APPENDIX A

Some analysis results of Chapter 6

Table A1 Data Descriptive Statistics for Log-difference of Ethanol, NYMEX, ICE, DME, Corn, Wheat

	Ethanol	NYMEX	ICE	DME	Corn	Wheat
Mean	-0.000055	0.000263	0.000312	0.000333	0.000060	0.000131
Median	0.000834	0.000990	0.000824	0.000906	0.000347	0.000000
Maximum	0.094029	0.164097	0.127066	0.133869	0.127571	0.103730
Minimum	-0.309978	-0.130654	-0.120559	-0.133661	-0.268620	-0.099728
Std. Dev.	0.022511	0.025823	0.022946	0.022044	0.023392	0.024523
Skewness	-3.357217	0.080635	-0.283888	-0.138357	-0.991917	0.051297
Kurtosis	42.480000	8.519100	7.362100	8.287600	15.546000	4.533400
p-value of Jarque–Bera	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
p-value of Augmented-Dickey-Fuller test	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
Number of observations	1,540	1,540	1,540	1,540	1,540	1,540

Table A2 Data Descriptive Statistics for Log-difference of Feed Wheat, Soybeans, Rapeseed, Palm Oil, Exrate

	Feed Wheat	Soybeans	Rapeseed	Palm Oil	Exrate
Mean	0.000327	0.000314	0.000192	-0.000022	-0.000013
Median	0.000000	0.001420	0.000857	0.000000	-0.000128
Maximum	0.133531	0.203209	0.066101	0.097638	0.017351
Minimum	-0.106018	-0.234109	-0.111042	-0.110391	-0.023029
Std. Dev.	0.016261	0.020350	0.013286	0.019477	0.003780
Skewness	0.445828	-0.994577	-0.866279	-0.355675	-0.069985
Kurtosis	10.447100	22.707700	8.433400	7.414700	6.805900
p-value of Jarque–Bera	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
p-value of Augmented-Dickey-Fuller test	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
Number of observations	1,540	1,540	1,540	1,540	1,540

Table A3 Results of ARMA(p,q)-GARCH(1,1) with Skewed Student-T Residual for Ethanol, NYMEX, ICE

	Ethanol	Std. error (p-value)	NYMEX	Std. error (p-value)	ICE	Std. error (p-value)
mu	4.258e-05	1.903e-04 (0.8229)	5.128e-04	4.643e-04 (0.2694)	5.422e-04	4.290e-04 (0.2063)
ar1	6.350e-01	3.093e-01 (0.0401 *)	-	-	-4.969e-02	2.553e-02 (0.0516 ·)
ma1	-5.965e-01	3.266e-01 (0.0678 ·)	-	-	-	-
ω	9.098e-06	4.244e-06 (0.0321 *)	4.322e-06	2.253e-06 (0.0551 ·)	1.806e-06	1.246e-06 (0.1472)
α	3.782e-02	1.365e-02 (0.0056 **)	7.185e-02	1.590e-02 (6.19e-06 ***)	5.328e-02	1.157e-02 (4.13e-06 ***)
β	9.426e-01	2.022e-02 (<2e-16 ***)	9.213e-01	1.716e-02 (< 2e-16 ***)	9.444e-01	1.176e-02 (< 2e-16 ***)
ν (degree of freedom)	3.777e+00	3.756e-01 (<2e-16 ***)	8.413e+00	1.643e+00 (3.03e-07 ***)	6.563e+00	1.136e+00 (7.62e-09 ***)
λ (skewness)	9.013e-01	3.247e-02 (<2e-16 ***)	9.253e-01	3.310e-02 (< 2e-16 ***)	9.170e-01	3.164e-02 (< 2e-16 ***)
Log-likelihood	4,013.701	-	3,795.822	-	3,938.475	-
GARCH(1,1) test, α+ β	0.9804	-	0.99315	-	0.9977	-

Note: Significant codes: 0 "***"; 0.001 "**"; 0.01 "*" 0.05.

Table A4 P-values of K–S Test and Box–Ljung Test for Marginal Distributions of Ethanol, NYMEX, ICE

	Ethanol (*p-value*)	NYMEX (*p-value*)	ICE (*p-value*)
K–S test (*p-value*)	(1)	(1)	(1)
Box–Ljung test (*p-value*)	-	-	-
1^{st} moment	(0.1842)	(0.6211)	0.8038
2^{nd} moment	(0.0380)	(0.6931)	0.8212
3^{rd} moment	(0.0855)	(0.8641)	0.9832
4^{th} moment	(0.0233)	(0.7884)	0.6320

Table A5 Results of ARMA(p,q)-GARCH(1,1) with Skewed Student-T Residual for DME, Corn, Wheat

	DME	Std. error (p-value)	Corn	Std. error (p-value)	Wheat	Std. error (p-value)
mu	5.591e-04	3.868e-04 (0.1484)	4.424e-04	5.208e-04 (0.3956)	-9.904e-05	5.223e-04 (0.850)
ar1	-	-	-	-	-	-
ma1	-4.609e-02	2.491e-02 (0.0643 .)	-	-	-	-
ω	1.273e-06	1.024e-06 (0.2136)	1.425e-05	6.218e-06 (0.0219 *)	6.014e-10	9.390e-07 (0.999)
α	5.168e-02	1.172e-02 (1.03e-05 ***)	7.185e-02	1.789e-02 (5.92e-05 ***)	3.445e-02	8.240e-03 (2.7e-05 ***)
β	9.481e-01	1.123e-02 (< 2e-16 ***)	9.036e-01	2.360e-02 (< 2e-16 ***)	9.638e-01	8.187e-03 (< 2e-16 ***)
ν (degree of freedom)	5.042e+00	6.890e-01 (2.53e-13 ***)	5.111e+00	6.390e-01 (1.33e-15 ***)	7.664e+00	1.361e+00 (1.8e-08 ***)
λ (skewness)	9.403e-01	3.239e-02 (< 2e-16 ***)	9.749e-01	3.443e-02 (< 2e-16 ***)	1.037e+00	3.841e-02 (< 2e-16 ***)
Log-likelihood	4,021.907	-	3,751.017	-	3,638.257	-
GARCH(1,1) test, α+ β	0.9998	-	0.9755	-	0.9983	-

Note: Significant codes: 0 "***"; 0.001 "**"; 0.01 "*" 0.05.

Table A6 P-values of K–S Test and Box–Ljung Test for Marginal Distributions of DME, Corn, Wheat

	DME (*p-value*)	Corn (*p-value*) lag10	Wheat (*p-value*)
K–S test (*p-value*)	(1)	(1)	(1)
Box–Ljung test (*p-value*)	-	-	-
1st moment	(0.8862)	(0.9555)	(0.4400)
2nd moment	(0.3708)	(0.0244)	(0.9234)
3rd moment	(0.8527)	(0.9370)	(0.2069)
4th moment	(0.3004)	(0.0264)	(0.8114)

Table A7 Results of ARMA(p,q)-GARCH(1,1) with Skewed Student-T Residual for Feed Wheat, Soybeans, Rapeseed

	Feed Wheat	Std. error (*p-value*)	Soybeans	Std. error (*p-value*)	Rapeseed	Std. error (*p-value*)
mu	6.053e-07	1.711e-05 (0.97178)	1.789e-04	2.581e-04 (0.48818)	4.301e-04	3.016e-04 (0.15386)
ar1	9.771e-01	2.157e-02 (< 2e-16 ***)	7.108e-01	3.743e-01 (0.05753 .)	1.108e-01	2.549e-02 (1.39e-05 ***)
ma1	-9.519e-01	3.288e-02 (< 2e-16 ***)	-7.197e-01	3.712e-01 (0.05253 .)	-	-
ω	8.722e-06	3.976e-06 (0.02824 *)	5.007e-06	1.781e-06 (0.00493 **)	1.403e-05	5.057e-06 (0.00555 **)
α	9.261e-02	2.839e-02 (0.00111 **)	4.623e-02	1.092e-02 (2.30e-05 ***)	1.230e-01	2.888e-02 (2.06e-05 ***)
β	8.830e-01	3.390e-02 (< 2e-16 ***)	9.408e-01	1.224e-02 (< 2e-16 ***)	8.043e-01	4.612e-02 (< 2e-16 ***)
ν (degree of freedom)	3.827e+00	4.003e-01 (< 2e-16 ***)	4.456e+00	5.376e-01 (2.22e-16 ***)	4.592e+00	5.452e-01 (< 2e-16 ***)
λ (skewness)	1.053e+00	3.467e-02 (< 2e-16 ***)	8.779e-01	3.047e-02 (< 2e-16 ***)	8.847e-01	3.194e-02 (< 2e-16 ***)
Log-likelihood	4,385.135	-	4,102.975	-	4,639.397	-
GARCH(1,1) test, α+ β	0.9756	-	0.9870	-	0.9273	-

Note: Significant codes: 0 "***"; 0.001 "**"; 0.01 "*" 0.05.

Table A8 P-values of K–S Test and Box–Ljung Test for Marginal Distributions of Feed Wheat, Soybeans, Rapeseed

	Feed Wheat (*p-value*)	Soybeans (*p-value*)	Rapeseed (*p-value*)
K–S test (*p-value*)	(1)	(1)	(1)
Box–Ljung test (*p-value*)	-	-	-
1st moment	(0.1399)	(0.9267)	(0.8369)
2nd moment	(0.4595)	(0.3683)	(0.5647)
3rd moment	(0.2607)	(0.2465)	(0.8231)
4th moment	(0.6145)	(0.5203)	(0.9033)

Table A9 Results of ARMA(p,q)-GARCH(1,1) with Skewed Student-T Residual and Student-T Residual for Palm Oil and Exrate, respectively

	Palm Oil	Std. error (*p-value*)	Exrate	Std. error (*p-value)*
mu	2.234e-04	3.725e-04 (0.5488)	- 9.847e-05	7.544e-05 (0.1918)
ar1	-	-	-	-
ma1	-	-	-	-
ω	3.488e-06	1.438e-06 (0.0153 *)	1.111e-07	5.403e-08 (0.0397 *)
α	7.093e-02	1.393e-02 (3.53e-07 ***)	5.665e-02	1.061e-02 (9.38e-08 ***)
β	9.186e-01	1.509e-02 (< 2e-16 ***)	9.362e-01	1.135e-02 (< 2e-16 ***)
ν (degree of freedom)	8.035e+00	1.528e+00 (1.46e-07 ***)	7.655e+00	1.445e+00 (1.16e-07 ***)
λ (skewness)	9.787e-01	3.548e-02 (< 2e-16 ***)	-	-
Log-likelihood	4,155.36	-	6,606.82	-
GARCH(1,1) test, α+ β	0.9895	-	0.99285	-

Note: Significant codes: 0 "***"; 0.001 "**"; 0.01 "*" 0.05.

Table A10 P-values of K–S Test and Box–Ljung Test for Marginal Distributions of Palm Oil, Exrate

	Palm Oil (*p-value*)	Exrate (*p-value*)
K–S test (*p-value*)	(1)	(1)
Box–Ljung test (*p-value*)	-	-
1st moment	(0.3624)	(0.5828)
2nd moment	(0.6184)	(0.4987)
3rd moment	(0.0670)	(0.8270)
4th moment	(0.8110)	(0.5531)

APPENDIX B

Dependence Structure between Crude Oil, Soybeans, and Palm Oil in ASEAN Region: Energy and Food Security Context

Teera Kiatmanaroch, Songsak Sriboonchitta

This is the original paper that was published in “Modeling Dependence in Econometrics”, Advances in Intelligent Systems and Computing Volume 251, pp 329 – 341.

