Impacts of Renewable Fuel Policy with Sentiment on the Energy and Agricultural Markets: A Vine Copula-based ARMA-GJR-GARCHX Model

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Abstract

This study investigates how the renewable fuel policy affects the investment decision making process in the U.S. energy and agricultural markets. The policy requires the U.S. transportation sector to contain a minimum volume of renewable fuels to reduce greenhouse gas emissions and dependence on imported oil. We use corn and sugar as proxies for ethanol and soybeans to represent biodiesel because these are the main components to produce alternative fuels. Meanwhile, crude oil is selected as another ingredient in conventional fuels. The effect of renewable fuel policies is evaluated on the corn, soybean, sugar, and cruel oil markets using a vine copula-based ARMA-GJR-GARCHX model. In order to capture investor reaction to fluctuations in the market, we incorporate the Sentiment Score provided by Thomson Reuters News into the model. Our results show the positive effects of the U.S. renewable energy policy and Sentiment Score on the volatility of commodity returns. Controlling for financial crisis of 2008, the average returns of the renewable energy market are increased after the passage of the updated renewable fuel policy, in particular, sugar that exhibits a significantly positive impact. This increase might be due to benefits from increasing biofuel production. In addition, using a vine copula technique to better capture the asymmetric and nonlinear dependencies among the commodities that make up the renewable energy market, our findings provide policymakers and industry participants with enhanced information on strategies for risk management, portfolio optimization, hedging, and asset pricing.

JEL Classification: C32, G13, Q11, Q13, Q41, Q48

Keywords: Agricultural commodity; crude oil; dependence; energy policy; sentiment; vine copula

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1. Introduction

The United States is the world's largest consumer of crude oil. Dependence on crude oil contributes to high greenhouse gas emissions and low energy security. The first national renewable fuel standard was established under the Energy Policy Act (EPA) of 2005 and expanded by the Energy Independence and Security Act (EISA) of 2007. The Congress passed the Energy Policy Act of 2005 (EPA 2005) to improve energy efficiency and prepare for the long-term transition to renewable energy sources. The EPA 2005 fortified the linkage between crude oil and agricultural commodity markets (McPhail, 2011; F. Wu, Guan, & Myers, 2011). In this legislation, the obligatory consumption of given biofuel volumes was first implemented with the inclusion of Renewable Fuel Standards (RFS1). RFS1 called for annual biofuel usage of 7.5 billion U.S. gallons by 2012 and established blending requirements for refiners and importers of gasoline. Due to this policy, the production of U.S. corn ethanol nearly doubled over the next few years, accounting for one third of U.S. corn production and raising the price of corn (National Agricultural Statistics Service, 2008). Concerns about the effects of these requirements on agricultural commodity prices led to a revision of the RFS (RFS2) under the Energy Independence and Security Act of 2007. This new requirement established volumetric standards for cellulosic and advanced biofuels that would use non-edible feedstocks in the production process. It requires the annual production of 36 billion gallons of renewable and other alternative fuels by 2022, and this law provides incentives for the development of clean renewable technology in bioenergy markets.

Corn, soybean, and sugar are not only the main crops in U.S. agricultural production, but also the main ingredients of producing clean renewable fuels. According to the USDA's 10-year projection for the food and agricultural sectors (Economic Research Services, 2018), corn production will continue to grow in the next decade in line with increased feed usage by meat production. Soybeans will also rise in importance in the food and agricultural sectors, and will exceed corn production due to strong demand, both globally and domestically. In 2008, the world demand for energy and agricultural commodities fell drastically due to the financial recession in 2008 (Creti, Joëts, & Mignon, 2013; Garcia-Appendini & Montoriol-Garriga, 2013; Ivashina & Scharfstein, 2010). Therefore, we isolate this effect of financial crisis from our analysis.

A wide range of empirical studies used economic models, which have shown that mandated biofuel policies increase the connection between energy and agricultural markets. Hertel & Beckman (2011) showed that ethanol policy is a significant driver of agricultural commodity price levels and volatility using an applied general equilibrium analysis. Their results indicated that an enacted policy yields a stronger relationship between energy and agricultural markets, and that the combination of a renewable fuel standard policy with the policy on blend walls increases agricultural price volatility. Chen et al. (2014) emphasized that the effect of biofuel policies on the production of biofuels will come at high social costs by applying a biofuel and environmental policy analysis model. Under the mandates-only scenario, they estimated that 50% of the total biofuel production in the 15-year period (from 2007 onward) would come from corn ethanol, and would result in higher corn prices and lower gasoline prices. Adding subsidies for advanced biofuels along with the mandates reduces the burden placed on food prices by corn ethanol production, while simultaneously reducing gasoline prices. Carter et al. (2016) summarized the corn prices would be increased by 31% in response to a demand increase by the RSF2 using a partially identified structural vector autoregression model.

