



The Impact of Trading Activity on Volatility Transmission and Interdependence among Agricultural Commodity Markets

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Abstract : This paper aims at studying the volatility and dependence structure among the main agricultural commodity markets. It also investigates the impact of the trading activity of agricultural commodities and the ethanol listing on the volatility transmission for the corn, soybean, and wheat markets. The C- and D-vine copula based GARCH model was used to explain the interdependence of corn, soybean, and wheat prices. We discovered that the listing of ethanol and the trading activity had an impact on the price volatility of corn, soybean, and wheat. The results support the argument that the roles of financialization and of the biofuel increase volatility in the agricultural commodity markets. Moreover, the dependencies between the corn and the wheat returns, and between the corn and the soybean returns have significant variability over time and have higher variations of dependence with symmetrical tail dependences. The higher dynamic dependence and symmetric tail dependence indicate that opportunities to use the related agricultural commodities for portfolio diversification are reduced, particularly during a downturn in the markets.

Keywords : Agricultural commodity prices; Volatility transmission; Vine Copula

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2010 Mathematics Subject Classification : 62P20; 91B84 (2010 MSC)

1 Introduction

From the past recent years the rising trend in the agricultural commodity prices has shown a significant increase. The recent spikes of agricultural prices during 2007/08 and 2010/11, and the high price fluctuation in the major grains commodities have led to increased concerns about the world food supply and security. These developments coincide with a growing faster demand in emerging economies and bad harvesting in North America, Russia, and Eastern Europe; these events have been deemed as the culprits behind the rising trend in grain prices.

In addition, growth in the demand for grain production from the biofuels industry is the one major factor that has led to the increase in the agricultural prices. During 2008–2011, the global productions of coarse grains and sugar were around 11% and 21%, respectively; they were used to produce ethanol, and 11% of the global production of vegetable oil was used to produce biodiesel[1]. An upward shift in ethanol based corn may cause spikes in soybean and/or wheat prices since all of these grains share a planted acreage and are also close as substitutes in animal fodder. Moreover, the role played by financialization in the commodity markets is another major factor which partly provides an explanation for the recent spike in the commodity prices. During the period from 2005 to 2010, the exchange–traded agricultural derivatives were growing by up to 29 percent per year. By 2010, the number of contracts traded in the exchange–traded agricultural derivatives was up to 1,436 million contracts [2]. A rise in trading activities tends to drive agricultural prices away from the levels that are justified by market fundamentals; this affects both the producers and the consumers.

The following phenomenon has caused an exacerbated the increase in volatility of the prices of the main agricultural commodities, especially the prices of corn. It has also caused volatility spillovers from the corn market to other related agricultural markets. Moreover, the price volatility co–move on futures markets is often motivated by herd behavior, and this also leads to increased volatility. It is important, therefore, to understand the volatility and dependence structure between different agricultural commodities, as it provides various benefits for market participants that are often impacted by uncertainty and risks in the commodity markets.

The presence of co–movement between food and energy prices, mostly in practice, has been constantly researched; various studies have attempted to explain this relationship by using different means and techniques. Chang and Su[3] reports that the substitutive effect can be represented in the period of high crude oil price, and they found out that there are significant price spillover effects of crude oil futures on corn and soybean futures. Similarly, Ciaian and Kancs[4] also discovered a cointegration between the prices of crude oil and food commodities,

and found that the interdependencies keep rising over time. In another other study done by Nazlioglu and Soytaş[5], Natanelov et al.[6], and Boonyanuphong et al.[7], it was discovered that the agricultural commodities have been in cointegration with crude oil, especially in the recent years. Moreover, the results from Boonyanuphong et al.[7] show that there exists an extreme tail dependence between agricultural commodity prices and crude oil prices.

With regard to the role of trading activity on the agricultural price level and volatility, Mattos and Garica[8] investigated the relationship between cash and futures prices in Brazilian agricultural market by focusing on the effects of trading activity on the price discovery. They found that higher trading activity, especially in coffee and live cattle, is related to the existence of co-movement between cash and futures prices. In more lightly traded markets, however, it was observed by them that neither long-run relationships nor short-run leads and lags could be found. In a subsequent work, Gilbert[9] also found that the index-based investment in the agricultural markets had a significant impact to changing food prices during the year 2007–2008. Sari et al.[10] discovered that the grain trading volume shows a significant effect across oil and gasoline in the short run than in the long run. Although the results for open interest show that money flows out from the ethanol market, there has been no evidence suggesting across-market inflows or outflows to the other grain markets. Demirer et al.[11] tested the impact of listing ethanol futures on spot and futures prices for corn. The empirical finding revealed that the listing of ethanol futures has a positive effect on both price and volatility in the corn market as well as on its interaction with the trading volume in the corn market.