Dependence Structure between Crude Oil, Soybeans, and Palm Oil in ASEAN Region: Energy and Food Security Context

Teera Kiatmanaroch and Songsak Sriboonchitta

Abstract. The increase in energy and food prices remains a challenge for the ASEAN Economic Community (AEC). Understanding the dependence between energy prices and food prices is imperative for the energy and food security for the people of the ASEAN countries. The C-vine copula model is a flexible tool to analyze the relationship between variables, in which the multivariate dependence modeling. It offers us to define the relationship structure between variables or we call pair-copula construction, according to the purpose of study. This study is interesting to examine an influence of crude oil price on palm oil price and soybeans price. The results can conclude that the change of crude oil price has influence on the prices of palm oil and soybeans. Moreover, the findings show that there exists the dependence between palm oil price and soybeans price, and crude oil price is one factor that has influence on relation of their prices. However, the dependence structure of the static copula for Crude oil–Palm oil (C,P), Crude oil–Soybeans (C,S), Palm oil–Soybeans (P,S), there exists a weak positive dependence in each pair-copula. This indicates that the price of each commodity is slightly related to the price of every other. In the case of soybeans, the ASEAN members should cooperate and incorporate their efforts to increase the capacity and performance in production to reduce relying on soybeans being imported from outside the region.

1 Introduction

By 2015, the nations in the Southeast Asian region consisting of Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam will agree on establishing an ASEAN Economic Community (AEC), which has a total population of approximately 600 million people. This regional integration shall lead to a single market and production that will induce free movement of goods, services, investment, capital, and skilled labor across the ASEAN

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V.-N. Huynh et al. (eds.), *Modeling Dependence in Econometrics*, 329
Advances in Intelligent Systems and Computing 251,
DOI: 10.1007/978-3-319-03395-2_21,

region [1, 2]. The ASEAN boundary is adjacent to the south of China and is linked to the east of India, both by sea and land. India and China are part of the BRIC countries, which are the newly industrialized countries, and are considered as two of the nations that have fast growing economies [3]. According to the information mentioned above, the premise is that the economic geography makes the AEC play an important role in the global economy. However, during the past several years, the AEC has remained restricted due to some challenging circumstances caused by the global financial crisis in 2008. In addition, the food and fuel crises have caused a huge burden on the people who are poor and near-poor in the ASEAN region, and created a negative impact with regard to their social and economic development [4]. The rise in food prices came about due to many factors, such as climate change which caused a decline in the agricultural production, a rise in fuel prices which led to a domino effect on the cost of production, and the increase in consumer demand [5].With regard to the rise in fuel prices, the incidence of such factors was due to an increasing demand in Asia, especially in the emerging markets of India and China [6]. The rise in food and energy prices is a real challenge for the ASEAN members while trying to find any crucial means to cooperate in the short- and long-term situations to solve the problems because food[1] and energy[2] security are fundamental for upholding the ASEAN economic and social development goals [7].

Palm oil and soybeans are food commodities that are related to food security in the ASEAN region because they are used as raw materials in food production and are converted to the necessary goods, and also used for other aspects of daily life. Palm oil can be modified as cooking oil, shortening, margarines, etc. Soybeans can be modified as cooking oil, soy milk, soy sauce, tempeh, tofu, etc. Moreover, palm oil and soybean oil can be used to produce alternative energy such as the biodiesel types, Palm Methyl Ester (PME) and Soy Methyl Ester (SME), respectively. In ASEAN, palm oil can be produced sufficiently for intra-regional demand and the remaining parts can be kept aside for exportation. In 2012/2013, Indonesia and Malaysia exported palm oil of an approximate volume of 37,300 thousand metric tons, or 89.66% of the total world exports, which was 41,603 thousand metric tons [8]. However, in the case of soybeans, it has to be imported from outside the region. In 2012/2013, Indonesia, Thailand, and Vietnam imported about 5,300 thousand metric tons or 5.66% of the total world imports, which was 93,587 thousand metric tons [9].

[1] FAO [14] definition: Food security exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life. The four pillars of food security are availability, access, utilization, and stability. The nutritional dimension is integral to the concept of food security.

[2] United Nations [15] definition: Energy security is a term that applies to the availability of energy at all times in various forms, in sufficient quantities, and at affordable prices, without unacceptable or irreversible impact on the environment. These conditions must prevail over the long term if energy is to contribute to sustainable development. Energy security has both a producer and a consumer side to it.

ASEAN has crude oil resources and oil production, but does not have a sufficient supply to meet the intra-regional demand. In 2011, ASEAN imported crude oil worth not less than 90,000 million US dollars [10]. ASEAN imports crude oil especially from the Middle East [11]. Although the crude oil benchmark prices of the international crude oil markets are from Brent, West Texas Intermediate (WTI), Dubai, and Maya, each of these markets is related to one another. It was found that in times of crude oil market stress, the crude oil price in each market tends to have co-movement with the same intensity [25]. In addition, we found that the crude oil markets are related to the food markets. As in the previous studies of the relationship between energy and agricultural prices, it can be concluded that the long-run agricultural prices can be driven by the energy prices and that volatility in the energy markets is transmitted to the food markets [13].

Over the past several years, there have been some evidences of significant volatility transmissions between the crude oil prices in each of these markets. Moreover, the volatility in the oil prices can be transmitted to the various food markets. Thus, it is interesting to analyze the relationship between the crude oil benchmark prices of the ASEAN and the prices of the two food commodities that can be used to generate alternative energy, which are the following: (1) palm oil, which can be produced and be sufficient for intra-regional demand and (2) soybeans, which rely on imports from outside the region. Since these commodities are related to the energy and food security for the people in the ASEAN region, and can also be substituted for each other, it would be quite interesting to learn about the dependence structure of these commodity prices. Furthermore, it will be useful for making decisions and plans for the economic and social development of the AEC. Therefore, the purposes of the study are as follows: (1) to analyze the dependence between crude oil prices (DME) and two food prices, namely, the prices of soybeans (CBOT) and palm oil (MDEX) and (2) to analyze the dependence between the soybeans and palm oil prices, with the crude oil prices as the conditioning variable. The GARCH model was applied to examine the volatility of the futures prices 1-Pos. of the three data series and the vine copula model was used to analyze the dependence structure between their marginal distributions. The data analyses were based on the daily observations from the period of June 2007 to March 2013.

The remainder of this work is organized as follows: part two is the methodology, and part three consists of the data and the empirical findings. Finally, part four comprises the conclusions.

2 Methodology

Over the past several years, there have been arguments about the relationship between the energy prices (e.g., crude oil, biodiesel, and ethanol) and the agricultural commodity prices (e.g., palm oil, soybeans, corn) as to whether they are related or not. The argument was always divided between a relation and an absence of relation. From the literature review, we come to know that relationships do exist between the energy prices and the agricultural commodity prices; what is more, there are relationships between the prices of the different agricultural commodities themselves. The findings on these relationships depend on many factors such as the period of study, the data frequency, the statistical analysis, and the modeling. As for modeling, a number of different models were used in the studies prior to this study. Baffes [16] used the ordinary least squares (OLS) to analyze the relationship between the commodity prices and the crude oil price. Serra and Zilberman [13] mentioned about many econometrics and statistical models that the previous studies used to find the relationship between the energy prices and the agricultural commodity prices, and the relationships between the prices of the different commodities. A few of such applicable tools are cointegration, causality, vector error correction model (VECM), vector autoregressive (VAR), autoregressive distributed lag models (ARDL), vector auto regression moving-average (VARMA), stochastic volatility model with Merton jumps (SVMJ), panel data, minimal spanning and hierarchical trees, random parameter model, wavelet, GARCH modeling, and copula modeling. As mentioned above, we found that the statistics used for analyzing are both parametric and non-parametric, and that the relationship analysis between the variables is both linear and non-linear.

There were several models and each of the models was based on different assumptions in order to test the data. Sriboonchitta et al. [17] applied the copula based GARCH for modeling the volatility and dependency of the agricultural price and production indices of Thailand. Based on the study, the work mentioned that this approach provided more flexibility for finding out the joint distributions and the transformation of the invariant correlation, without the assumption of linear correlation. Therefore, in this study, we used the GARCH(1,1) model [18] to examine the volatility of the commodity daily prices which are generally non-normal distributions and applied the vine copula model to examine the relationship between each commodity.

The R-package fGarch by Wuertz and Chalabi [19] was used to estimate the GARCH(1,1) model with the skewed student T (SkT) residual distribution for the marginal distribution of the log-difference $\ln \frac{P_t}{P_{t-1}}$ or the growth rate of crude oil prices, palm oil prices, and soybeans prices. The standardized residuals with the skewed student T were transformed to copula data $(F_1(x_1), F_2(x_2), F_3(x_3))$ by using the empirical distribution function. After that, we used the R-package CDVine which was developed by Brechmann and Schepsmeier [20] to estimate the bivariate copula and C-vine copula.

This study used the C-vine copula modeling to analyze the dependence between the crude oil prices from the Dubai market (DME) and the two food prices consisting of palm oil prices from the Malaysia market (MDEX) and soybeans prices from the Chicago market (CBOT), which no one has studied before. The structure of the C-vine model is shown in Figure 1. This study selected crude oil which was the first root node, as Brechmann and Schepsmeier [20] hold the view that a vine structure can be chosen manually or through expert knowledge. Aas et al. [21] said that modeling C-vine might be advantageous when we know a main variable that governs the interactions in the data, or when it plays an important role in the dependence structure and when the others are linked to it. Therefore, our assumption in

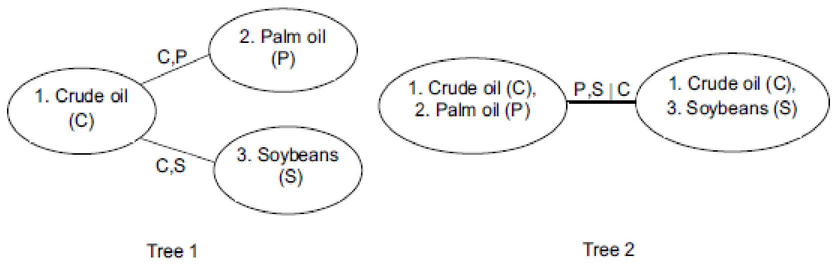

Fig. 1 The pair-copulas of three-dimensional C-vine trees

this study is that crude oil prices is a key variable as Serra and Zilberman [13] point out that energy prices can drive the long-run agricultural price levels.

3 Data and Empirical Findings

To analyze the relationship between crude oil prices and two food prices (palm oil and soybeans), we selected the commodity prices that are related to the AEC. The crude oil benchmark price for the Asian market is the Dubai (Oman) crude oil price [22] since the Middle East is the major source of crude oil for ASEAN [11]. Thus, the crude oil price of the Dubai Mercantile Exchange (DME) was used in this study. Palm oil prices were obtained from the Malaysia Derivatives Exchange (MDEX) because Malaysia is a major producer and a world exporter of palm oil [8]. In ASEAN, soybean production in the intra-region was insufficient for meeting the demand; most of the soybeans was imported from Brazil, Argentina, and America. Indonesia, Thailand, and Vietnam are the major importers of soybeans in the Asian region due to their demand for soybeans in the food industry, livestock industry, and so on [9, 23, 24, 25]. Therefore, we used the soybeans prices of the Chicago Board of Trade (CBOT) since it provides an updated data and it can be used as a reference price in the world market. The observations were based on the Futures 1-Pos of the daily close prices during the period from 1 June 2007 to 15 March 2013, from the EcoWin database. Each price data series was transformed into the log-difference $\ln \frac{P_t}{P_{t-1}}$, or the growth rates of the prices before were used to analyze by using the vine copula based GARCH model.

