Log-likelihood	3688.991	4070.234	3856.541	3694.421	4146.561	3494.009
AIC	-4880.734	-5396.714	-5117.310	-48906.34	-5490.421	-4623.596
Ljung-Box Q (10)	0.24	0.8304	0.1969	0.01395	0.5981	0.4747

* Parameters not present in lags

Figure 3: Marginal distribution of prices return series (Before EISA 2007)

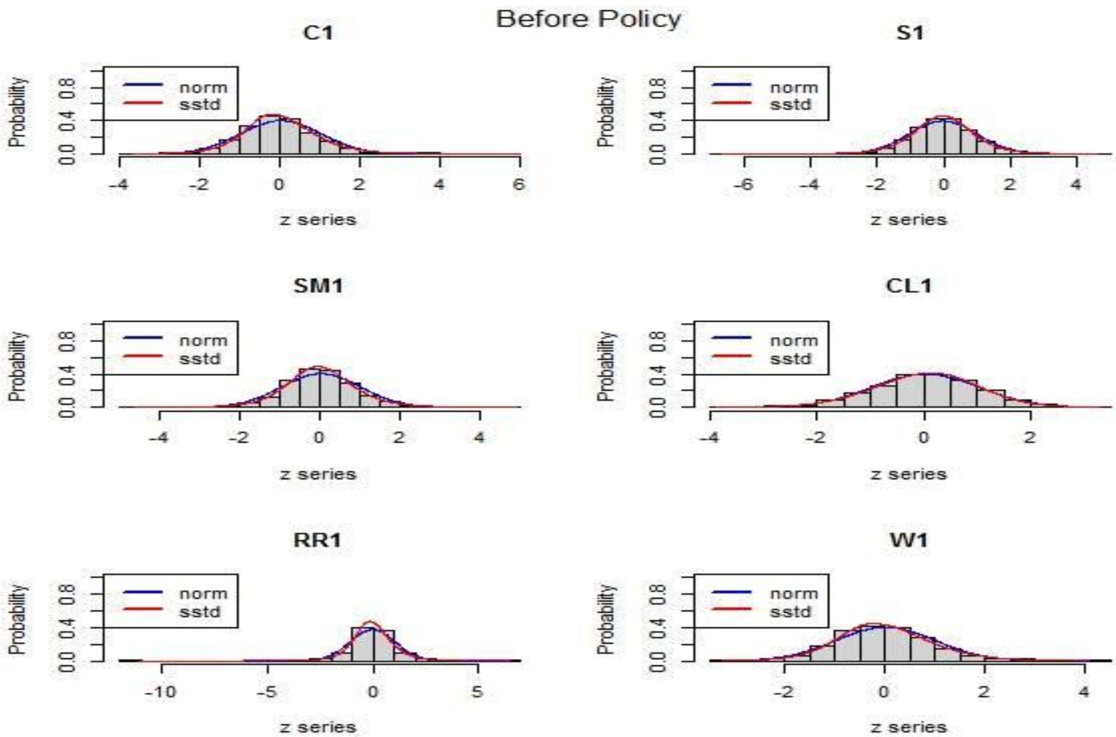


Figure 4: Marginal distribution of prices return series (After EISA 2007)