Recently, increased attention has been paid to research examining the linkages between energy and agricultural commodities markets. Tyner (2010) stated that the ethanol market has established a link between crude oil and corn prices that did not exist historically. He found that the correlation between crude oil and corn prices was negative from 1988 to 2005, but it became positive in 2006. Du et al. (2011) investigated the spillover of crude oil volatility to agricultural markets (specifically corn and wheat). They found that the spillover effects are not statistically significant from zero over the period from November 1998 to October 2006. However, the results indicated significant volatility spillover from the crude oil market to the corn market from October 2006 to January 2009. De Nicola et al. (2014) discovered stronger co-movement between energy and agricultural commodity price returns in recent years, particularly with respect to soybean oil and corn that are used to produce biofuels. Campiche et al. (2007) found that corn and soybean prices were cointegrated with the price of crude oil in 2006 and 2007 using a VECM. Finally, Serra & Zilberman (2013) concluded that an expanded biofuel production drives up the demand for agricultural commodities, which validates the fundamental relationship between energy prices.

Several studies suggested that investor sentiment plays a significant role in the financial market. For example, Baker & Wurgler (2006), Chan (2003), and Chuang & Lee (2006) found that investor sentiment has an impact on stock returns. Kurov (2010) and Lutz (2015) showed that investor sentiment has a significant influence on the effect of monetary policy in the stock market. Smales (2014) examined the relationship between news sentiment provided by Thomson Reuters News Analytics (TRNA) and returns in the gold futures market. He found that both response to news releases (negative news invoking a greater response than positive news) and magnitude of the news sentiment are asymmetric. Therefore, we would like to explore the role of sentiment in the impact of renewable fuel policy on the interconnection between energy and agricultural markets.

While the linear relationship of crude oil and agricultural commodities is well documented (Frank & Garcia, 2010; Harri et al., 2009; Myers et al., 2014; Nazlioglu et al., 2013; Serra et al., 2011), we attempt to further analyze the dependence structure of the renewable fuel supply chain in United States markets, in particular the linkages between energy and agricultural markets. To do so, we build upon the copula introduced by Sklar (1959), which provides a more flexible measure for combining marginal distributions into multivariate distributions and showed the dependence structure of two or mode distributions. Patton (2001) defined the conditional version of Sklar's theorem, which extends the copula applications to the time series analysis. Patton (2012) pointed out copula-based multivariate models provide a great degree of flexibility in estimating the economic time series. Many studies have analyzed the asymmetric dependence structure of crude oil and agricultural commodities using a copula technique. Using copula-based modeling, Ahmed & Goodwin (2015) studied the dependence structure between commodity prices among international food grain markets, and identified strong and significant dependence structures of the majority of price pairs in the global food grain markets. Hernandez (2014) estimated the dependence structure of energy portfolios in the Australian market using vine copula model. To further generalize their findings, we apply copula modeling in this study to capture asymmetric dependencies among commodities.

Our study makes three important contributions to the existing literature. First, we investigate the effect of renewable fuel policies on the renewable energy markets using a vine copula-based ARMA-GJR-GARCHX model. Our findings show that positive effects of renewable energy policies are on the mean and volatility of commodities returns. The average returns of renewable energy commodities are increased by the revised renewable fuel policy due to increasing biofuel production. Second, we incorporate news sentiment into our model to better capture investor reaction to the fluctuation of market. Our results show that sentiment has a positive effect on the volatility of renewable energy commodities returns after controlling for the financial crisis of 2008. Third, we evaluate the influence of the passage of renewable fuel policies on the nonlinear dependencies among the commodities that make up the renewable energy market using a copula technique. To this end, this research informs policymakers and industry participants with better strategies for risk management, portfolio allocation, hedging and asset pricing.

The remainder of this article is organized as follows: Section 2 introduces the methodology and empirical model; Section 3 describes the data and the data collection process; Section 4 provides empirical findings; and Section 5 concludes with our results and policy implications.

2. Methodology

In the section 2.1, we construct the univariate ARMA-GJR-GARCHX (1, 1) model, and interpret parametric copulas in section 2.2. Next, we specify the vine copula technique in section 2.3, followed by an illustration of the algorithm for R-vine copulas in section 2.4.

2.1 Univariate ARMA-GJR-GARCHX Model

The volatility of prices today can trigger a higher price volatility the following day. In order to deal with volatility clustering usually referred to as conditional heteroscedasticity, the ARCH model was introduced by Engle (1982) to describe the variance of returns series changes over time. Bollerslev (1986) extended the ARCH model to the generalized ARCH (GARCH) model, and Glosten et al. (1993) proposed the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model in handling asymmetric effects between positive and negative asset returns. In this study, ARMA (p, q)-GJR-GARCHX (1, 1) with the skewed student t distributed innovations is used to deal with the leverage effect and volatility clustering. Furthermore, we add two dummies on the conditional means and variances of commodities returns in order to evaluate the effects of revised renewable energy policy and financial crisis of 2008. The first dummy was added on December 19, 2007, the date mandated by the Energy Independence and Security Act of 2007 for RFS2. The second dummy was added on September 15, 2008, the date when Lehman Brothers bankruptcy took place, to control the effect of financial crisis.