Table 1 presents a descriptive statistics of the growth rates of crude oil, palm oil, and soybeans. Crude oil and soybeans have positive average growth rates but palm oil has negative average growth rates. All of three data series exhibit negative skewness. If skewness is negative, the market has a downside risk or there is a substantial probability of a big negative return. The kurtosis of these data is greater than 3. Therefore, this kurtosis is called super Gaussian and leptokurtic. This means that the growth rates of the empirical data have a typically spiky probability distribution function with heavy tails. The null hypothesis of the normality of the Jarque-Bera tests are rejected in all the data series. The Dickey-Fuller test shows that these data series are stationary at p-value 0.01.

Table 1 Data Descriptive Statistics for Log-difference of Crude Oil, Palm Oil, and Soybeans Prices

	Crude oil	Palm oil	Soybeans
Mean	0.000354	−0.000107	0.000403
Median	0.000899	0.000000	0.001304
Maximum	0.133869	0.097638	0.203209
Minimum	−0.133661	−0.110391	−0.234109
Std. Dev.	0.023000	0.020276	0.020557
Skewness	−0.157438	−0.347154	−0.898968
Kurtosis	7.68	7.03	23.50
Jarque-Bera	1,265.75	961.06	24,341.97
(p-value)	(0.0000)	(0.0000)	(0.0000)
p-value of Dickey-Fuller test	0.01	0.01	0.01
Number of observations	1,379	1,379	1,379

From the data given in Table 1, it can be seen that the three data series are inappropriate with normal distribution, and exhibit negative skewness and excess kurtosis. Therefore, the GARCH(1,1) with the skewed student T residual distribution, $\varepsilon_t \sim SkT(\nu,\gamma)$, was modeled for examining the volatility and for estimating the marginal distributions.

Table 2 presents the result of GARCH(1,1) with skewed student T residual. The asymmetry parameters, γ, are significant and less than 1, exhibiting that all the data series are skewed to the left. For crude oil, palm oil, and soybeans, the $\alpha+\beta$ are 0.9980, 0.9901, and 0.9894, respectively; this implies that their volatilities have long-run persistence. For the short-run effect of the unexpected factors, we consider the event from the α parameter. Therefore, we can see that they have close values (0.0529, 0.0746 and 0.0483) and a small impaction for volatility.

Next, we transformed the standardized residuals from the GARCH(1,1) model into uniform [0,1] by using the empirical distribution function $F_n(x) = \frac{1}{n+1}\Sigma_{i=1}^{n} 1$ $(X_i \leq x)$, where $X_i \leq x$ is the order statistics and 1 is the indicator function. The transformed data were used in the Kolmogorov-Smirnov (K-S) test for uniform [0,1] and the Box-Ljung test for serial correlation. More details are illustrated in Patton [26] and Manthos [27]. These tests are necessary to check for the marginal distribution models' misspecification before using the copula model.

The results of the K-S test show that these marginal distributions are uniform, by accepting the null hypothesis at p-values equal to 1 or nearly 1. The results of the Box-Ljung test provide that all of the four moments of all the marginal distributions are i.i.d. by accepting the null hypothesis that does not have a serial correlation at p-value greater than 0.05. Therefore, our marginal distributions were not misspecified and can be used for the copula model.

Table 2 Results of GARCH(1,1) with Skewed Student T Residual for Log-difference of Crude Oil, Palm Oil, and Soybeans Prices

	Crude oil	Std. error (p-value)	Palm oil	Std. error (p-value)	Soybeans	Std. error (p-value)
ω	2.325e-06	1.749e-06	3.903e-06	1.721e-06	4.428e-06	1.674e-06
		(0.184)		(0.0233 *)		(0.00817 **)
α	0.0529	1.214e-02	0.0746	1.501e-02	0.0483	1.115e-02
		(1.32e-05 ***)		(6.75e-07 ***)		(1.52e-05 ***)
β	0.9451	1.231e-02	0.9155	1.606e-02	0.9411	1.173e-02
		(< 2e-16 ***)		(< 2e-16 ***)		(< 2e-16 ***)
ν	5.067	7.455e-01	7.681	1.485e+00	4.917	6.933e-01
(degree of freedom)		(1.07e-11 ***)		(2.31e-07 ***)		(1.32e-12 ***)
γ	9.418e-01	3.112e-02	9.685e-01	3.557e-02	8.795e-01	2.889e-02
(skewness)		(< 2e-16 ***)		(< 2e-16 ***)		(< 2e-16 ***)
Log likelihood	3,499.523	-	3,654.827	-	3,659.68	-
K-S test	-	-	-	-	-	-
(p-value)		(1)		(0.9208)		(1)
Box-Ljung test	-	-	-	-	-	-
(p-value)						
1st moment	-	-	-	-	-	-
		(0.5832)		(0.2515)		(0.9540)
2nd moment	-	-	-	-	-	-
		(0.7921)		(0.8898)		(0.4999)
3rd moment	-	-	-	-	-	-
		(0.7765)		(0.0732)		(0.4433)
4th moment	-	-	-	-	-	-
		(0.6423)		(0.8803)		(0.6692)

Note: Significant codes: 0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1.

3.1 Results of C-vine Copula Analysis

Figure 1, in the Part 2, presents each of the pair-copulas of the three-dimensional C-vine tree; there are two pair-copulas in Tree 1 and one pair-copula in Tree 2. The first and second pair-copulas in Tree 1 are Crude oil–Palm oil (C,P) and Crude oil–Soybeans (C,S), respectively. The third pair-copula in Tree 2 is a conditional pair-copula, Palm oil–Soybeans given Crude oil (P,S|C).

We use the Gaussian copula, Student's T copula, Clayton copula, Gumbel copula, Frank copula, Joe copula, rotated Clayton 180°, rotated Gumbel 180° copula, and rotated Joe 180° copula to fit the data. The AIC and the BIC are used to appraise as to which copula is the best fit. Kendall's tau correlation which was transformed from the copula parameter was used because each family of copula has a different range of copula parameters; hence we inverse a copula parameter into a Kendall's tau correlation, and it is bound on the interval $[-1,1]$. Kendall's tau is a measure of concordance which is a function of copula; thus, we can use it to assess the range of dependence covered by the families of copula. A goodness-of-fit test based on Kendall's tau provides the Cramér-von Mises (CvM) and Kolmogorov-Smirnov (KS) test statistics and the estimated p-values by bootstrapping [20] to test the appropriateness of the copula model under the null hypothesis that the empirical copula C belongs to a parametric class C' of any of the copulas, $H_0 : C \in C'$.

The results of the pair-copulas Crude oil–Palm oil (C,P), Crude oil–Soybeans (C,S), and Palm oil–Soybeans given Crude oil (P,S|C) are presented in Table 3.

The first pair-copula, Crude oil–Palm oil, considering the values of the AIC and the BIC, the three most appropriate copulas in order are the Gaussian, Student's T, and rotated Gumbel 180°. But the second parameter (ν) of the Student's T copula is insignificant with p-values greater than 0.05. The CvM and KS tests of the Gaussian, Student's T, and rotated Gumbel 180° copula accept the null hypothesis with p-values greater than 0.05, which means that the dependence structure of the data series is appropriate for a chosen family. Therefore, the Gaussian copula is chosen to explain the dependence structure of this pair-copula with a copula parameter 0.2495 and a Kendall's tau correlation 0.16.

The second pair-copula, Crude oil–Soybeans, considering the values of the AIC and the BIC, the three most appropriate copulas in order are Student's T, Gaussian, and Frank. Although the Student's T copula is the best fit according to the AIC and the BIC, it does not give any results for the CvM and KS tests by estimation in the R-package CDVine. The Gaussian copula is a second order of the AIC and the BIC values, and shows that the CvM and KS tests accept the null hypothesis with p-values greater than 0.05. For the Frank copula, the CvM and KS tests reject the null hypothesis with p-values less than 0.05, which means that the Frank copula is not an appropriate model. Therefore, the Gaussian copula is chosen to explain the dependence structure of this pair-copula with a copula parameter of 0.3545 and a Kendall's tau correlation of 0.23.

The parameter of each pair-copula from an appropriate copula family in Tree 1 was used to construct the conditional pair-copula of Palm oil–Soybeans given Crude oil (P,S|C) in Tree 2 of the C-vine copula model, and the results are shown in Table 3.

For the conditional pair-copula, Palm oil–Soybeans given Crude oil, considering the values of the AIC and the BIC, the three most appropriate copulas in order are the Gaussian, Student's T, and Frank. Although the second parameter (ν) of the Student's T copula is insignificant with p-values greater than 0.05, it does not give any results for the CvM and KS tests by estimation in the R-package CDVine. The CvM and KS tests of the Gaussian and Frank copulas accept the null hypothesis with p-values greater than 0.05, which means that the dependence structure of the data series is appropriate for a chosen family. Therefore, the Gaussian copula is chosen to explain the dependence structure of this conditional pair-copula with a copula parameter 0.2303 and a Kendall's tau correlation 0.15.

In addition, the results of the bivariate copula analysis of Palm oil and Soybeans (P,S) are shown in Table 4. The Gaussian copula was chosen to explain the dependence structure between Palm oil and Soybeans by considering the AIC and the BIC values, and the CvM and KS tests accepted the null hypothesis with p-values greater than 0.05. The Gaussian copula gives a copula parameter of 0.2970 and a Kendall's tau correlation of 0.19.

Table 3 Results of C-vine Copula Model

Tree	Pair-copula	Copula family	Copula parameter	Std. error (p-value)	Kendall's tau	AIC	BIC	p-value CvM	KS
1	C,P	Gaussian	0.2495	0.0245 (0.0000)	0.1600	−86.4655	−81.2364	0.24	0.19
		Student's T	0.2494	0.0250 (0.0000)	0.1605	−84.8997	−74.4415	0.59	0.61
			ν =53.4942	82.9504 (0.2596)					
		rotated Gumbel 180°	1.1675	0.0222 (0.0000)	0.1434	−77.9826	−72.7535	0.05	0.07
1	C,S	Gaussian	0.3545	0.0222 (0.0000)	0.2307	−182.9177	−177.6885	0.07	0.08
		Student's T	0.3606	0.0236 (0.0000)	0.2349	−190.5264	−180.0682	NA	NA
			ν =13.6722	5.1333 (0.0039)					
		Frank	2.2742	0.1692 (0.0000)	0.2407	−179.5645	−174.3354	0.01	0.01
2	P,S|C	Gaussian	0.2303	0.0249 (0.0000)	0.1480	−73.0587	−67.8296	0.98	0.99
		Student's T	0.2318	0.0258 (0.0000)	0.1489	−73.7226	−63.2643	NA	NA
			ν =26.1814	17.5220 (0.0677)					
		Frank	1.4004	0.1657 (0.0000)	0.1526	−69.5958	−64.3667	0.61	0.67

Table 4 Results of Palm Oil–Soybeans (P,S) of a Bivariate Copula Model

Pair-copula	Copula family	Copula parameter	Std. error (p-value)	Kendall's tau	AIC	BIC	p-value CvM	KS
P,S	Gaussian	0.2970	0.0236 (0.0000)	0.1920	−125.1169	−119.8878	0.30	0.35
	Student's T	0.2990	0.0244 (0.0000)	0.1933	−125.5547	−115.0965	NA	NA
		ν =26.4778	18.4553 (0.0758)					
	Frank	1.8284	0.1666 (0.0000)	0.1967	−118.7307	−113.5015	0.02	0.16

By doing a comparison between a C-vine copula model, given in Table 3, and a bivariate copula model, given in Table 4, we found out that our results show that the copula parameters and the Kendall's tau correlations of a conditional pair-copula (P,S|C) in all the copula families are less than those that were obtained from the bivariate pair-copula (P,S); for example, the Gaussian copula of the conditional pair-copula (P,S|C) offers the copula parameter and the Kendall's tau correlation as 0.2303 and 0.15, respectively. Further testing reveals that the Gaussian copula of the bivariate copula (P,S) offers the copula parameter and the Kendall's tau correlation as 0.2970 and 0.19, respectively.