Concerning with literature reviews on this matter, however, we have had to come to the conclusion that there is hardly any literature that deals with the explanation of the interrelation that exists between the prices of the various agricultural commodities. Zhao and Goodwin[12] investigated the relationships and the transmission between implied volatilities in the corn and soybean markets. Their work reported that there exists a volatility spillover effect from the corn market to the soybean market, but there is no volatility spillover effect vice versa. A research done by Du et al.[13] also found evidence of volatility spillover effect from the corn market to the wheat market before 2006, and vice versa after 2006. Gardebroeck et al.[14] examined the volatility transmission between the corn, wheat, and soybean markets in the U.S. In general, they found that there is a weak interdependence between the corn, wheat, and soybean markets at the mean level; however, they also discovered significant volatility spillovers between these three markets.

Most of the methods that have been employed to study a price link and a price volatility interaction consist of cointegration analysis, VECM, BEKK, and GARCHtype models[15]. However, they are based on some strong assumptions that were not conforming to the data in the empirical studies. For example, VAR and multivariate GARCH models were assumed to have a linear relationship with a multivariate normal or a Student-t distribution. But the copulas were able to overcome this problem. The copula models separate the joint distributions of the random variables into two components, namely, the marginal distributions and

the dependence structure. Hence, the marginal time series are modeled with the GARCH-type models, which effectively capture the main observed characteristics in the financial markets, while copulas are applied for the dependence structure. Moreover, in a multivariate case, the vine copulas, first proposed by Joe[16] and developed further by Bedford and Cooke[17], provide a very flexible way for modeling multivariate distributions. The vine copulas can be constructed using a cascade of bivariate copulas; they produce large collections of bivariate copulas that are available in the cases of multivariate distributions.

Therefore, in this paper, we attempt to fill this gap by re-examining the price link and price volatility among agricultural commodity markets by employing vine copula based GARCH models. The main purpose of this paper is to analyze the roles of the U.S. biofuel and the financialization of commodities which impact the price and the volatility in the corn, soybean, and wheat markets. Moreover, we also focus on the dependence structure between the corn, soybean, and wheat markets. In order to illustrate the trading activity in the agricultural markets, we used the trading volume and the open interest as a reflection for our study. It is useful to examine how the ethanol markets and the trading activity have affected the price level and the volatility in the agricultural markets.

In the next section, we describe our methodology. In section 3, we present the data used. The empirical results and the discussion are presented in section 4 and section 5, respectively. The last section provides the conclusion of this paper.

2 Methodology

The vine copula based GARCH method was chosen for this study because it is considered to be a flexible way for modeling the interdependence among the univariate time series in multivariate distributions. We can separately construct the marginal distributions of the copulas for any asset returns by first using the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model and then the vine copula to construct the dependence structure of the multivariate distributions via a cascade of bivariate copulas functioning as the building blocks.

2.1 Marginal distribution models

In order to consider the important characteristics of the agricultural commodity returns such as fat tails or leverage effects, we constructed the marginal distributions of each returns series by using an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model.

By following the method propounded by Nelson[18], the EGARCH, or the exponential GARCH, model can be written as follows:

$$r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} - \sum_{i=1}^q \theta_i \varepsilon_{t-i} + \varepsilon_t, \quad (2.1)$$

where r_t is the log-difference of the agricultural commodity prices, and ϕ and θ are the autoregressive (AR) and moving average (MA) parameters, respectively. The error term ε_t follows a Student-t distribution and $h_t = \sigma_t^2$ is the conditional variance of ε_t , which is given by

$$\log(h_t) = \alpha_0 + \alpha_1 \log(\sigma_{t-1}^2) + \alpha_2 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \alpha_3 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}, \tag{2.2}$$

where α_0 is a constant term, σ_{t-1}^2 is the previous periods forecast error variance, ε_{t-1} is the news about volatility from the previous periods, and α_3 captures the leverage effects. For $\alpha_3 < 0$, the future conditional variance will proportionally increase more following a negative shock than following a positive shock of the same magnitude.