In addition to dummy variables, we add Sentiment Score of commodities provided by Thomson Reuters News as an exogenous variable to the GARCHX model. The sentiment of news items which arrive during each trading day are aggregated into a daily sentiment measure. The values of sentiment indicate the predominant sentiments class for this news item with respect to this asset, such as 1 means positive, 0 means neutral, and -1 means negative. We also assign 0 to sentiment if there is no news occurred. Following Dzielinski (2011), the sentiment of each news item is multiplied with its probability to compute a weighted average of the prevailing sentiment for that day. Although neutral news items do not enter the sentiment calculation in the numerator (owing to their sentiment of 0) the number shows up in the denominator pushing the measure downward, so that a day with many neutral news items would still be classified as neutral. This procedure is repeated for each trading day to obtain a complete history of news days and their respective sentiment classification. The ARMA (*p*, *q*)-GJR-GARCHX (1, 1) model is

$$r_t = \mu + \sum_{i=1}^{p} \varphi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + a_1 D_1 + a_2 D_2 + \epsilon_t,$$

$$\epsilon_t = \sigma_t z_t,$$

$$\sigma_t^2 = \omega + \alpha_t \epsilon_{t-1}^2 + \beta_t \sigma_{t-1}^2 + \xi_t \epsilon_{t-1}^2 I_{t-1} + b_1 D_1 + b_2 D_2 + c_1 X_{1,t-1},$$

where r_t is the log return; μ_t is the drift term; ϵ_t is the error term; σ_t^2 is conditional variance; α_t is ARCH term and β_t is GARCH term; ξ_t captures the leverage effect of ϵ_{t-1} and the innovation term z_t is the skewed student *t* distribution; $I_{t-1} = 0$ if $\epsilon_{t-1} \geq 0$, and $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$. Fernandez and Steel (1998) proposed skewness into unimodal and symmetric distribution by introducing inverse scale factors in the positive and negative real half lines. Let the density of a random variable z can be presented as $p\ (z|\ \eta, f)\ =\ \frac{2}{\eta+\frac{1}{\eta}}\left[f\left(\frac{z}{\eta}\right)I_{[0,\infty)}(z)+f(\eta z)I_{[0,\infty)}(z)\right]$ where η is the asymmetric parameter, and η = 1 is the symmetric Student's t distribution; f is a univariate pdf that is symmetric around 0, and I_S is the indicator function on S. D_1 and D_2 are the indicator variables on the conditional mean and variance for RFS2 and financial crisis of 2008. $X_{1,\mathrm{t}-1}$ is the exogenous variable with lag one on the conditional variance for Sentiment Score.

2.2 Parametric Copulas

Sklar's theorem (1959) defined that the joint cumulative distribution function F and continuous marginal distribution functions $F_1, F_2, \ldots, F_n$ with given random variables $X_1, X_2, \ldots, X_n$, is characterized by a unique copula function C for all $x = (x_1, x_2, \ldots, x_n) \in R^n$ such that:

$$F(x) = C\big(F_1(x_1), F_2(x_2), \ldots, F_n(x_n)\big)$$

Building on Sklar's research (1959), Patton (2003) added to the conditional interpretation of Sklar's theorem. Patton (2003) stated that the bivariate joint distribution $F_t(X_1, X_2|\mathcal{F}_{t-1})$ and continuous marginal distributions $F_{1,t}(X_1|\mathcal{F}_{t-1})$ and $F_{2,t}(X_2|\mathcal{F}_{t-1})$ with the given conditioning set $\mathcal{F}_{t-1}$, is identified by a unique conditional copula function C_t such that:

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

Copula methodology has been implemented in several fields such as financial economics, energy economics, agricultural economics, etc. (Aloui et al., 2013; Goodwin & Hungerford, 2014; Joe, 1997; Nelsen, 1999; Wu et al., 2012). We apply copula functions to assess the degree and the structure of dependency among the agricultural and crude oil price returns in the United State for different time periods. In this study, we consider copula functions shown as follows (Joe, 1997; Nelsen, 1999):

(1) Let Φ_ρ be the joint cumulative distribution function of the bivariate standard normal

distribution function with correlation ρ, Φ^{-1} denotes the inverse distribution function of the univariate standard normal distribution, and the bivariate Gaussian copula is defined as:

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

(2) Let $t_{\rho,\nu}$ be a standard bivariate *t* distribution, ρ is the correlation, ν is the degree of freedom, and the bivariate student *t* copula is characterized as:

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

(3) Let $\varphi(u) = u^{-\theta} - 1$ be the Clayton generator where $\theta > 0$, and the Clayton family is determined as:

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

(4) Let the generator of Gumbel copulas be $\varphi(u) = (-\ln u)^\theta$, $\theta \geq 1$ denotes the copula parameter, and the bivariate Gumbel copula is established as:

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

(5) Let $\varphi(u) = ln(\frac{e^{-\theta u} - 1}{e^{-\theta} - 1})$ for $\theta \in \mathbb{R} \setminus \{0\}$ be the copula family generator, and the Frank family is factorized as:

$$C(u_1, u_2; \theta) = -\frac{1}{\theta} log\left(1 + \frac{\left(e^{-\theta u_1} - 1\right)\left(e^{-\theta u_2} - 1\right)}{e^{-\theta} - 1}\right), \theta \in \mathbb{R} \setminus \{0\}$$

(6) Let $\varphi(u) = u^{-\theta} - 1$, $\theta \geq 1$ be the generator, and the Joe copula is developed as:

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

(7) The BB1 (Clayton-Gumbel) copula allows for asymmetric tail dependence, and it is designated as:

$$C(u_1, u_2; \theta, \delta) = (1 + [(u_1{}^{-\theta} - 1)^\delta + (u_2{}^{-\theta} - 1)^\delta]^{\frac{1}{\delta}})^{\frac{-1}{\theta}}, \theta > 0 \cap \delta \geq 1$$

(8) The BB6 (Joe-Gumbel) copula allows for asymmetric tail dependence, and it is construed as:

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

(9) The BB7 (Joe-Clayton) copula allows for asymmetric tail dependence, and it is specified as:

$$C(u_1, u_2; \theta, \delta) = 1 - (1 - [(1 - \overline{u_1}^{\theta})^{-\delta} + (1 - \overline{u_2}^{\theta})^{-\delta} - 1]^{-\frac{1}{\delta}})^{\frac{1}{\theta}}, \theta \geq 1 \cap \delta > 0$$

(10) The BB8 (Frank-Joe) copula allows for asymmetric tail dependence, and it is formalized as:

$$C(u_1, u_2; \theta, \delta) = \frac{1}{\delta}(1 - [1 - \frac{1}{1 - (1 - \delta)^{\theta}}(1 - \left(1 - \delta u_1\right)^{\theta}\right)\left(1 - \left(1 - \delta u_2\right)^{\theta}\right)]^{\frac{1}{\theta}}\Big), \theta \geq 1 \cap \delta > 0$$

2.3 Vine Copulas

In this paper, we employ the vine copulas models to investigate interdependency of the crude oil and agricultural markets in the United States. Limits exist to capturing dependence structures with one or two parameters using multivariate Archimedean copulas. The vine copula method, which is a more flexible measure to capture the dependency structure among assets, allows a joint distribution to be established based on bivariate and conditional bivariate copulas arranged together as building blocks which Bedford & Cooke (2001) and Joe (1996) referred the graphical structure as regular vines (R-vines). Bedford & Cooke (2002) introduced canonical vine copulas, called the C-vines. The center (hub) of each star structure, which is selected based on having the highest sum of correlations with the other variables, plays a crucial role for constructing the graphical structure of pair copulas. Kurowicka & Joe (2011) summarized the general n-dimensional canonical vine copula such as:

$$f(x_1, \dots, x_n) = \prod_{k=1}^{n} f_k(x_k) \times \prod_{i=1}^{n-1} \prod_{j=\mathrm{i}+1}^{n} c_{i,j|\mathrm{i}+1,,\dots,j-1}$$

where f is the joint probability density function, f_k is the marginal probability density function and c is the copula function.

Similarly, each node cannot be linked more than two edges in D-vines, which refers to the line structure. Using D-vines, the structure is composed by a specific order for the variables (nodes) based on the highest sun of correlations. Min & Czado (2010) compiled the general n-dimensional D-vine copula such as:

$$f(x_1, \dots, x_n) = \prod_{k=1}^{n} f_k(x_k) \times \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{i,i+j|i+1,\dots,i+j-1}$$

2.4 Algorithm of R-Vine Copulas

Dissmann et al. (2013) presented an automated algorithm for searching for an appropriate R-vines tree structure, the pair-copula families, and the parameter values of the chosen pair-copula families based on the Bayesian Information Criterion (BIC) values. The total six steps for the algorithm of selecting an R-Vine model as following. In the first initial step, we calculate the empirical Kendall's tau for all possible variable pairs. Second, we select the tree that maximizes the sum of absolute values of Kendall's τ. Third, we determine a copula for each pair and fit the corresponding parameters based on the BIC. Fourth, we transform the observations using the copula and parameters from the third step and to obtain the transformed values. Fifth, we use transformed observations to calculate empirical Kendall's τ for all possible pairs. Lastly, we proceed with the second step and repeat all following steps until the R-Vines is fully specified.

3. Data and descriptive analysis

We obtained from Bloomberg[1] daily futures data spanning from July 29, 2005 to December 31, 2015 for a total of 2,720 observations to evaluate the effect of the renewable energy policy on the crude oil future[2] and agricultural futures (corn[3], soybean[4], and sugar[5]) markets in the United States. The period of our sample started from July 29, 2005 because it is the date enacted by the EPA of 2005 for RFS1. Corn, soybean, sugar, which are the main crops in U.S. agricultural production, are mainly used in biofuels or biodiesel in the transportation sector. They compete with the derived demand for alternative energy production, especially when oil prices are high. The weighted daily sentiment scores are collected from Thomson Reuters News Analytics[5] (TRNA) for four commodities. Table 1 presents all variables and abbreviations in the paper with a short description. Summary statistics for price returns of four commodities are presented in Table 2; they demonstrate that the sugar provides the highest average daily return over the sample period (0.016%), following by corn (0.015%). However, the high average returns of sugar accompany with the high risk, with a standard deviation of 2.17%, followed by corn (2.02%).

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

[2] Crude oil future is the crude oil futures contract, and price (dollars per barrel) is adjusted price from Bloomberg. Raw futures data is collected from New York Mercantile Exchange (NYMEX).

[3] Corn future is the no. 2 yellow corn future contract, and price (cents per bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[4] Soybean future is the soybean future contract, and price (cents per bushel) is adjusted price from Bloomberg. Raw futures data is collected from Chicago Board of Trade (CBOT).