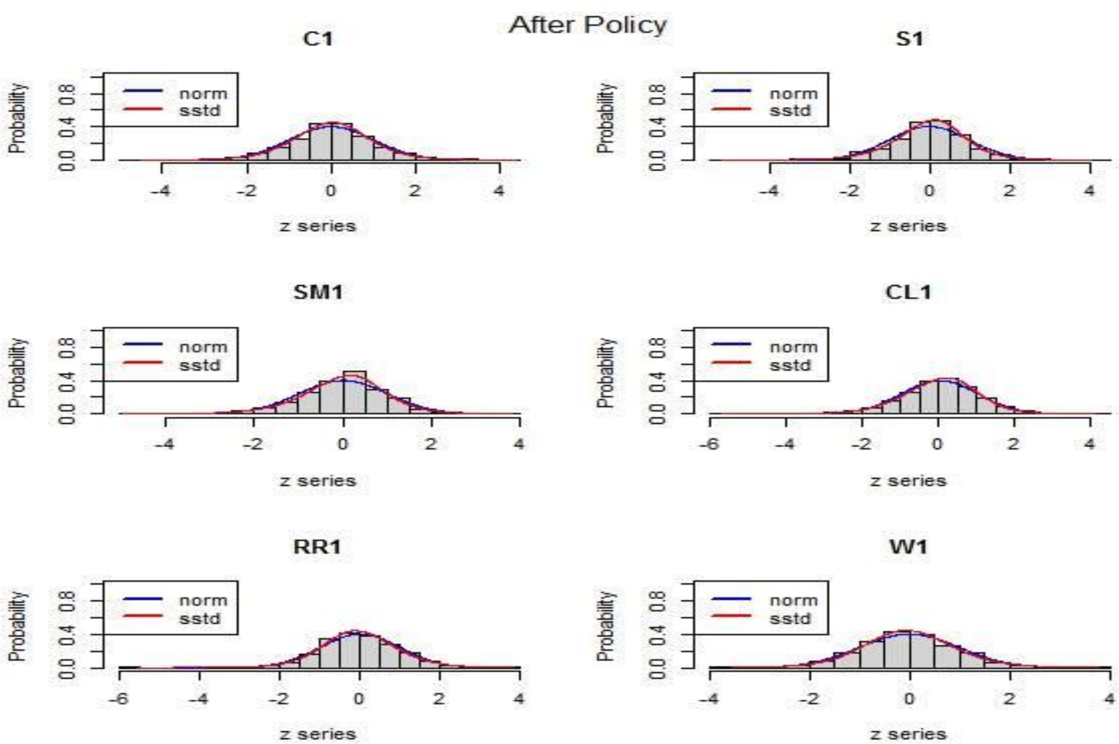


Figure 5: The scatterplot of residuals (Before EISA 2007)

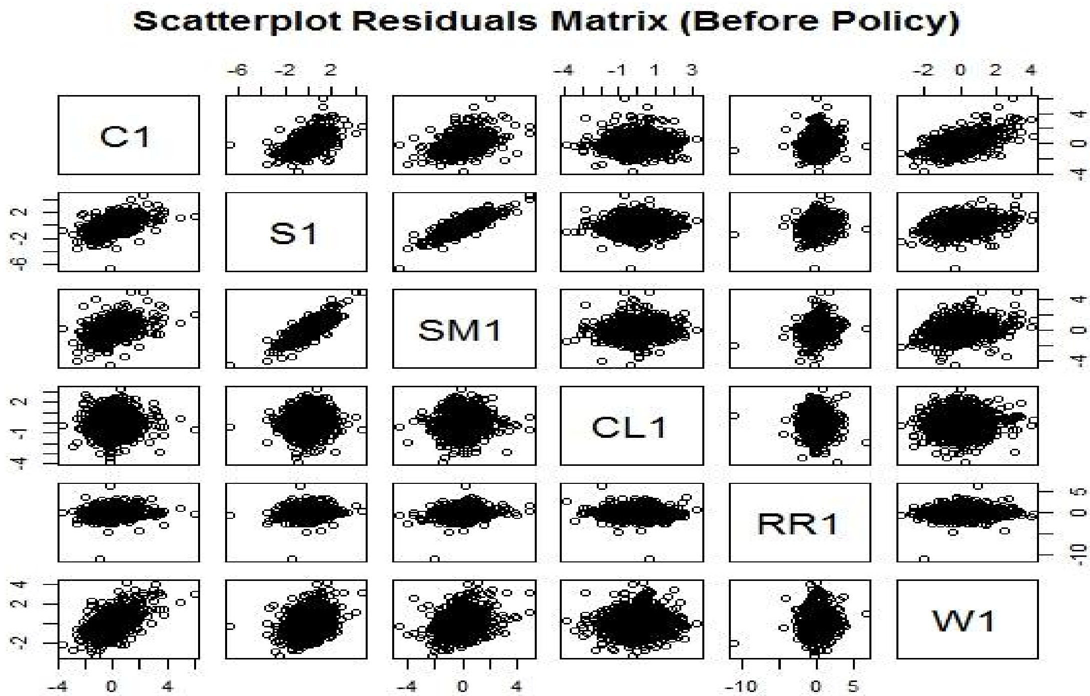


Figure 6: The scatterplot of residuals (After EISA 2007)