2.2 Copula models

Recently, copula models have been widely applied for measuring the dependence structure of joint probability distributions. The copula concept was first developed by Sklar[19]. Consider a vector $X = (X_1, X_2, \dots, X_n)$ of random variables with marginal distributions $F_i, i = 1, \dots, n$; there exists a unique function C , called copula, for which

$$F(x_1, \dots, x_n) = C(F_1(x_1), \dots, F_n(x_n)) \tag{2.3}$$

For an absolutely continuous function F with strictly increasing and continuous marginal densities F_1, F_2, \dots, F_n , the density function can be written as

$$f(x_1, \dots, x_n) = \prod_{i=1}^n f_i(x_i) \times c(F(x_1), \dots, F(x_n)), \tag{2.4}$$

where c is the copula density function. In other words, copulas can be separately decomposed in the modeling of the marginal densities and the dependency part in terms of the copula density.

A very useful property of the copula is the tail dependence, which is the amount of dependence in the upper (right) or lower (left) joint tail of a bivariate distribution. It is crucially applied to study the dependence of the extreme situation, which becomes helpful in managing the risk of portfolio management. The upper (right) and lower (left) tail dependence coefficients are defined by Joe[20] as follows:

$$\lambda_U = \lim_{u \rightarrow 1} Pr[X \geq F_X^{-1}(u) | Y \geq F_Y^{-1}(u)] = \lim_{u \rightarrow 1} \frac{1 - 2u + C(u, u)}{1 - u}, \tag{2.5}$$

$$\lambda_L = \lim_{u \rightarrow 0} Pr[X \leq F_X^{-1}(u) | Y \leq F_Y^{-1}(u)] = \lim_{u \rightarrow 0} \frac{C(u, u)}{u}, \tag{2.6}$$

where λ_U and $\lambda_L \in [0, 1]$. If λ_U or λ_L is positive, then X and Y are said to have upper (right) or lower (left) tail dependence; otherwise there is said to be upper or lower tail independence.

In this paper, the Gaussian copula, the t-copula, and the Archimedean copula family, such as the Clayton copula, Gumbel copula, Joe copula, BB1 copula, BB7 copula, and rotated copula, have been used to analyze the dependence structure. Two of the most commonly used copulas in the financial field are the Gaussian copula and the t-copula[21]. The Gaussian copula has zero tail dependence, whereas the t-copula has symmetric non-zero tail dependence. The Archimedean Clayton copula and Gumbel copula are non-symmetric[22, 23]. The Clayton copula provides strong lower tail dependence and the Gumbel copula exhibits strong upper tail dependence. Likewise, the Joe copula has a higher dependence in the upper tail than in the lower tail, where it is zero. Moreover, Joe[20] employed two bivariate copula families, namely BB1 and BB7, that provide non-zero upper and lower tail dependences.

2.3 Vine copulas

Although, there exists a large collection of bivariate copula families, the multivariate distributions carry many restrictions on the dependence relationships between the random variables. Vine copula is helpful in constructing multivariate distributions by incorporating the bivariate copula into the dependence structure under the specified marginal conditional distributions. For the n-dimensional, the density corresponding to a C-vine (canonical vine) and a D-vine are given by Aas et al.[24] as

$$f(x_1, \dots, x_n) = \prod_{k=1}^n f(x_k) \cdot \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{j,j+i|1,\dots,j-1}(F(x_j|x_1, \dots, x_{j-1}), F(x_{j+i}|x_1, \dots, x_{j-1})) \quad (2.7)$$

$$f(x_1, \dots, x_n) = \prod_{k=1}^n f(x_k) \cdot \prod_{j=1}^{n-1} \prod_{i=1}^{n-j} c_{i,j+i|i+1,\dots,i+j-1} \times (F(x_i|x_{i+1}, \dots, x_{i+j-1}), F(x_{i+j}|x_{i+1}, \dots, x_{i+j-1})) \quad (2.8)$$

For example, the 3-dimensional version of C-vine density (2.7) can be written as

$$f(x_1, \dots, x_3) = \prod_{i=1}^3 f(x_i) \cdot c_{12}(F(x_1), F(x_2)) \cdot c_{13}(F(x_1), F(x_3)) \cdot c_{23|1}(F(x_2|x_1), F(x_3|x_1)). \quad (2.9)$$