[5] Sugar future is the sugar no. 11 future contract, and price (cents and hundredths of a cent per pound) is adjusted price from Bloomberg. Raw futures data is collected from Intercontinental Exchange (ICE). The sugar no. 11 contract is the world benchmark contract for raw sugar trading. The contract prices the physical delivery of raw cane sugar, free-on-board the receiver's vessel to a port within the country of origin of the sugar.

Negative skewness are shown in four commodities, implying an investor has a greater probability of large increase in negative returns than in positive returns. Moreover, the values of the kurtosis statistics across the commodities are significant higher than three, implying that the distribution of returns has fatter tails than the normal distribution.

We used the augmented Dickey-Fuller (ADF) test to examine stationarity for each of the commodity price return series (Banerjee et al., 1993). The test statistics indicated that the null hypothesis of a unit root can be rejected at the 5% significant level for each series, which confirms stationarity. Moreover, the Lagrange multiplier (ARCH) test is used to examine heteroscedasticity in the price return series (Engle, 1982). The test statistics indicate that the null hypothesis can be rejected at the 5% significant level, implying that the data is not independently distributed so that ARCH effects are most likely to be found in all price return series. Therefore, we applied the GJR-GARCH model to deal with volatility clustering and leverage effect.

Tables 3 reports the correlation matrix of four commodities, indicating a high correlation of 61% between the series for corn and soybean returns. This correlation is expected because corn and soybean meal are primary inputs in many feed rations, and thus they serve many of the same demand centers. In addition, corn and soybean have been used in the U.S. for producing ethanol and other alternative fuels. As expected, the crude oil has a positive correlation with these agricultural commodities.

Figure 1 shows the price trends of crude oil and agricultural futures, exhibiting trends that are similar over time. All commodity price series have increasing trends after the RFS2 mandated up to the period of the financial crisis of 2008, indicating that the subprime mortgages crisis escalated and caused the meltdown of the global financial system. After 2009, they all follow a similar path with an upward movement and reach another price spike in 2011. Figure 2 illustrates the returns of crude oil and agricultural futures prices, demonstrating that volatility in price series is somewhat clustered for each commodity market, in particular, during the financial crisis of 2008.

4. Results

We evaluated the lags of autoregressive and moving average terms ranging from zero up to a maximum lag of five, with the most suitable model selected according to BIC values. The Jarque-Bera (J-B) test for the normality of residuals indicated that the null hypothesis can be rejected at the 5% significant level, indicating price return series of all commodities are not normally distributed. This is entirely consistent with the error terms that do not follow the normal distribution reported in Table 2, implying that the assumption of skewed student *t* distribution is more appropriate in our study. Furthermore, we use the Ljung-Box Q test with 5 lags and ARCH test to examine each series for serial correlation in the model residuals (Engle, 1982; Hamilton, 1994; Ljung & Box, 1978). The test statistics for all commodities indicate the null hypothesis cannot be rejected at the 5% significant level, thus supporting no serial correlation. ARMA (1, 1)-GJR-GARCHX (1, 1) with the skewed student *t* innovation is selected as the preferred model for the appropriate marginal distributions. Then, we selected a copula family from forty possible copulas based on the BIC model-fitting criterion to capture the appropriate dependence structure among three different price return series (Dissmann et al., 2013). Figure 3 further suggests that the skewed student *t* distribution fits better than normal distribution for each commodity's residuals. This result is consistent with the evidence reported in Table 2. Ahmed & Goodwin (2015) also found that the skewness coefficients, which capture asymmetry in the distribution, are significant for each series which justify the rationale of using the skewed student *t* innovation and GJR-GARCH model. On the other hand, not every joint distribution follows a multivariate normal distribution based on the residual plots in Figure 4. Taking the characteristics of non-normal and skewed price changes into consideration, we employed the vine copula-based ARMA-GJR-GARCHX (1, 1) model with the skewed student *t* innovation to capture the asymmetry for the marginal distributions. Using copula modeling, we can capture an appropriate flexible dependency structures among residuals.

Table 4 presents the results from a vine copula-based ARMA-GJR-GARCHX (1, 1) model for corn, soybean, sugar, and crude oil between July 29, 2005 and December 31, 2015. We can see that the means of corn, soybean, sugar, and crude oil returns increased for RFS2, in particular, sugar returns that exhibit significant positive impact. In addition, the renewable energy policy has a positive effect on the volatility of all commodities, which are increased by the renewable energy policy due to increase in biofuel production. However, the technology of alternative fuels production is still premature to commercialize that implies increasing volatility. Not surprisingly, the financial crisis corresponded to a fall of the average of price returns across all commodities, and the effects are the most pronounced for crude oil and sugar. This result is consistent with the findings by Creti et al. (2013), Garcia-Appendini & Montoriol-Garriga (2013), and Ivashina & Scharfstein (2010). Sentiment have a positive influence on volatility of four commodities, from which we conclude that the reaction of investors engenders fluctuation of the market.