This implies that crude oil price (C) has an influence on the relationship between palm oil price (P) and soybeans price (S). The crude oil price (C) is an important variable that governs the interactions in the dependence structure between the palm oil price (P) and the soybeans price (S).

4 Conclusions

The AEC plays an important role in the global economy. However, it remains in a state of challenge due to the many problems it faces, such as the global economic recession combined with food and fuel crises, which have an effect on the people who are poor and near-poor in the ASEAN region and can have a negative impact on the social and economic development. The rising prices of food and energy are the challenges for the ASEAN members to overcome. There exist evidences of significant price transmissions between the energy market and the food market. Thus, it is interesting to study the relationship between the crude oil benchmark prices of the ASEAN and the prices of the two food commodities that can be used to produce alternative energy, which are as follows: (1) palm oil, which can be produced and be sufficient for intra-regional demand and (2) soybeans, which relies on imports from outside the region. Gaining an understanding of the dependence structure of these commodity prices will be useful in making decisions and plans for the economic and social development of the AEC.

In this study, the data analyses were based on the daily observations from June 2007 to March 2013. The GARCH model was used to examine the volatility of the future prices 1-Pos. of the three data series and applied the C-vine copula model to examine the relationship between each commodity.

The empirical results of the GARCH(1,1) model with skewed student T residual show that the crude oil prices, palm oil prices, and soybeans prices have long-run persistence in volatility. The C-vine copula model was used to study the dependence structure between crude oil price, soybeans price, and palm oil price that related to ASEAN region. This study is interesting to examine an influence of crude oil price on palm oil price and soybeans price. The C-vine copula model is a flexible tool to analyze the relationship between variables, in which the multivariate dependence modeling. It offers us to define the relationship structure between variables according to the purpose of study, and it can describe the relationship between variables through the graphical model or are called pair-copulas, as shown in Figure 1. In this study, we assume crude oil price is a condition variable in C-vine structure. The finding results can conclude that the change of crude oil price has an influence on the prices of palm oil and soybeans. Moreover, the findings show that there exists the dependence between palm oil price and soybeans price, and crude oil price is one factor that has an influence on relation of their prices.

The C-vine copula contains three pair-copulas: Crude oil–Palm oil (C,P) and Crude oil–Soybeans (C,S) in the first tree and a conditional pair-copula, Palm oil–Soybeans given Crude oil (P,S|C), in the second tree. For the pair-copula Crude oil–Palm oil (C,P), the Gaussian copula is chosen to explain its dependence structure with a copula parameter of 0.2495 and a Kendall's tau correlation of 0.16. Similarly, Crude oil–Soybeans (C,S) offers the Gaussian copula as the best fit with a copula parameter of 0.3545 and a Kendall's tau correlation of 0.23. For the last pair-copula, the conditional pair-copula, Palm oil–Soybeans given Crude oil (P,S|C), the Gaussian copula is chosen to explain its dependence structure with a copula parameter of 0.2303 and a Kendall's tau correlation of 0.15. Furthermore, considering to a bivariate pair-copula, Palm oil–Soybeans (P,S), we found that there exists a weak positive dependence and that the Gaussian copula is the best fit with a copula parameter 0.2970 and Kendall's tau correlation of 0.19. This indicates that the price of one commodity is slightly correlated with the prices of the other commodities.

Our results show that the dependence between the crude oil prices and the soybeans prices is stronger than the dependence between the crude oil prices and the palm oil prices due to the increase in biofuel demand and soybeans consumption [28]. Moreover, palm oil is produced on a large scale within the intra-ASEAN region, and the ASEAN nations do not have to rely on imports from the outside region. So the price of palm oil is slightly related to the change in crude oil prices. Thus, to reduce the price transmission and volatility spillover between crude oil prices and food prices, and to increase food security, the ASEAN members should get together and cooperate to incorporate innovative and effective plans to increase the capacity and performance in food production in order to reduce the reliance on food imports from outside the region, especially in the case of soybeans.

Acknowledgements. This work was granted support by the Energy Conservation Promotion Fund, the Energy Policy and Planning Office, the Ministry of Energy of Thailand. The first author is grateful for being granted a PhD scholarship to do his studies.

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APPENDIX C

Relationship between Exchange Rates, Palm Oil Prices, and Crude Oil Prices: A Vine Copula Based GARCH Approach

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This is the original paper that was published in “Modeling Dependence in Econometrics”, Advances in Intelligent Systems and Computing Volume 251, pp 399 – 413.

Relationship between Exchange Rates, Palm Oil Prices, and Crude Oil Prices: A Vine Copula Based GARCH Approach

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Abstract. The dollar is the leading international currency, and it is used widely in the majority of international financial transactions. The various food products that comprise agricultural commodities, as also crude oil, have been using the dollar exchange rate for international trade. Over the past several years, the changes in the dollar exchange rate have shown more volatility in addition to a depreciation trend, which has had an influence on the prices of those commodities. We analyzed the relationship between the dollar exchange rates and the prices of two commodities, palm oil and crude oil, by using the GARCH(1,1) model to examine the volatility of the exchange rates and the future prices 1-Pos. of the prices of both the commodities. The vine copula model is used to analyze the dependence structure between their marginal distributions. The data analyses were based on the daily observations from June 2007 to March 2013. The empirical results of GARCH(1,1) show that the exchange rates, palm oil prices, and crude oil prices have a long-run persistence in volatility. The C-vine copula model reveals that there exists a weak negative dependence for each pair-copula, that is, Exchange rate–Palm oil (E,P) and Exchange rate–Crude oil (E,C) in tree 1. Also, a conditional pair-copula of Palm oil–Crude oil given Exchange rate (P,C|E) in tree 2 offers a weak positive dependence. Moreover, the findings of this study provide evidence that the exchange rate (E) is an important variable that governs the interactions in the dependence structure between palm oil price (P) and crude oil price (C).

1 Introduction

At present, there are continuous changes in food prices due to the complex interactions between the several factors. The demand-side factors include population growth, and rising food consumption of emerging economies. The supply-side

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V.-N. Huynh et al. (eds.), *Modeling Dependence in Econometrics*, 399
Advances in Intelligent Systems and Computing 251,
DOI: 10.1007/978-3-319-03395-2_25, © Springer International Publishing Switzerland 2014

factors include the simultaneous use of food grains to produce biofuel, in which gives rise to a yield of low crops. The others are cyclical factors, such as the depreciation of the U.S. dollar, speculative activities, rising oil prices, input costs in food production, and trading policies of nations [1]. Therefore, it is difficult to take all the factors into account to estimate the percentage of food price changes. To elaborate on the increase of food prices, there exist pieces of literature that have a mention of energy prices and exchange rates which have an effect on food or agricultural commodity prices. There has also been a wide study on energy prices that are related to many types of agricultural commodities, from which it can be concluded that the long-run agricultural prices are driven by the energy prices and that the volatility in the energy markets is transmitted to the food markets [2]. A study on the exchange rate's effect was conducted by Abbott et al. [3] who reviewed and analyzed the twenty five studies and arrived at the conclusion that there were three board factors that drive up the food price. The first is the global changes in production and consumption of key commodity goods. The second is the changing rate of the U.S. dollar. The final factor is the increase in the production of biofuels. The other studies have been those pertaining to econometric modeling, which is based on utilization, to explain the relationship between the exchange rate, energy prices, agricultural commodity prices, and other variables. Their empirical results showed that the depreciation of the U.S. dollar can have an influence on the energy price and/or commodity price [4, 5, 6, 7, 8, 9, 10, 11]. Moreover, Anzuini et al. [12] also found that the expansionary U.S. monetary policy was the cause of the increase in the crude oil price, food price, and other components of the broad commodity price index.

The rise in food and energy prices have caused a burden on the people who are poor and near-poor in the ASEAN region as well as created a negative impact on social and economic development [13]. Under these circumstances, these are major challenges for all the ASEAN members, and they have to find any crucial means to cooperate in the short- and long-term situations in these solving problems because food[1] and energy[2] security are fundamental for upholding the ASEAN economic and social development goals [16]. It also well known that the dollar is a leading currency that is widely used in international financial transactions. The dollar is also used in the international trade of food, agricultural commodities, and crude oil; thus, it is clear that it has been used constantly in the market. Over the past several years, it has been found that the changes in the dollar exchange rate have more

[1] FAO [14] definition: Food security exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life. The four pillars of food security are availability, access, utilization, and stability. The nutritional dimension is integral to the concept of food security.

[2] United Nations [15] definition: Energy security is a term that applies to the availability of energy at all times in various forms, in sufficient quantities, and at affordable prices, without unacceptable or irreversible impact on the environment. These conditions must prevail over the long term if energy is to contribute to sustainable development. Energy security has both a producer and a consumer side to it.

volatility and show a depreciation trend [3, 17]. Thus, it is interesting to analyze the manner in which the volatility of the dollar exchange rates influence the relationship between palm oil prices (MDEX) and crude oil prices (DME), These two commodity prices spark an interest in this study whose results are relevant for ASEAN. In the ASEAN region, palm oil can be produced sufficiently intra-regional demand and the remaining parts can be kept aside for exportation [18]. Moreover, it can be used for producing alternative energy in the form of biodiesel to reduce the effects from the crude oil price crisis. ASEAN has relied on imported crude oil from the Middle East [19]: its price is related to the crude oil prices of other regions such as West Texas Intermediate (WTI) [20].

The purpose of this study are the following: (1) to analyze the dependence between the exchange rates (the strength of the U.S. dollar) and two commodity prices: palm oil (MDEX) and crude oil prices (DME); (2) to analyze the dependence between palm oil and crude oil prices by considering the exchange rate as a conditioning variable.

The copula based GARCH model provides more flexibility for finding out the joint distribution and the transformation of the invariant correlation, without having to assume linear correlation [21]. Therefore, in this study, we used the GARCH(1,1) model [22] to examine the volatility of the exchange rate and the commodity daily prices, which are generally non-normal distributions, and applied the vine copula model to examine the relationship between each commodity, by using the R-package CDVine which was developed by Brechmann and Schepsmeier [23].

The remainder of this paper is organized as follows: part two is the methodology, and part three consists of the data and the empirical findings. Finally, part four provides the conclusions and the policy implications.

2 Methodology

2.1 *Marginal Distribution Model*

We adopt the GARCH(1,1) model [22] with an appropriate distribution (D), residual distribution, for the marginal distribution of the log-difference $\ln \frac{P_t}{P_{t-1}}$ of the three data series: palm oil prices, crude oil prices, and exchange rates.

$$y_t = \mu_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = z_t \sqrt{h_t}, z_t \sim (D) \tag{2}$$

$$h_t = \omega_t + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3}$$

In equation (1), we decompose the log-difference y_t into a mean μ_t and an error term ε_t. Equation (2) define the error term ε_t as the product between conditional variance h_t and a residual z_t. The residual z_t will be assumed to follow an appropriate distribution. Equation (3) presents GARCH(1,1) process where $\omega_t > 0, \alpha \geq 0, \beta \geq 0$

are sufficient to ensure that the conditional variance $h_t > 0$. The $\alpha\varepsilon_{t-1}^2$ represent the ARCH term and α refers to the short run persistence of shocks, while βh_{t-1} represent the GARCH term and β refers to the contribution of shocks to long run persistence $(\alpha + \beta)$. The properties of the GARCH(1,1) model require stationary and persistence of the conditional variance, h_t, of the error term, ε_t. This paper used the second moment condition that was $\alpha + \beta < 1$ to check for these properties. In this study, the R-package fGarch by Wuertz and Chalabi [24] was used to estimate the parameters of GARCH(1,1) model.