The 3-dimensional version of D-vine density (2.8), in our case, can be written as

$$f(x_1, \dots, x_3) = \prod_{i=1}^3 f(x_i) \cdot c_{12}(F(x_1), F(x_2)) \cdot c_{23}(F(x_2), F(x_3)) \cdot c_{13|2}(F(x_1|x_2), F(x_3|x_2)). \quad (2.10)$$

The vine copula requires marginal conditional distributions of the form $F(x|\nu)$. Joe[16] showed that for every v_j in the vector ν , we can write $F(x|\nu)$ as

$$F(x|\nu) = \frac{\partial C_{x,v_j|\nu_{-j}}\{F(x|\nu_{-j}), F(v_j|\nu_{-j})\}}{\partial F(v_j|\nu_{-j})} \tag{2.11}$$

where $C_{x,v_j|\nu_{-j}}$ is an arbitrary bivariate copula distribution function. If ν is univariate, the marginal conditional distribution becomes a special case that can be defined as

$$F(x_2|x_1) = \frac{\partial C_{1,2}\{F(x_2), F(x_1)\}}{\partial F(x_1)} \tag{2.12}$$

Hence, each of the marginal conditional distributions can be calculated from bivariate copulas and marginal distributions.

2.4 Dynamic vine copula

The vine copula used in our study is flexible in a multivariate setting. However, the afore-mentioned models assume that the dependence structures remain constant over time. By following Heinen and Valdesogo[25] and Patton[26], we proceeded to introduce the time-varying aspect into the multivariate dependence model. The method consists of using the C-vine or D-vine copula to model the multivariate structure, and then in each of the building blocks, the bivariate copula allows the dependence parameters to be time-varying. As for the time-varying models in our paper, we will allow the dependence parameter of the copula to evolve according to an ARMA(1,10)-type process. The following are some of the time-varying copula candidates.

The time-varying Gaussian copula can be defined as

$$\rho_t = \Lambda(\psi_0 + \psi_1\rho_{t-1} + \psi_2\frac{1}{10}\sum_{j=1}^{10}\Phi^{-1}(u_{t-j})\Phi^{-1}(v_{t-j})), \tag{2.13}$$

where $\Lambda = (1 - e^{-x})(1 + e^{-x})^{-1}$ is the modified logistic transformation used to maintain the correlation coefficient, ρ_t , belonging to $(-1, 1)$ at all times. For the t-copula with the time-varying aspect, $\Phi^{-1}(x)$ is replaced by $t_\nu^{-1}(x)$.

At the same time, the time-varying Gumbel copula also assumes the tail dependence parameters to follow the ARMA(1,10)-type process. We proposed that the time-varying Gumbel copulas could be given as follows:

$$\delta_t = \Lambda(\psi_0 + \psi_1\delta_{t-1} + \psi_2\frac{1}{10}\sum_{j=1}^{10}|(1 - u_{t-j}) - (1 - v_{t-j})|), \tag{2.14}$$

where $\Lambda = (1 + e^{-x})^{-1}$ is the logistical transformation which guarantees that τ_t and δ_t will be in the interval $(0,1)$ at all times.

Table 1: Data Description of Returns

	Mean	Std	Skew	Kurt	JB stat
Corn	3.9e-04	0.019	0.185	5.602	0.000
Soybean	3.5e-04	0.017	-0.699	7.603	0.000
Wheat	3.2e-04	0.021	0.079	4.897	0.000
Cvl	67,175.20	58,866.12			
Wvl	25,676.08	38,323.12			
Svl	40,689.98	22,601.73			
Coi	230,252.30	197,189.30			
Woi	89,368.25	77,596.01			
Soi	83,792.14	82,353.80			

Notes: Cvl, Svl, and Wvl stand for the trade volumes of corn, soybean, and wheat; Coi, Soi, and Woi stand for the open interests of corn, soybean, and wheat.

3 Main Results

3.1 Data

This paper uses a daily time series data on the close futures prices of corn, soybean, and wheat over the period from January 3, 2000, to February 28, 2013. The data set also includes the trading volume and the open interest for corn, soybean, and sugar, which are considered exogenous variables that contribute to the market volatility of corn, soybean, and wheat. Moreover, we used the dummy variable which is a proxy variable for the listing of ethanol in the Chicago Board of Trade (CBOT) market. It takes on the value of one at and after the ethanol futures are traded on the CBOT, and 0 for the previous dates. All the data regarding the futures prices were collected from Datastream, where corn, soybean, and wheat commodities are traded on the CBOT.