Table 5 summarizes the evidence for the vine copula model to be the best one compared with two common Gaussian and Student *t* copula models based on the BIC criterion. Figure 3 reports marginal distributions of price returns series for each commodity, exhibiting the skewed student *t* distribution (with red lines) fitted better than the normal distribution (with blue lines). Figure 4 presents scatter plots of the copula data for pair residuals, indicating the majority of observations lies close and along the positive diagonal. This suggests a positive association between each pair of commodities returns. Figure 5 demonstrates that soybean is stabilized after the policy change than other price returns.

5. Conclusions

The purpose of this study is to evaluate the factors driving investment decisions on the renewable energy markets from renewable fuel policies, sentiment, and financial crisis. We use daily futures data from July 29, 2005 until December 31, 2015 to examine the impacts of those factors on crude oil, corn, soybean, and sugar futures markets in the United States. Applying the ARMA (1, 1)-GJR-GARCHX (1, 1) model, we cope with volatility clustering and the leverage effect which is common in the commodity market.

Our results suggest that the vine copula-based ARMA-GJR-GARCHX (1, 1) model is the appropriate model to analyze the impacts of policy, sentiment, and financial crisis on energy and agricultural commodities markets based on the lowest BIC values. The financial crisis in 2008 had a negative impact on the means and volatility of price returns for all commodities. Isolating the effect of financial crisis, the means of price returns for energy and agricultural commodities increased after passage of the updated renewable fuel standard (RFS2). This offers an incentive for agricultural producers to increase their renewable fuel production. Furthermore, RFS2 makes corn returns more volatile due to uncertainty of changing requirements for sources of advanced biofuels. This might provide potential substitutes for other renewable energy sources. Finally, sentiment shows a positive effect on returns volatility across all markets, a finding that is consistent with other studies.

In conclusion, this research recognizes the factors driving investment decisions in the renewable energy market for policymakers, agricultural producers, and industry insiders to more efficiently allocate portfolios, manage risks, or adjust economic strategies. For example, the significant increase in the uncertainty for crude oil demand might be attributed to the substitutive effect of edible feedstock (such as corn, soybean, or sugar) with fossil fuels that is stated in RFS. This provides an incentive for hedging opportunities and assets allocation across different commodities. To this end, agricultural producers could take advantage of this opportunity to expand their markets. In response to declining commodities prices, government can provide subsidies to farmers to induce the expansion of biofuel production and to reduce dependence on conventional fuel sources.

Appendix

Table 1: Descriptions of the Variables

Commodity	Short description
C1	No. 2 yellow corn future with continuous contract number 1
S1	Soybean with continuous contract number 1
CL1	Crude oil with continuous contract number 1
SB1	The sugar no. 11 contract with continuous contract number 1

Table 2: Descriptive statistics (July 29, 2005 – December 31, 2015)

	C1	**S1**	**CL1**	**SB1**
Mean	0.00015	0.00010	0.00008	0.00016
Std. Dev.	0.02021	0.01640	0.01919	0.02169
Skewness	-0.65601	-0.77254	-1.08916	-0.02516
Kurtosis	13.41148	7.73087	12.18235	7.16568
ADF test	-13.725***	-14.48***	-12.198***	-13.496***
J-B test	12499***	2812.5***	2120.1***	1971.2***
ARCH test	14.899***	74.259***	516.29***	60.081***

Note: Source: www.bloomberg.com/markets/stocks/futures (database). 2,720 observations.
* p<0.1 ** p<0.05 *** p<0.01
The stationarity test statistics ADF stands for Augmented Dickey-Fuller with null hypothesis: a unit root.
The normality test statistics J–B stands for Jarque–Bera with null hypothesis: normality.
The autoregressive conditional heteroscedasticity (ARCH) test with null hypothesis: no ARCH errors

Table 3: Correlation matrix (July 29, 2005 – December 31, 2015)

	C1	**S1**	**CL1**	**SB1**
C1	1			
S1	0.611	1		
CL1	0.279	0.339	1	
SB1	0.233	0.226	0.227	1

Table 4: Results and parameter estimates of the ARMA-GJR-GARCHX (1, 1) model

	C1	**S1**	**CL1**	**SB1**
P	1	1	1	1
Q	1	1	1	1
μ	3.78E-4	7.57E-04	7.84E-04	2.68E-04
φ_1	-0.569 **	0.282 *	-4.65E-04	-0.075
θ_1	0.592 **	-0.310 **	-0.058 **	0.065
a_1	0.002	5.99E-04	0.001	4.89E-04 ***
a_2	-0.002	-0.001	-0.003 ***	-0.001 **
Ω	5.79E-6 *	2.49E-06	1.13E-06	2.22E-06
α	0.049 ***	0.046 ***	0.011 ***	0.052 ***
β	0.929 ***	0.951 ***	0.959 ***	0.949 ***
ξ	0.019 ***	-0.014	0.054 ***	-0.003
b_1	9.16E-9	6.61E-09	2.80E-09	2.66E-08
b_2	1.12E-11	9.00E-14	1.84E-13	7.57E-13
c_1	1.17E-8	9.37E-09	1.03E-08	1.25E-08
η	1.020 ***	0.922 ***	0.933 ***	1.058 ***
ν	5.278 ***	5.066 ***	9.420 ***	4.764 ***
Log-likelihood	7033.161	7651.582	6938.510	6867.919
AIC	-14038.321	-15275.165	-13849.019	-13707.838
BIC	-13955.609	-15192.452	-13766.307	-13625.126
J-B	49.011 ***	53.227 ***	67.759 ***	50.481 ***
ARCH	0.698	1.209	4.397	0.806
Ljung-Box (Q5)	1.984	4.574	2.148	4.245

Note: * p<0.1 ** p<0.05 *** p<0.01
The normality test statistics J–B stands for Jarque–Bera with null hypothesis: normality.
ARCH is Engel's LM test for the ARCH effect in the residuals with null hypothesis: no ARCH errors.
Ljung-Box Q (5) is the Ljung–Box statistics for serial correlation in the squared returns computed with 5 lags.