For the next analysis by copula functions, the standardized residuals from GARCH(1,1) model were transformed to copula data $(F_1(x_1), F_2(x_2), F_3(x_3))$.

2.2 Copula Function

One approach of modeling the multivariate dependence is the copula. The copula functions can offer us to merge univariate distributions to get a joint distribution with an appropriate dependence structure. The fundamental theorem of copula was given by Sklar [25] as Sklar's theorem. The standard reference book of the copula theory was made by Nelson [26].

Let F be an n-dimensional distribution function with marginal distributions $F_1, ..., F_n$. Then there exists a copula C for all $x = (x_1, ..., x_n)' \in [-\infty, \infty]^n$,

$$F(x) = C(F_1(x_1), ...F_n(x_n)) \tag{4}$$

If $F_1, ..., F_n$ are continuous, then C is unique. Conversely, if C is a copula and $F_1, ..., F_n$ are distribution functions, then the above function $F(x)$ in (4) is a joint distribution function with the marginal distribution $F_1, ..., F_n$. C can be interpreted as the distribution function of an n dimensional random variable on $[0,1]^n$ with uniform margins [23].

We used various copula families contained in the R-package CDVine to measure the dependence of the pair-copula. Table 1 presents the characteristics of the copula families that were used in this study. Table 2 presents the function of Kendall's tau.

2.3 Vine Copula Modeling

Modeling copulas with high dimension is a difficult task because there are large numbers of variables. Vine copulas can cross over this restriction, vine copulas are a flexible tool for describing the multivariate copulas through the graphical model. The multivariate copulas are constructed from a cascade of bivariate copulas or are called pair-copulas. The principles of vine copulas propounded by Joe [29] and extended by Bedford and Cooke [30, 31]. For statistical inference techniques of two classes of C-vines and D-vines are described by Aas et al. [32]. Brechmann and Schepsmeier [23] said that a vine structure can be chosen manually or through expert knowledge, or be given by the data itself. Aas et al. [32] was of the opinion that modeling C-vine might be an advantage when we know that the main variable

Table 1 Characteristics of Copula Families

Name	Pair-copula function	Parameter range
Gaussian	$C(u_1,u_2;\rho) = \Phi_G(\Phi^{-1}(u_1),\Phi^{-1}(u_2);\rho)$ $= \int_{-\infty}^{\phi^{-1}(u_1)}\int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\Pi\sqrt{(1-\rho^2)}} \times [\frac{-(s^2-2\rho st+t^2)}{2(1-\rho^2)}]dsdt$	$\rho \in (-1,1)$
Student's T	$C^T(u_1,u_2;\rho,v) = \int_{-\infty}^{T_v^{-1}(u_1)}\int_{-\infty}^{T_v^{-1}(u_2)} \frac{1}{2\Pi\sqrt{(1-\rho^2)}} \times$ $[1+\frac{(s^2-2\rho sT+T^2)}{v(1-\rho^2)}]^{-(\frac{v+2}{2})}dsdT$	$\rho \in (-1,1)$, $v > 2$
Clayton	$C(u_1,u_2;\theta) = (u_1^{-\theta}+u_2^{-\theta}-1)^{-1/\theta}$	$\theta \in (0,\infty)$
Gumbel	$C(u_1,u_2;\theta) = exp(-[(-\ln(u_1))^\theta+(-\ln(u_2))^\theta]^{\frac{1}{\theta}})$	$\theta \in [1,\infty)$
Frank	$C(u_1,u_2;\theta) = -\frac{1}{\theta}\log(1+\frac{(e^{-\theta u_1}-1)(e^{-\theta u_2}-1)}{e^{-\theta}-1})$	$\theta \in (-\infty,\infty)\backslash\{0\}$
Joe	$C(u_1,u_2;\theta) = 1-[(1-u_1)^\theta+(1-u_2)^\theta-(1-u_1)^\theta(1-u_2)^\theta]^{\frac{1}{\theta}}$	$\theta \in [1,\infty)$
Rotated Clayton 90°	$C(u_1,u_2;\theta) = u_2-[(1-u_1)^{-\theta}+u_2^{-\theta}-1]^{-\frac{1}{\theta}}$	$\theta \in (-\infty,0)$
Rotated Gumbel 90°	$C(u_1,u_2;\theta) = u_2-exp(-[(-\ln(1-u_1))^\theta+(-\ln(u_2))^\theta]^{\frac{1}{\theta}})$	$\theta \in (-\infty,-1]$
Rotated Joe 90°	$C(u_1,u_2;\theta) = u_2-1-[u_1^\theta+(1-u_2)^\theta-u_1^\theta(1-u_2)^\theta]^{\frac{1}{\theta}}$	$\theta \in (-\infty,-1)$
Rotated Clayton 180°	$C(u_1,u_2;\theta) = u_1+u_2-1+[(1-u_1)^{-\theta}+(1-u_2)^{-\theta}-1]^{-\frac{1}{\theta}}$	$\theta \in (0,\infty)$
Rotated Gumbel 180°	$C(u_1,u_2;\theta) = u_1+u_2-1+exp(-[(-\ln(1-u_1))^\theta+$ $(-\ln(1-u_2))^\theta]^{\frac{1}{\theta}})$	$\theta \in [1,\infty)$
Rotated Joe 180°	$C(u_1,u_2;\theta) = u_1+u_2-(u_1^\theta+u_2^\theta-u_1^\theta u_2^\theta)^{\frac{1}{\theta}}$	$\theta \in [1,\infty)$

Source: The copula functions are given as presented in Trivedi and Zimmer [27], Nelson [26], and Fisher [28].

governs interactions in the data or plays an important role in the dependence structure, and that the others are linked to it. So, the C-vine copula model offers us to define the relationship structure between variables according to the purpose of study, and it can describe the relationship between variables through the graphical model or are called pair-copulas.

This study used C-vine copula modeling to analyze the dependence between the palm oil prices, crude oil prices, and exchange rates, a kind of analysis which no one has attempted before with a view to exploring it in depth. The structure of the C-vine model is shown in Figure 1. This study selected the exchange rate which was the first root node. Therefore, our assumption in this study is that the exchange rate is a key variable that plays a role in the linkage between palm oil prices and crude oil prices; this is based on the available literature, and includes the currency, the dollar, which is widely used in international financial transactions. Moreover, the

Table 2 Function of Kendall's tau and Tail Dependence for Bivariate Copula

Copula family	Kendall's tau
Gaussian	$\frac{2}{\Pi}\arcsin\rho$
Student's T	$\frac{2}{\Pi}\arcsin\rho$
Clayton	$\frac{\theta}{\theta+2}$
Gumbel	$1-\frac{1}{\theta}$
Frank	$1-\frac{4}{\theta}+4\frac{D_1(\theta)}{\theta}$
Joe	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}dt$
Rotated Clayton 90°	$\frac{\theta}{\theta-2}$
Rotated Gumbel 90°	$-1-\frac{1}{\theta}$
Rotate Joe 90°	$-1-\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{-2(1+\theta)/\theta}dt$
Rotated Clayton 180°	$\frac{\theta}{\theta+2}$
Rotated Gumbel 180°	$1-\frac{1}{\theta}$
Rotate Joe 180°	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}dt$

Source: Kendall's tau is as presented in Brechmann and Schepsmeier [23].
Note: $D_1(\theta)=\int_0^\theta\frac{c/\theta}{exp(x)-1}$ is the Debye function.

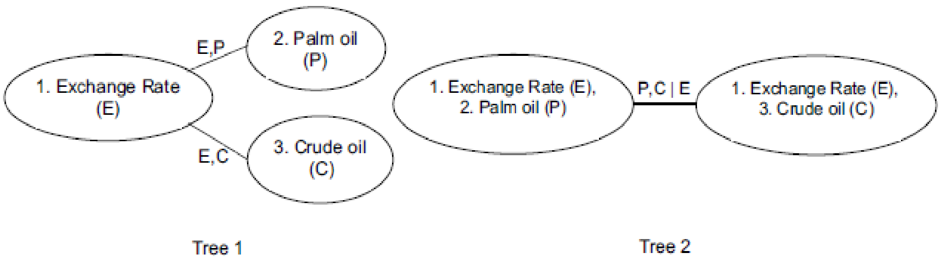

Fig. 1 The pair-copulas of three-dimensional C-vine trees

international trading of food, agricultural commodities, and crude oil is done using the dollar in their respective markets [3, 17].

We presented the three dimensions, which was what we used in this paper. Let $X=(X_1,X_2,X_3)\sim F$ with marginal distribution functions F_1,F_2,F_3 and their density functions f_1,f_2,f_3, which was proposed as follows (see Aas et al. [32]).

$$F(x_1,x_2,x_3)=C(F_1(x_1),F_2(x_2),F_3(x_3)) \tag{5}$$

$$\begin{aligned} f(x_1,x_2,x_3)&=f(x_1)\cdot f(x_2)\cdot f(x_3)\cdot c_{1,2}(F_1(x_1),F_2(x_2))\cdot c_{1,3}(F_1(x_1),F_3(x_3))\\ &\cdot c_{2,3|1}(F_{2|1}(x_2\mid x_1),F_{3|1}(x_3\mid x_1)) \end{aligned} \tag{6}$$

where $c_{1,2}$, $c_{1,3}$, and $c_{2,3|1}$ denote the densities of bivariate copulas $C_{1,2}$, $C_{1,3}$, and $C_{2,3|1}$, respectively. $F_{2|1}$ and $F_{3|1}$ are the marginal conditional distributions that can be derived from formula (7).

The vine copulas involve marginal conditional distributions. The general form of a conditional distribution function is $F(x \mid v)$,

$$F(x \mid v) = \frac{\partial C_{x,v_j|v_{-j}}(F(x \mid v_{-j}), F(v_j \mid v_{-j}))}{\partial F(v_j \mid v_{-j})} \tag{7}$$

where v denotes all the conditional variables and $C_{x,v_j|v_{-j}}$ is a bivariate copula distribution function. For v is univariate, the marginal condition distribution, e.g. $F_{3|1}$ can be presented as

$$F_{3|1}(x_3 \mid x_1) = \frac{\partial C_{31}(F_3(x_3), F_1(x_1))}{\partial F_1(x_1)} \tag{8}$$

2.4 *Vine Copula Estimation*

In the R-package CDVine, the maximum likelihood was used to estimate the parameters of copulas. The log-likelihood of C-vine copula with three dimensions in (6) can be written as

$$\sum_{t=1}^{T} \log[c_{1,2}(F_1(x_{1,t}), F_2(x_{2,t})) \cdot c_{1,3}(F_1(x_{1,t}), F_3(x_{3,t})) \cdot c_{2,3|1}(F_{2|1}(x_{2,t} \mid x_{1,t}), F_{3|1}(x_{3,t} \mid x_{1,t}))]. \tag{9}$$

3 Data and Empirical Findings

To analyze the relationship between the exchange rate and the two commodity prices (palm oil and crude oil), we selected the commodity prices that are related to the AEC. Palm oil prices were obtained from the Malaysia Derivatives Exchange (MDEX) because Malaysia is a major producer and world exporter of palm oil [18]. The crude oil benchmark price for the Asian market is the Dubai (Oman) crude oil price [33] since the Middle East is the major source of crude oil for ASEAN [19]. Hence, the crude oil price of Dubai Mercantile Exchange (DME) was used in this study. The exchange rate data, or the broad dollar index, was measured as a weighted average of the foreign exchange values of the U.S. dollar against the currencies of a large group of major U.S. trading partners (definition from the EcoWin database).