The descriptive summaries for corn, soybean, and wheat returns, and the exogenous trading volume and open interests for corn, soybean, and wheat are demonstrated in Table 1. The returns for soybean and the wheat returns have negative skewness, thus indicating that the soybean and wheat futures have longer left tails than right tails, which is different from that of the corn futures series that have longer right tails than left tails. With respect to the excess kurtosis statistics, the returns for corn, soybean, and wheat show that all the return series are highly leptokurtic with respect to the normal distribution, thus indicating that there is a higher probability for extreme movement occurring in these futures markets. The Jarque–Bera test results confirm non-normal distributions in the corn, soybean, and wheat returns series.

Moreover, the results for the trading volumes and the open interests, as pre-

sented in Table1, show that the trading volume and the open interest for the entire grain variables are extremely volatile, relative to the futures prices. Corn has the highest trading volume, while wheat has the lowest. In similar events, corn has the highest open interest, while soybean has the lowest. Also, in this case, we observed that the open interest for all the grain variables is more volatile than the trading volume.

3.2 Results of marginal models

The findings given in Table2 present our estimation for each of the futures returns series. We estimated several alternative EGARCH (1,1) models in order to capture the listing effect of ethanol and the trading activity of commodity markets on the corn, soybean, and wheat markets. The top panel reports the estimated coefficients of the conditional mean equation; the result shows that the trading volume is significant only in the case of the corn futures returns, and that the sign is negative, suggesting that the trading volume of corn has also had an indirect marginal effect on the corn prices. While the open interest is positive and significant in the cases of corn and wheat returns and the listing dummy is also a positive significant in the case of soybean returns, there is an indication that the open interests of corn and soybean as well as the listing of ethanol have had a direct marginal effect on the corn and soybean prices, respectively.

As for the bottom panel, the reports give the estimated coefficients of the conditional variance equation. The result reveals that all of the coefficients are significant, thus indicating that the models fit the data well. However, the coefficient parameters α_3 for corn and soybean returns are statistically insignificant, whereas α_3 for wheat returns is significant and $\alpha_3 > 0$, thus indicating that the conditional variance does not have a leverage effect.

The sums of α_1 , α_2 , and α_3 are greater than 1, thus indicating that shocks to the conditional variance of the corn, soybean, and wheat returns during the sample period have a long memory and are permanent. The degree of freedom parameters of the t-distribution are found to be ranging from 7.07 to 11.15, thus suggesting that the error terms were not normal. The listing dummy parameter shows that there is significant and positive returns for corn, thus suggesting a positive marginal contribution of ethanol listing on corn price volatility, which is corresponding with the results obtained by Demirer et al.[27]. The remaining results for the conditional variance indicate that the trading volume variable is significant and positive for all returns series, thus indicating a positive marginal contribution of the trading volume on the price volatility of corn, soybean, and wheat. With regard to the open interest parameters, it has significant impacts on the price volatility of all the returns series with the open interest having a negative effect. The negative relationship with the open interest also indicates active arbitrage activity in the corn, soybean, and wheat markets.

To evaluate the correct specification for the marginal models, we followed the method proposed by Diebold et al.[28], who suggested that if marginal distributions were correctly specified, then and should be i.i.d. uniform (0,1). In

Table 2: Parameter Estimates for Marginal Distribution Models

	Corn	Soybean	Wheat
Mean equation			
Vol	-0.002 (0.0002)		
Oi	0.003 (0.0002)		0.003 (0.0002)
Dt	0.0008 (0.0003)		
Volatility equation			
α_0	-0.247 (0.057)	-0.185 (0.036)	-0.108 (0.025)
α_1	0.984 (0.006)	0.989 (0.004)	0.995 (0.003)
α_2	0.148 (0.019)	0.124 (0.016)	0.083 (0.013)
α_3	0.006 (0.011)	0.008 (0.009)	0.037 (0.008)
Vol	0.342 (0.038)	0.402 (0.043)	0.375 (0.032)
Oi	-0.209 (0.029)	-0.301 (0.036)	-0.277 (0.028)
Dt	0.012 (0.007)		
T-DIST. DOF.	7.077 (0.811)	7.437 (0.925)	11.153 (1.605)