Table 5: Comparison of Copula Functions with Gaussian and Student *t*

Function	**Log-likelihood**	**AIC**	**BIC**
Gaussian	861.6403	-1711.281	-1667.515
Student *t*	893.7646	-1773.529	-1722.469
Vine Copula	906.4564	-1796.913	-1749.649

Figure 1: Crude oil and agricultural futures prices

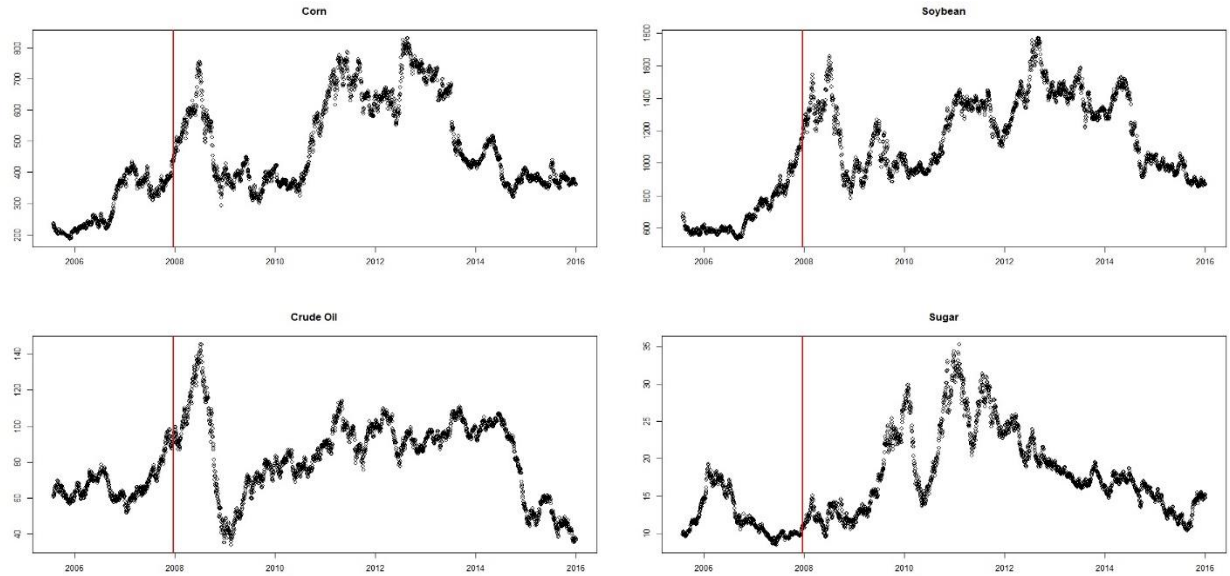


Figure 2: Returns of crude oil and agricultural futures prices