The observations of the three data series were obtained from the EcoWin database during the period from 1 June 2007 to 15 March 2013. For the prices of palm oil and crude oil, we used the Futures 1-Pos of daily close prices. Each data series was transformed into the log-difference, $\ln \frac{P_t}{P_{t-1}}$, before it was used to analyze using the vine copula based GARCH model.

Table 3 presents the descriptive statistics of the log-difference of exchange rate, palm oil price, and crude oil price. Palm oil has a negative average growth rate but crude oil has a positive average growth rate. All of the three data series exhibited negative skewness. If skewness is negative, the market has a downside risk, or there is substantial probability of a big negative return. The kurtosis of these data is greater

Table 3 Data Descriptive Statistics for Log-difference of Exchange Rate, Palm Oil Price, and Crude Oil Price

	Exchange rate	Palm oil	Crude oil
Mean	0.0000	−0.0001	0.0004
Median	−0.0001	0.0000	0.0009
Maximum	0.0174	0.0976	0.1339
Minimum	−0.0230	−0.1104	−0.1337
Std. Dev.	0.0039	0.0203	0.0230
Skewness	−0.1172	−0.3472	−0.1574
Kurtosis	6.5570	7.0304	7.6829
Jarque-Bera	730.13	961.06	1265.75
(p-value)	(0.0002)	(0.0000)	(0.0001)
p-value of Dickey-Fuller test	0.01	0.01	0.01
Number of observations	1,379	1,379	1,379

than 3. Hence, this kurtosis can be said to be super Gaussian and leptokurtic. This means that the growth rates of the empirical data have a typically spiky probability distribution function with heavy tails. The null hypothesis of normality of the Jarque-Bera tests are rejected in all the data series. The Dickey-Fuller test shows that these data series are stationary at p-value 0.01.

Table 4 Results of GARCH(1,1) Test with Normal Residual for Exchange Rate Data, and of Skewed Student T Residual for Palm Oil and Crude Oil Data

	Exchange rate	Std. error (p-value)	Palm oil	Std. error (p-value)	Crude oil	Std. error (p-value)
ω	1.007e-07	5.176e-08 (0.0518*)	3.903e-06	1.721e-06 (0.0233*)	2.325e-06	1.749e-06 (0.184)
α	0.0636	1.049e-02 (1.34e-09***)	0.0746	1.501e-02 (6.75e-07***)	0.0529	1.214e-02 (1.32e-05***)
β	0.9304	1.107e-02 (<2e-16***)	0.9155	1.606e-02 (<2e-16***)	0.9451	1.231e-02 (<2e-16***)
ν (degree of freedom)	-	-	7.6810	1.485e+00 (2.31e-07***)	5.0670	7.455e-01 (1.07e-11***)
γ (skewness)	-	-	0.9685	3.557e-02 (<2e-16 ***)	0.9418	3.112e-02 (<2e-16 ***)
Log likelihood	5,869.953	-	3,654.827	-	3,499.523	-
K-S test	-	-	-	-	-	-
(p-value)		(1)		(0.9208)		(1)
Box-Ljung test	-	-	-	-	-	-
(p-value)						
1st moment	-	(0.4301)	-	(0.2515)	-	(0.5832)
2nd moment	-	(0.9363)	-	(0.8898)	-	(0.7921)
3rd moment	-	(0.6521)	-	(0.0732)	-	(0.7765)
4th moment	-	(0.8513)	-	(0.8803)	-	(0.6423)

Note: Significant codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 4 presents the results of GARCH(1,1) with normal residual for the exchange rate data and skewed student T residual for the palm oil and crude oil data. The asymmetry parameters, γ, are significant and less than 1, thus indicating that the palm oil and crude oil data series are skewed to the left.

For the exchange rate, palm oil, and crude oil, the $\alpha+\beta$ are 0.9940, 0.9901, and 0.9980, respectively; this implies that their volatilities have a long-run persistence. For the short-run effect of the unexpected factors, we considered the event from the α parameter. Therefore, we can see that they nearly have the values 0.0636, 0.0746, and 0.0529, and a small impaction for volatility.

Next, we transformed the standardized residuals from the GARCH(1,1) model into the uniform [0,1] by using the empirical distribution function $F_n(x) = \frac{1}{n+1}\Sigma_{i=1}^{n} 1$ $(X_i \leq x)$, where $X_i \leq x$ the order statistics and 1 is the indicator function. The transformed data were used in the Kolmogorov-Smirnov (K-S) test for uniform [0,1] and the Box-Ljung test for serial correlation. More details are available in Patton [34] and Manthos [35]. These tests are necessary to check for the marginal distribution models' misspecification before using the copula model.

The results of the K-S test show that these marginal distributions are uniform, by accepting the null hypothesis at p-values equal to 1 or nearly 1. The results of the Box-Ljung test provide that all of the four moments of all the marginal distributions are i.i.d., by accepting the null hypothesis that there is no serial correlation at p-values greater than 0.05. Therefore, our marginal distributions were not misspecified and can be used for the copula model.

3.1 *Results of C-vine Copula*

Figure 1 presents each pair-copula of the three-dimensional C-vine tree; there are two pair-copulas in tree 1 and one pair-copula in tree 2. The first and second pair-copulas in tree 1 are Exchange rate–Palm oil (E,P) and Exchange rate–Crude oil (E,C), respectively. The third pair-copula in tree 2 is a conditional pair-copula, Palm oil–Crude oil given Exchange rate (P,C|E).

We used the Gaussian copula, Student's T copula, Clayton copula, Gumbel copula, Frank copula, Joe copula, rotated Clayton 90° and 180°, rotated Gumbel 90° and 180°, and rotated Joe 90° and 180° copula to fit the data.

The AIC and the BIC are used to appraise which copula is the best fit. The Kendall's tau correlation which was transformed from the copula parameter was used because each family of copula has a different range of copula parameters; hence we inverse a copula parameter into a Kendall's tau correlation, and it is bound on the interval $[-1,1]$. Kendall's tau is a measure of concordance and is a function of copula; hence, we can use it to assess the range of dependence covered by the families of copula. A goodness-of-fit test based on Kendall's tau provides the Cramér-von Mises (CvM) and Kolmogorov-Smirnov (K-S) test statistics and the estimated p-values by bootstrapping [23] in order to test the appropriateness of the copula model under the null hypothesis that the empirical copula C belongs to a parametric class C' of any copulas, $H_0 : C \in C'$.

The results of the pair-copulas, the Exchange rate–Palm oil (E,P), the Exchange rate–Crude oil (E,C), and the Palm oil–Crude oil given Exchange rate (P,C|E), are presented in Table 5.

Table 5 Results of C-vine Copula Model

Tree	Pair-copula	Copula family	Copula parameter	Std. error (p-value)	Kendall's tau	AIC	BIC	p-value CvM	KS
1	E,P	Gaussian	−0.2438	0.0246 (0.0000)	−0.1568	−82.3568	−77.1276	0.38	0.47
	E,C	Gaussian	−0.4260	0.0203 (0.0000)	−0.2802	−273.8174	−268.5883	0.76	0.74
2	P,C|E	Gaussian	0.1660	0.0259 (0.0000)	0.1062	−36.4692	−31.2401	0.61	0.38

Table 5 presents the results of C-vine copula model. The first pair is the Exchange rate–Palm oil (E,P), the Gaussian copula provided the smallest AIC and BIC, and the CvM and K-S tests accepted the null hypothesis with p-values greater than 0.05, which means that the dependence structure of the data series is appropriate for a chosen family. Therefore, the Gaussian copula is the best fit copula, with a copula parameter of −0.2438 and a Kendall's tau correlation of −0.16. This implies that when the exchange rate increases (i.e., when the U.S. dollar is stronger), the palm oil price decreases, and vice versa. However, there exists a weak negative dependence in this pair-copula, thus indicating that a change in palm oil price is slightly related to a change in exchange rate.

For the second pair, the Exchange rate–Crude oil (E,C), the Gaussian copula is chosen to explain the dependence structure of this pair-copula with a copula parameter of −0.4260 and a Kendall's tau correlation of −0.28. This means that when the exchange rate increases (i.e., when the U.S. dollar is stronger), the crude oil price decreases, and vice versa. However, this pair-copula has a weak negative dependence, thereby indicating that a change in crude oil price is slightly related to a change in exchange rate, which is similar to the result of the first pair-copula.

The parameter of each pair-copula from an appropriate copula family in tree 1 was used to construct a conditional pair-copula of Palm oil–Crude oil given Exchange rate (P,C|E) in tree 2. This pair-copula provides the Gaussian copula is the best fit with the copula parameter of the Gaussian copula is 0.1660 and the Kendall's tau correlation is 0.11. Therefore, whether it is an upward or a downward trend, both the commodity prices tend to move together. However, this pair-copula has a weak positive dependence; this means that a change in palm oil price is slightly related to a change in crude oil price.

According to our results, the copula parameters and the Kendall's tau correlations of a conditional pair-copula (P,C|E), 0.1660 and 0.11, are less than those that are obtained for the bivariate pair-copula Palm oil–Crude oil (P,C). Further testing reveals that the Gaussian copula of a bivariate copula (P,C) offers a copula parameter and a Kendall's tau correlation of 0.2495 and 0.16, respectively. This implies that the exchange rate (E) has an influence in the relationship between the palm oil price (P) and the crude oil price (C). The exchange rate (E) is an important variable that governs the interactions in the dependence structure between the palm oil price (P) and the crude oil price (C).

4 Conclusions and Policy Implications

We analyzed the relationship between the dollar exchange rates and two commodity prices, palm oil price and crude oil price. The analysis was done by using the GARCH(1,1) model to examine the volatility of the exchange rates and the future prices 1-Pos. of both the commodity prices. The vine copula model was used to analyze the dependence structure between their marginal distributions. The data analyses were based on the daily observations during the period from June 2007 to March 2013. The empirical results of GARCH(1,1) showed that the exchange rates, palm oil prices, and crude oil prices have a long-run persistence in volatility. The C-vine copula consisted of three pair-copulas (Figure 2), which are Exchange rate–Palm oil (E,P), Exchange rate–Crude oil (E,C), and Palm oil–Crude oil given Exchange rate (P,C|E). Of the three, the Exchange rate–Palm oil (E,P) and Exchange rate–Crude oil (E,C) are in the first tree, and the conditional pair-copula, Palm oil–Crude oil given Exchange rate (P,C|E), is in the second tree.

The Gaussian copula was chosen to explain the dependence structure of the Exchange rate–Palm oil (E,P) pair-copula with a copula parameter of -0.2438 and a Kendall's tau correlation of -0.16. Similarly, the Exchange rate–Crude oil (E,C) indicates the Gaussian copula as the best fit with a copula parameter of -0.4260 and a Kendall's tau correlation of -0.28.

As for the last pair-copula, the conditional pair-copula Palm oil–Crude oil given Exchange rate (P,C|E), the Gaussian copula was chosen to explain the dependence structure with a copula parameter of 0.1660 and a Kendall's tau correlation of 0.11. Furthermore, the findings of this research provide evidence that the exchange rate (E) is an important variable that governs the interactions in the dependence structure between the palm oil price (P) and the crude oil price (C).