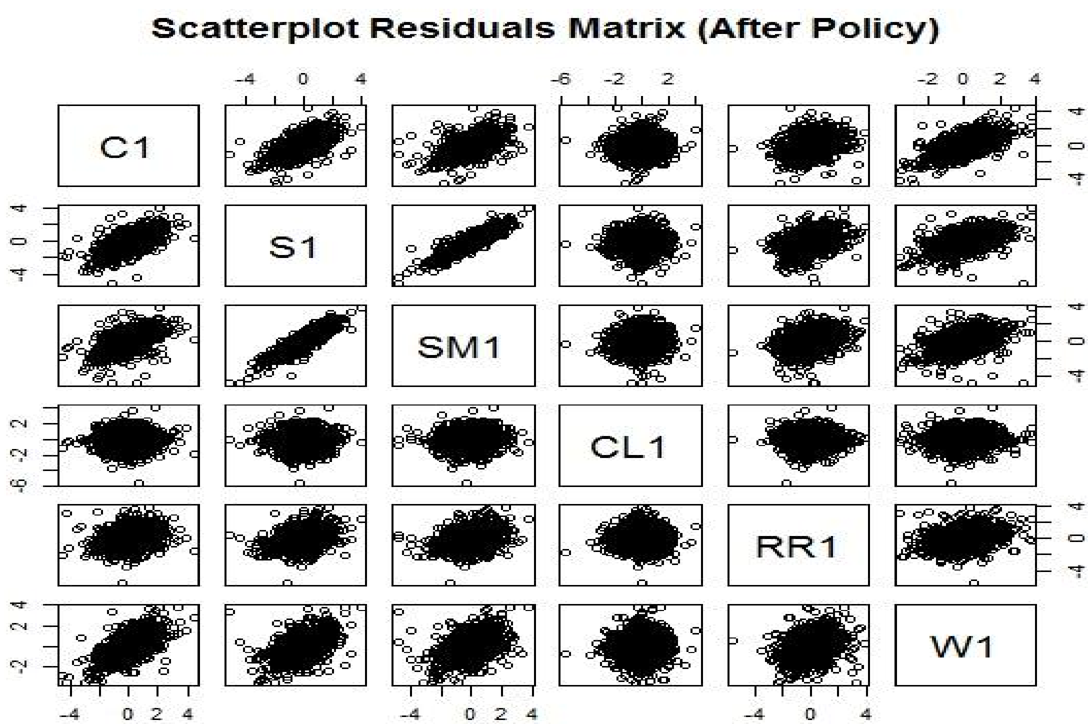
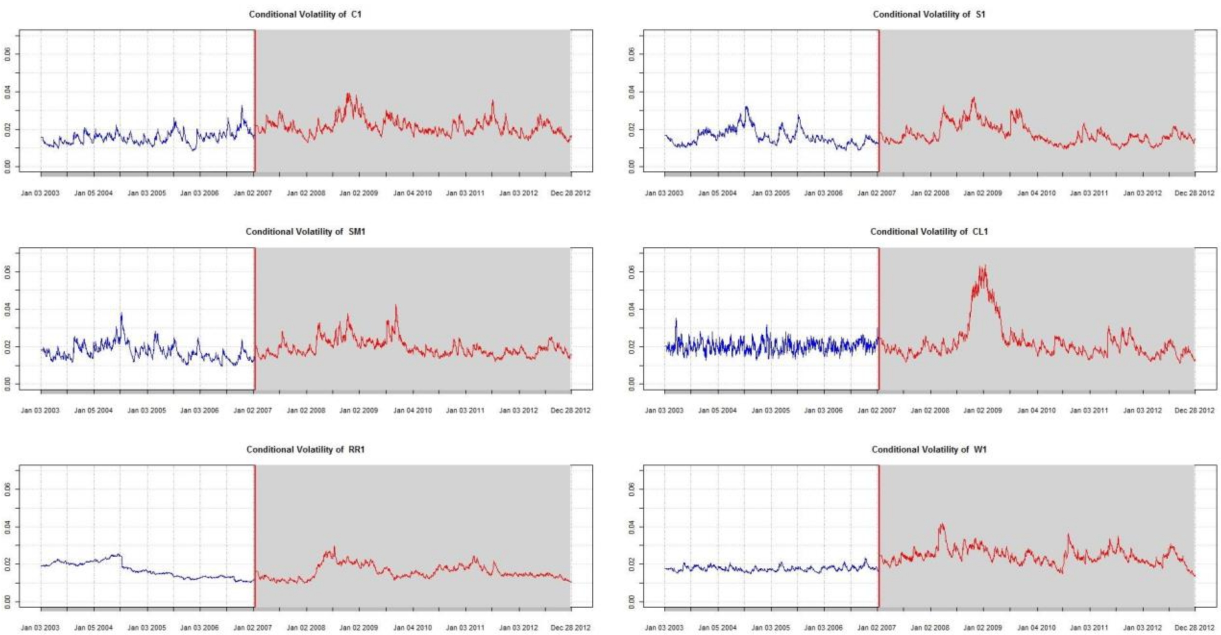


Figure 7: Conditional volatility of prices return series with the policy mandated



5. CONCLUSION

The purpose of this study is to evaluate the degree and the dependence structure of returns with the policy effect along the biofuel supply chain in the United States agricultural market before EISA 2007 (January 1st, 2003 – January 17th, 2007) and after EISA 2007 (January 18th, 2007 – December 31st, 2012). We use the daily futures data from January 1st, 2003 until December 31st, 2012 to examine linkages among the crude oil futures, corn futures, soybean futures, soybean meal futures, rice futures, and wheat futures markets in the United States. In modeling the dependency of agricultural futures price returns in the United States, we use the skewed student's t to describe the marginal distribution and vine copulas to build the joint distribution of residuals according to the lowest AIC values. The empirical results provide that vine Copula-based ARMA-EGARCH (1, 1) is an appropriate model to analyze returns dependency of crude oil and agricultural commodities. Moreover, crude oil, rice, and wheat prices return series are more volatile after the policy changed than other prices return series. The strong asymmetric dependence between crude oil and agricultural commodity markets might play a crucial role in the commodity price boom in 2007 and 2008. From a research standpoint, it is critical to recognize the relationship among energy and agricultural commodities for policymakers or agricultural producers to allocate portfolios, manage risks, or adjust strategies.

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