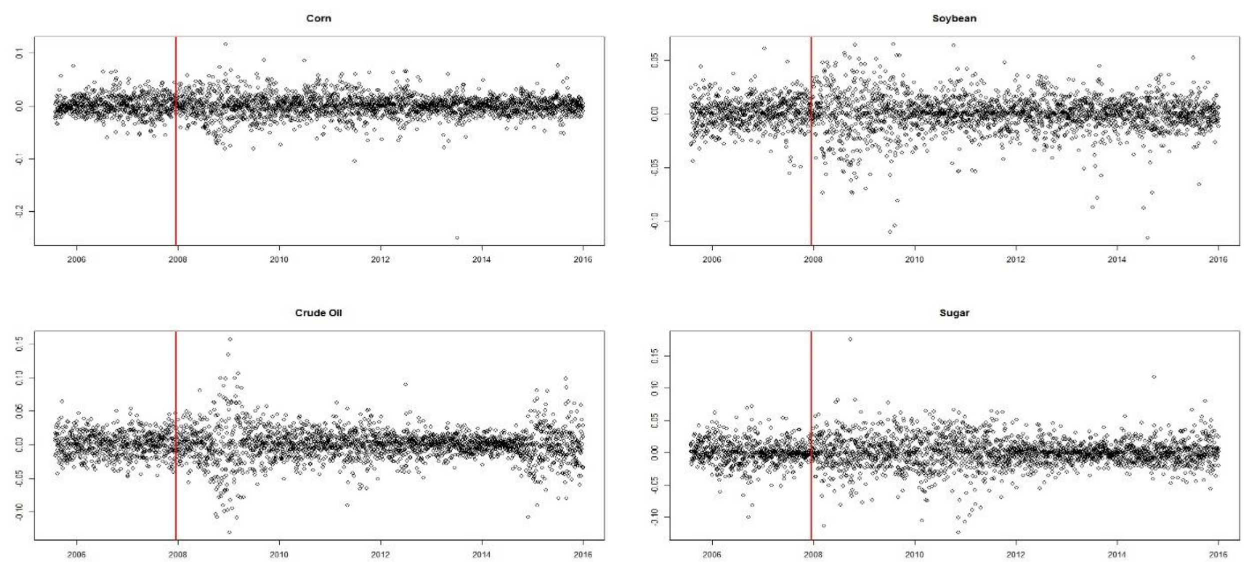


Figure 3: Marginal distribution of prices return series

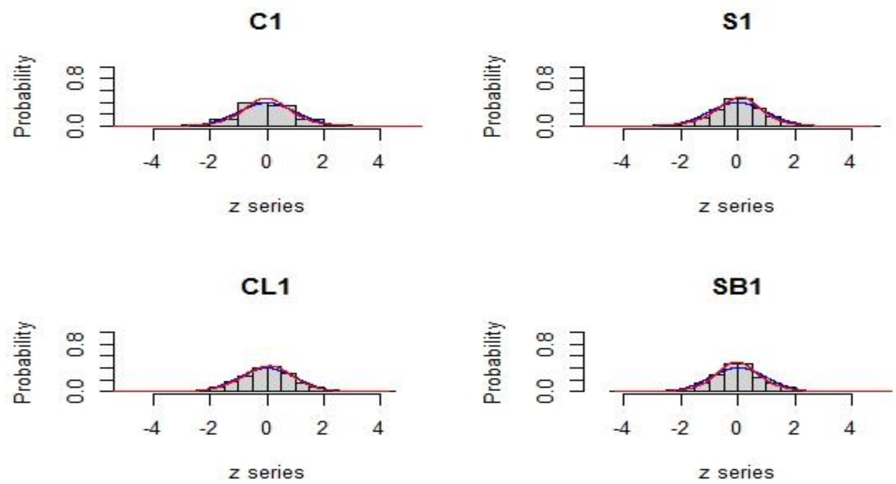


Figure 4: The scatterplot of residuals

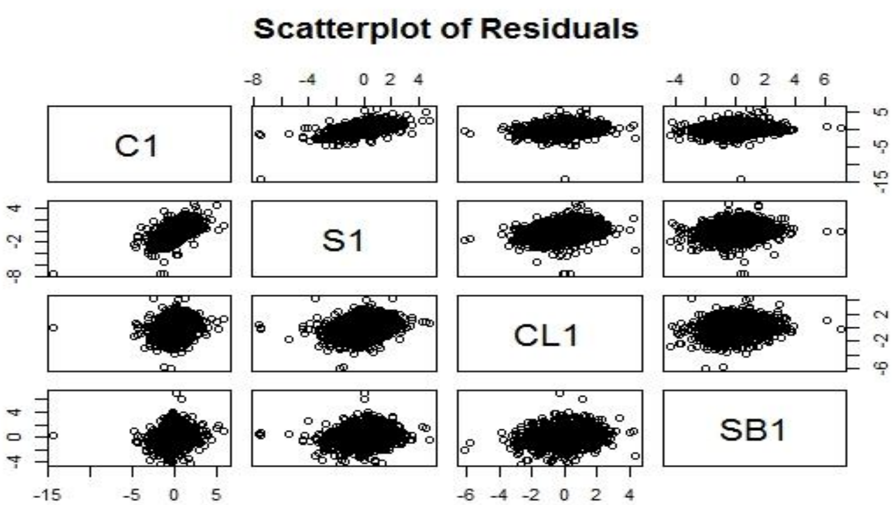
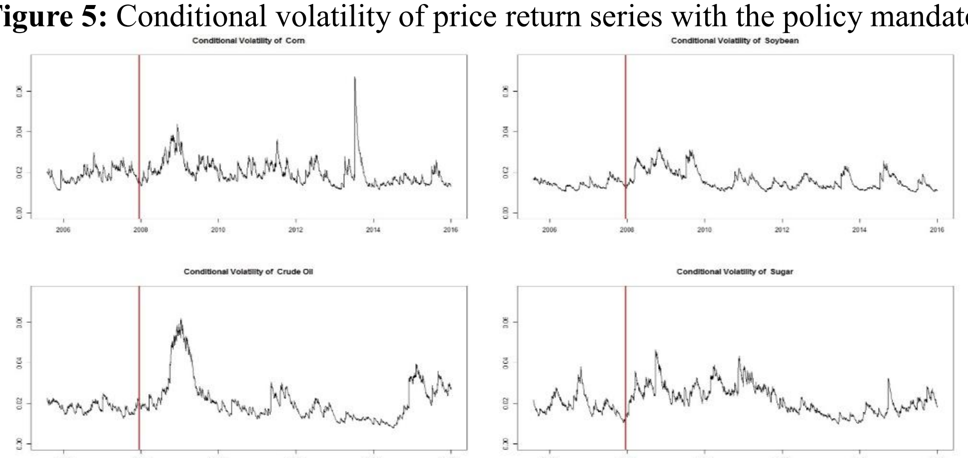


Figure 5: Conditional volatility of price return series with the policy mandated



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