Our results showed that the volatility of the exchange rate, palm oil price and crude oil price are interrelated (see Figure 2). Considering the Kendall's tau correlation, the pair-copulas Exchange rate–Palm oil (E,P) and Exchange rate–Crude oil (E,C) have a weak negative correlation. The conditional pair-copula Palm oil–Crude oil given Exchange rate (P,C|E) has a weak positive correlation.

This study found some evidences of excess kurtosis, skewness, and non-normal distribution in each data series, exchange rate, palm oil price and crude oil price. That is why the copula model is an appropriate tool to measure the relationship between each variable considered in this study. The copula can model the dependence between random variables without an assumption of linear correlation.

From the empirical results of this study, it can be concluded that a depreciating exchange rate has a relation with an increase in palm oil price in the Malaysian market (MDEX) and crude oil price in the Dubai market (DME). As far as the palm

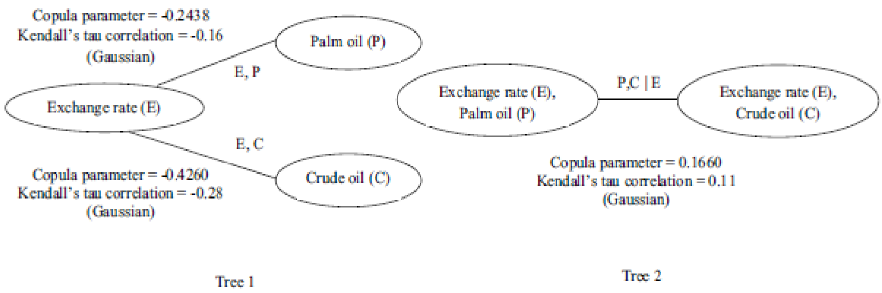

Fig. 2 The C-vine copula for the exchange rate, and palm oil and crude oil data with the pair-copula families and the Kendall's tau values

oil exports of ASEAN are concerned, a depreciating dollar exchange rate would prove advantageous to ASEAN because that would generate more income for the region. But, on the other hand, the incentive in world market price and the increased profitability in international trade will cause an increase in the volume of palm oil that is exported from the region. The consequences can be negative in that it can lead to a rise in the local price, or a shortfall for consumers in some areas of the ASEAN region. For example, if this were to occur in Indonesia, it would tend to make palm oil producers increase exports when the world market price increases, and this would create a shortfall for domestic consumers [18]. Thus, the palm oil producers and exporters of ASEAN who are from Indonesia, Malaysia, and Thailand should endeavor to keep the balance between the intra-regional demand and the exportation demand. As for the crude oil imports of ASEAN, a rise in crude oil price will increase the cost of living of the people living in the ASEAN region.

So, a depreciation in the exchange rate is related to an increase in the palm oil price and the crude oil price. The dollar exchange rate is an important variable in that the ASEAN nations have to monitor and manage its impact in terms of food security and energy security. As for the investors, they should take into consideration the risk that could arise from a change in the exchange rate, which, again, is related to the palm oil price and the crude oil price.

ASEAN can produce enough quantity of palm oil and is the world largest exporter of this food commodity [18]. However, ASEAN has to rely on import crude oil from the Middle East [19]: the fact is that the crude oil price of the Dubai Mercantile Exchange (DME) is related to the West Texas Intermediate (WTI) as well as the other markets in the world [20]. Thus, the dollar exchange rate should have more influence on the crude oil price from the Middle East (DME) than the palm oil price from Malaysia (MDEX). This corresponds to the empirical results of this research: the negative dependence between the dollar exchange rate and the crude oil price (DME) is greater than the negative dependence between the dollar exchange rate and the palm oil price (MDEX).

For the bivariate copula analysis of palm oil price and crude oil price, there exists a weak positive dependence (a copula parameter 0.2495 and Kendall'stau correlation 0.16); this means that the intensity of the co-movement of their prices is less. It can be explained by the fact that ASEAN has a high production capacity of palm oil, and so it can reduce the direct and indirect effects of fluctuations in crude oil prices in the world market. This is the reason why the dependence between the two commodity prices is weak.

From our findings, it is evident that the dependence between the palm oil price and the crude oil price is still weak. Also, there exists a high production capacity of palm oil in ASEAN. Therefore, using biodiesel as alternative energy is one of the choices that should be considered. Palm biodiesel can reduce energy cost for consumers when they are faced with a continuous rise in crude oil prices. For example, in Malaysia, where there are a lot of cultivated areas of oil palm trees and there is a high potential for producing palm biodiesel, if the production of biodiesel were implemented very effectively, it would have a positive impact on the economy in many ways [36]. However, while deciding to use the produce from the oil palm tree for biodiesel production, the policy makers should take into consideration the suitability as regards food security, environment, and critical social needs [18, 37].

Acknowledgements. This work was granted support by the Energy Conservation Promotion Fund, the Energy Policy and Planning Office, the Ministry of Energy of Thailand. The first author is grateful for being granted a PhD scholarship to do his studies.

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APPENDIX D

Dependence Structure between World Crude Oil Prices: Evidence from NYMEX, ICE, and DME Markets

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This is the original paper that was submitted and presented at

“The Seventh International Conference of the Thailand Econometric Society,

Faculty of Economics, Chiang Mai University, Thailand,

January 8-10, 2014”.

Dependence Structure between World Crude Oil Prices: Evidence from NYMEX, ICE, and DME Markets

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Abstract
This paper examines the dependence structure between world crude oil prices using the D-vine copula based GARCH model to analyze three random variables, namely, Light crude futures 1-Pos (NYMEX), Brent crude futures 1-Pos (ICE), and Oman crude futures 1-Pos (DME). We find that NYMEX–ICE, NYMEX–DME, and ICE–DME have relatively strong dependence. In addition, we find the evidences for asymmetric tail dependence in each pair with the values of upper tail and lower tail dependences of three pair-copulas as being quite close to each other. Therefore, our findings support the "one great pool" hypothesis. Moreover, the results from the D-vine copula model indicate that the ICE is an important variable that governs the interactions in the dependence structure between the NYMEX and the DME. In other words, the change in the oil price of the ICE will impact quite significantly the prices of the NYMEX and the DME.

Keywords: futures crude oil prices, empirical Kendall's tau, distance measure, vine copula

1. Introduction

The observation "The world oil market, like the world ocean, is one great pool" was proposed by Adelman [1, 2]. This assumption implies that the crude oil markets in each region are linked together or have integration. Moreover, Adelman [3] said that the transportation of oil between nations was relatively easy; oil exporters tend to seek the markets that make it more profitable for them and, thus, cause those oil markets to become "a single world market." As for the point of view of Adelman [1, 2], there were different empirical studies that supported the "one great pool" assumption. The crude oil benchmark prices in the international market (e.g., Brent, West Texas Intermediate [WTI], Dubai, Oman, and Maya) were used for the studies and several types of econometric models were utilized to analyze the data. Starting with Hammoudeh et al. [4], they used the threshold cointegration method to study the relationship between pairs of crude oil benchmark prices. They found out that there was a long-run equilibrium relationship between different crude oil benchmark prices. Reboredo [5] used copula based GARCH model to study the dependence structure between the crude oil benchmark prices in international crude oil markets. It was found that in times of crude oil market stress, the crude oil price in each market tends to have co-movement with the same intensity. AlMadi and Zhang [6] used vector error correction model (VECM) and Granger causality tests. The empirical results showed that the four crude oil benchmarks prices were found to be cointegrated; in addition, the following facts were identified: WTI significantly leads Brent, Dubai, and Oman; Brent significantly leads Dubai and Oman; and Oman moderately leads Dubai. Therefore, we can definitely say that if a market has supply and demand shocks/price shock, then it has an impact on other regional markets.

For analyzing the relationship of crude oil prices between the markets, most of the studies in the previous works (see [4], [5], [6]) used the bivariate model. In fact, the random variables that were used in those studies were also related to other variables. For hypothesis testing, in the context of world crude oil, the market is globalized or regionalized? Clearly, it is a multivariate model that we need in order to analyze the relationship between several markets (where there are more than two random variables) or to analyze the multivariate joint probability in higher dimensions. As a result, we are convinced that this model would be more appropriate than the bivariate model because the multivariate model can take all the variables to be considered into account. In order to fill the gap of bivariate model, this paper proposes the vine copula model [7, 8] to study the dependence structure between the prices of crude oil in three continents, namely, North America, Europe, and Asia, which are likely to share significant relationship, as is evident from Figure 1. The vine copula model is a flexible tool to analyze the relationship between random variables, in which is used the multivariate dependence modeling. It allows us to define the relationship structure between the variables by using expert knowledge or concordance of data, or both, and it can describe the relationship between the variables through the graphical model, or through what are called pair-copulas, as shown in Figure 2.

Figure 1 displays the graph of crude oil futures prices and presents the major events which affected the prices during the period from 1 June 2007 to 28 June 2013.

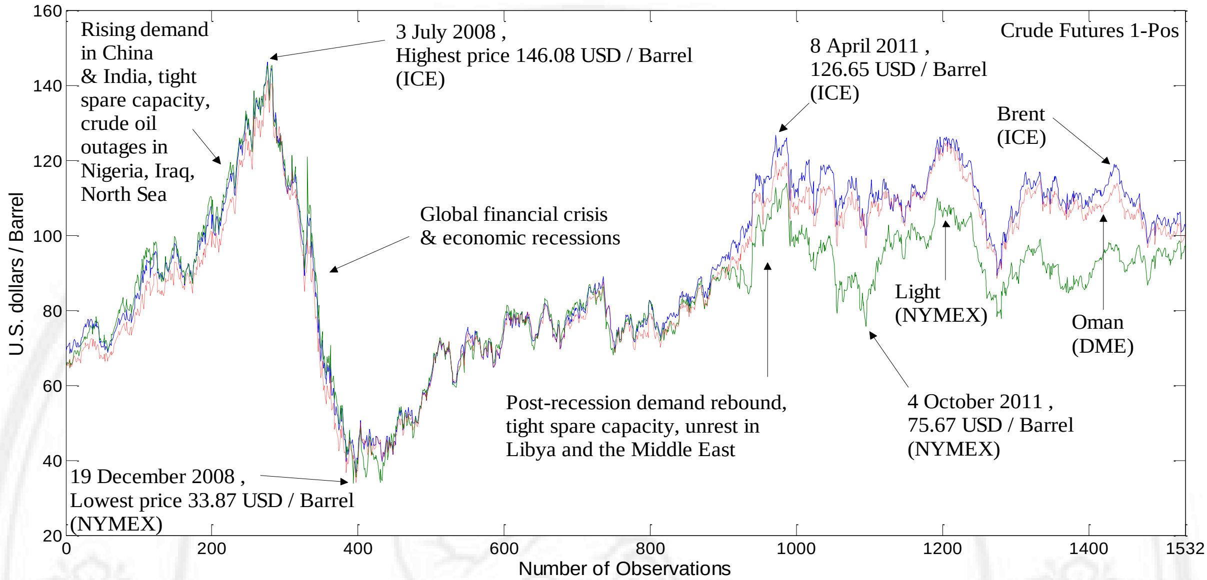

Figure 1. The crude oil futures prices of the NYMEX, ICE, and DME (sources: Ecowin database, Hamilton [9], OECD [10], Australian Institute of Petroleum [11]).

In this study, we used the crude oil futures prices which represented the crude oil prices of each continent: Light crude futures 1-Pos of the New York Mercantile Exchange (NYMEX), for North America; Brent crude futures 1-Pos of the Intercontinental Exchange (ICE), for Europe; and Oman crude futures 1-Pos of the Dubai Mercantile Exchange (DME), for Asia. The daily closing prices during the period from 26 December 2008 to 28 June 2013 were used for the analysis. We used the data of this period because it is a period in which the oil prices have rebounded from being the lowest after the shocks from the global financial crisis.