Table 3: Goodness-of-fit Test for Marginal Distributions

	Corn	Soybean	Wheat
Box-Ljung test			
first moment	0.065	0.663	0.421
second moment	0.362	0.861	0.295
third moment	0.167	0.143	0.462
fourth moment	0.353	0.813	0.349
K-S test	1.000	1.000	1.000

Note: The table presents p-values from the Box-Ljung tests and the K-S tests, respectively.

accordance with Diebold et al.[28], we checked that the marginal models were well-specified by introducing the Box-Ljung test to assess the serial correlation for the first four moments of each return series and used the Kolmogorov-Smirnov (K-S) test to check the density specification of the marginal distribution assumption. The p-values presented in Table3 suggest that for all the series, the null hypothesis of no serial correlation could be rejected at the 5% significance level; also, the p-values from the K-S test show that all the marginal distribution series can pass at the 5% significance level. Hence, the results imply that all the marginal distribution models were in correct specification.

3.3 Results of copula models

Based on our case, we focused on the three-dimensional model which is agriculture-related. As a result, all the three combinations of the ordering variables were estimated for the C-vine structure and the D-vine structure. We selected the best-fit model by performing the Vuong[29] tests. The appropriate sequential arrangements of the variables for the C-vine structure and the D-vine structure are the following: C-vine: corn, wheat, and soybean and D-vine: wheat, corn, and soybean, respectively.

Table4 reports the estimate of the bivariate copula parameters that were selected according to the AIC and BIC criteria for each of the building blocks for the appropriate C- and D-vine structures. The sequential procedure is used to select the appropriate C-vine copula and D-vine copula for all the related copula data. The procedure then uses those parameters as the starting values to calculate the corresponding maximum likelihood estimation (MLE) parameters.

The better-fit models for C- and D-vine in our analysis have the same number of parameters. In order to determine the better-fitting vine copula model for the data set, we employed the Vuong test by comparing both the models. The Vuong statistics cannot reject the null hypothesis of no difference between those two models, thus indicating that the C-vine and the D-vine copula models for our

data set cannot be different statistically.

Table 4: Structure and Parameter Estimate Results of C–vine and D–vine Copulas for Static Cases

	copula	par1	par2	λ_L	λ_U	τ	AIC	BIC
Panel A: C–vine								
C_{12}	t	0.627 (0.011)	6.625 (0.861)	0.225	0.225	0.432	-1692.70	-1680.52
C_{13}	t	0.596 (0.012)	5.706 (0.653)	0.236	0.236	0.407	-1505.41	-1493.23
$C_{23 1}$	R-G	1.080 (0.012)		0.100	0.000	0.074	-55.38	-49.29
Panel B: D–vine								
C_{21}	t	0.627 (0.011)	6.625 (0.861)	0.225	0.225	0.432	-1692.70	-1680.52
C_{13}	t	0.596 (0.012)	5.706 (0.653)	0.236	0.236	0.407	-1505.41	-1493.23
$C_{23 1}$	R-G	1.080 (0.012)		0.100	0.000	0.074	-55.38	-49.29

Note: 1 = corn, 2 = wheat, 3 = soybean. The numbers in the parentheses are the standard errors.

The dependence parameters from Table 4 are statistically significant and they have quite a strong dependence. The corresponding values of Kendalls tau are also strong for the pairs of corn–wheat and corn–soybean, respectively. According to the AIC and BIC criteria, the optimal choice of copula is the t–copula for both the pairs; the degree of freedom of the t–copula ranges from 5.71 to 6.63. These facts imply that the co–movements and tail dependences between corn and wheat, and between corn and soybean are in substantial extreme, especially during the extreme market events. As for the relationship between wheat and soybean with a conditional corn price, it has a very low Kendalls tau, 0.07, which has fallen by 74.9% when compared to the unconditional bivariate wheat and soybean. The best bivariate copula between wheat and soybean is t–copula with the Kendalls tau parameter as 0.296. Therefore, it can be safely concluded that the corn price has affected the dependence structure between wheat and soybean.

The time–varying copula was applied in all the trees within our study by following the ARMA (1,10) process of Patton[26]. The data given in Table 5 reveal that all the time–varying copulas were able to improve the performance of the entire static copulas in each tree, which is consistent with the AIC and BIC criteria.

The values of the autoregressive parameter φ_1 for the pairs of corn–wheat and corn–soybean are relatively low, which implies that the time–varying dependence

Table 5: Parameter Estimate Results of C-vine Copula for Time-varying Cases

	copula	φ_0	φ_1	φ_2	AIC	BIC
C_{12}	t	-0.299 (0.0002)	0.041 (0.0007)	2.774 (7.7e-04)	-1717.40	-1707.20
C_{13}	t	0.1046 (0.0017)	0.110 (0.0043)	1.990 (0.0035)	-1541.38	-1541.38
$C_{23 1}$	R-G	0.660 (0.0004)	0.984 (0.0028)	-0.409 (0.0036)	-65.54	-65.54

Note: 1 = corn, 2 = wheat, 3 = soybean. The numbers in the parentheses are the standard errors.

has low persistence, while the values of the autoregressive parameter φ_1 for wheat and soybean with a conditional corn price show the high autocorrelation. Meanwhile, the variability of the values of the dependence parameter (φ_2) is significant and displays a greater variability over time on the dependence between corn and wheat returns, and between corn and soybean returns.

4 Discussion

Our findings show that the listing of ethanol futures causes the price volatility in the corn market and also triggers an impact price in the soybean market. Also, the trading volume for all agricultural commodities has a positive impact on the price volatility of the corn, soybean, and wheat markets. This evidence is consistent with the findings of Demirer et al.[27] who reported on the effect of ethanol listing on the returns and the volatility in the corn market. Analogous to this, Yang et al.[30] illustrated the effect of futures trading on the agricultural commodity prices. While, the open interest for all agricultural commodities has significant impacts on the price volatility of the corn, soybean, and wheat prices with a negative effect. The sign of the relationship of open interest on the price volatility is negative, which suggests that the arbitrage activity caused an increase in the futures price volatility of the corn, soybean, and wheat markets. The above-mentioned results support the argument that the role of financialization and the role of biofuel are considerably influential in determining the price and the volatility of the agricultural commodity markets.

Moreover, the empirical evidence reveals that the dependence between the corn and wheat returns, and between the corn and soybean returns are relatively strong. In addition, it was discovered that corn price has more influence to examine the dependence structure between the wheat and soybean returns. The results indicate that the high price volatility in the corn markets leads to an increase in the soybean and wheat price volatility. The reason is that grains are shared in

the planted acreage and are closer substitutes for animal fodder. Interestingly, we do observe that the agricultural markets have become more interdependent in the present times, in consistency with the apparent higher financial market integration of agricultural commodities.

Additionally, there exists extreme tail dependence between the corn and wheat prices, and between the corn and soybean prices. The symmetry tail dependence generally implies that corn price and related agricultural commodity prices are likely to move together during the boom and bust marketing periods. This evidence argues that policy makers should consider the effects that will be manifested on the price volatility in a situation of high trading activity in the agricultural commodities markets and an ensuing biofuel policy. For investors, the co-movement between the corn price and the closely related grains prices may worsen when there is use of related agricultural markets as an alternative for portfolio diversification.

5 Conclusion

This paper has examined the price volatility and the dependence structure among agricultural commodity markets, especially among corn, soybean, and wheat markets by using vine copula based GARCH models. The vine copula is a very flexible multivariate copula, which can measure asymmetry and time variation in the dependence structures of multivariate series of financial returns. The main purpose of this paper is to analyze the impacts of the ethanol listing and the trading activity of agricultural commodity markets on price level and price volatility of corn, soybean, and wheat. From this study, we constructed the dependence structure among these three main agricultural commodities markets.

The empirical evidence shows that the ethanol listing and the trading activity do have an impact on the price level and price volatility of corn, soybean, and wheat. These results confirm the concern regarding the increased price volatility in agricultural markets due to the role of financialization and the role of biofuel. Moreover, the dependencies between the corn and wheat returns, and between corn and soybean returns are significant in variability over time and have a higher variation of dependence with symmetrical tail dependences. The higher time-varying dependence and the symmetric tail dependences between the corn and wheat returns, and between the corn and soybean returns are an indication that the main agricultural commodities are most likely to move together during the boom and bust marketing periods. It reduces the alternative of use in related agricultural markets for portfolio diversification purpose.

Acknowledgement(s) : We would like to thank the Prince of Songkla University for providing the PhD fellowship funding for Mr. Phattanan Boonynuphong.

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(Received 30 April 2014)

(Accepted 10 September 2014)