The vine copula model is used to analyze the dependence structure between three random variables of the crude oil futures prices. More specifically, we want to examine the following: (1) the order of the relationship of the three crude oil markets through an appropriate vine tree structure and (2) the particular market that is a key variable that governs the interactions within these three markets. The research results from this study will provide more understanding regarding the relationships between crude oil markets and their dependence structure, which will be useful for policy makers in that they will be able to monitor the changes in the crude oil prices for risk prevention, in the energy security context, and risk management, for investment in the commodity market; furthermore, the results will be useful for an improved understanding of the "one great pool" hypothesis.

The remainder of this work is organized as follows: part two is the methodology, and part three consists of the data and the empirical findings. Finally, part four makes up the conclusions.

2. Methodology

The objective of the study is to analyze the relationships between three crude oil prices: the NYMEX, ICE, and DME. First, we have to give the definitions of the variables, which are as follows: the NYMEX is the Light crude futures 1-Pos price, the ICE is the Brent crude futures 1-Pos price, and the DME is the Oman crude futures 1-Pos price. The ARMA-GARCH model is used to find out the "marginal distributions" for the copula model since this model has been widely used for modeling the volatility of the time series data in the financial field. The residuals (ε_t) from the appropriate marginal models of the three data series will be standardized. The standardized residuals (z_t) will then be transformed using the empirical distribution function and, thereafter, we obtain the marginals. These marginals are then used as inputs to the copula data $(F_1(x_1), F_2(x_2), F_3(x_3))$. Next, the vine copula model is used to analyze the dependence structure; also used are two approaches for specifying the structure of the D-vine model: (1) the empirical Kendall's tau, which is rank correlation, and (2) the distance measure that is based on the idea of information-theoretic entropy.

2.1 Marginal distribution model

Different models are appropriate for different time series data. Therefore, we adopt ARMA(p,q)-GARCH(1,1) model [12] with skewed student-T distribution residual (*SkT*) for the marginal distribution of the log-difference $\ln\frac{P_t}{P_{t-1}}$ of the crude oil future prices 1-Pos (y_t): the NYMEX, ICE, and DME.

2.1.1 ARMA(p,q)-GARCH(1,1)

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \sum_{i=1}^{q} b_i \varepsilon_{t-i} + \varepsilon_t \quad (1)$$

$$\varepsilon_t = z_t\sqrt{h_t},\ z_t \sim SkT(\nu, \lambda) \quad (2)$$

$$h_t = \omega_t + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (3)$$

In equation (1) is presented the ARMA(p,q) process, where y_{t-i} is an autoregressive term of y_t and ε_t is an error term. Equation (2) then defines this residual as the product between the conditional variance h_t and a random variable z_t. The residual ε_t will be standardized by $\frac{\varepsilon_t}{\sqrt{h_t}}$ to be a standardized residual z_t. The z_t is assumed to follow the skewed student-T (*SkT*) distribution with the degree of freedom parameter ν and the skewness parameter λ. Equation (3) presents the GARCH(1,1) process, where $\omega_t > 0$, $\alpha \geq 0$, $\beta \geq 0$ are sufficient to ensure that the conditional variance $h_t > 0$. The $\alpha\varepsilon_{t-1}^2$ represents the ARCH term and α refers to the short-run persistence of shocks, while βh_{t-1} represents the GARCH term and β refers to the contribution of shocks to the long-run persistence $(\alpha + \beta)$. The second moment condition is $\alpha + \beta < 1$.

As for the skewed student-T (*SkT*) distribution $p(z_i|v,\lambda)$ with the degree of freedom parameter ν and the skewness parameter λ in the R-package, as introduced by Fernandez and Steel [13], it can be written as $p(z_i|v,\lambda) = \frac{2}{\lambda+1/\lambda}\left\{f_v\left(\frac{z_i}{\lambda}\right)I_{[0,\infty)}(z_i) + f_v(\lambda z_i)I_{(-\infty,0)}(z_i)\right\}$, where $f_v(\cdot)$ is unimodal and symmetric around zero, the standardized residuals z_i are assumed to be iid, and I denotes the indicator function.

In this study, the R-package fGarch by Wuertz and Chalabi [14] is used to estimate the parameters of the ARMA(p,q)-GARCH(1,1) model.

For the next analysis using the copula functions, the standardized residuals from the GARCH(1,1) model were transformed to the copula data $(F_1(x_1), F_2(x_2), F_3(x_3))$ by using the empirical distribution function.

2.2 Copula functions

One approach toward modeling the multivariate dependence is the copula. The copula functions offer us the flexibility to merge univariate distributions to get a joint distribution with an appropriate dependence structure. The fundamental theorem of copula is the Sklar's theorem, which was proposed by Sklar [15]. The standard reference book of the copula theory was put together by Nelson [16].

Let F be an n-dimensional distribution function with marginal distributions $F_1, \ldots, F_n$. Then there exists a copula C for all $x = (x_1, \ldots, x_n)' \in [-\infty, \infty]^n$, given by

$$F(x) = C(F_1(x_1), \ldots, F_n(x_n)). \tag{4}$$

If $F_1, \ldots, F_n$ are continuous, then C is unique. Conversely, if C is a copula and $F_1, \ldots, F_n$ are distribution functions, then the above function $F(x)$ in equation (4) is a joint distribution function with marginal distribution $F_1, \ldots, F_n$. C can be interpreted as the distribution function of an n-dimensional random variable on $[0, 1]^n$ with uniform margins [7].

We used the various copula families contained in the R-package CDVines to measure the dependence of the pair-copula. Table 1 presents the characteristics of the copula families that were used in this study. Table 2 presents the functions of Kendall's tau and the tail dependence in each copula family.

Table 1. Characteristics of Copula Families

Name	Pair-copula function	Parameter range
Gaussian	$C(u_1, u_2; \rho) = \Phi_G(\Phi^{-1}(u_1), \Phi^{-1}(u_2);\ \rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\rho^2)}} \times \left\{\frac{-(s^2-2\rho st+t^2)}{2(1-\rho^2)}\right\} dsdt$	$\rho \in (-1, 1)$
Student's T	$C^T(u_1, u_2; \nu, \rho) = \int_{-\infty}^{T_\nu^{-1}(u_1)} \int_{-\infty}^{T_\nu^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} \times \left\{1 + \frac{s^2-2\rho sT+T^2}{\nu(1-\rho^2)}\right\}^{-(\frac{\nu+2}{2})} dsdT$	$\rho \in (-1, 1)$, $\nu > 2$
Clayton	$C(u_1, u_2; \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}$	$\theta \in (0,\infty)$
Gumbel	$C(u_1, u_2; \theta) = exp\left(-[(-logu_1)^\theta + (-logu_2)^\theta]^{\frac{1}{\theta}}\right)$	$\theta \in [1,\infty)$
Frank	$C(u_1, u_2; \theta) = -\frac{1}{\theta} log\left(1 + \frac{(e^{-\theta u_1} - 1)(e^{-\theta u_2} - 1)}{e^{-\theta} - 1}\right)$	$\theta \in (-\infty,\infty)$
Joe	$C(u_1, u_2; \theta) = 1 - [(1-u_1)^\theta + (1-u_2)^\theta - (1-u_1)^\theta(1-u_2)^\theta]^{\frac{1}{\theta}}$	$\theta \in [1, \infty)$
BB1	$C(u_1, u_2; \theta, \delta) = \left\{1 + [(u_1{}^{-\theta} - 1)^\delta + (u_2{}^{-\theta} - 1)^\delta]^{\frac{1}{\delta}}\right\}^{-\frac{1}{\theta}}$	$\theta \in (0, \infty)$, $\delta \in [1, \infty)$
Rotated Clayton 180°	$C(u_1, u_2; \theta) = u_1 + u_2 - 1 + [(1-u_1)^{-\theta} + (1-u_2)^{-\theta} - 1]^{-\frac{1}{\theta}}$	$\theta \in (0,\infty)$
Rotated Gumbel 180°	$C(u_1, u_2; \theta) = u_1 + u_2 - 1 + exp\left(-[(-\log(1-u_1))^\theta + (-log(1-u_2))^\theta]^{\frac{1}{\theta}}\right)$	$\theta \in [1,\infty)$
Rotated Joe 180°	$C(u_1, u_2; \theta) = u_1 + u_2 - (u_1{}^\theta + u_2{}^\theta - u_1{}^\theta u_2{}^\theta)^{\frac{1}{\theta}}$	$\theta \in [1, \infty)$
Rotated BB1 180°	$C(u_1, u_2; \theta, \delta) = u_1 + u_2 - 1 + \left\{1 + [((1-u_1)^{-\theta} - 1)^\delta + ((1-u_2)^{-\theta} - 1)^\delta]^{\frac{1}{\delta}}\right\}^{-\frac{1}{\theta}}$	$\theta \in (0, \infty)$, $\delta \in [1, \infty)$

Source: Copula functions were presented in Trivedi and Zimmer [17], Nelson [16], Fisher [18], and Manner [19].

2.2.1 Tail dependence

Tail dependence explains the degree of dependence in the upper and lower tails of a bivariate distribution. The distributions of the tail dependences in the case of financial risk are interesting because tail dependences can model the dependence of loss events across portfolio assets. Joe [20] explained the dependence of the tails of the bivariate copula.

Let *X* and *Y* be the random variables with marginal distribution functions *F* and *G*. The tail dependence of *X* and *Y* can be given as

$$\tau^U = \lim_{u\to 1}(P(X > F^{-1}(u) | Y > G^{-1}(u)) = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u} \quad (5)$$

If $\tau^U \in (0,1]$, the joint distribution of X and Y, shows upper tail, indicating that the probability of the joint occurrence of the extreme values is positive; if $\tau^U = 0$, then there is no upper tail dependence. Similarly, in

$$\tau^L = \lim_{u \to 0} \frac{C(u,u)}{u}, \tag{6}$$

if $\tau^L \in (0,1]$, the joint distribution of X and Y shows lower tail dependence, indicating that the probability of the joint occurrence of the extreme values is negative; if $\tau^L = 0$, then there is no lower tail dependence.

Table 2. Function of Kendall's tau and Tail Dependence for Bivariate Copula

Copula family	**Kendall's tau**	**Tail dependence (lower, upper)**
Gaussian	$\frac{2}{\pi}\arcsin(\rho)$	0
Student's T	$\frac{2}{\pi}\arcsin(\rho)$	$\tau^L = \tau^U = 2T_{\nu+1}\left(-\sqrt{\nu+1}\sqrt{\frac{1-\rho}{1+\rho}}\right)$
Clayton	$\frac{\theta}{\theta+2}$	$\left(2^{-\frac{1}{\theta}}, 0\right)$
Gumbel	$1-\frac{1}{\theta}$	$\left(0, 2-2^{\frac{1}{\theta}}\right)$
Frank	$1-\frac{4}{\theta}+4\frac{D_1(\theta)}{\theta}$	$(0,0)$
Joe	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}dt$	$\left(0,\ 2-2^{\frac{1}{\theta}}\right)$
BB1	$1-\frac{2}{\delta(\theta+2)}$	$\left(2^{-\frac{1}{\theta\delta}}, 2-2^{\frac{1}{\delta}}\right)$
Rotated Clayton 180°	$\frac{\theta}{\theta+2}$	$\left(0, 2^{-\frac{1}{\theta}}\right)$
Rotated Gumbel 180°	$1-\frac{1}{\theta}$	$\left(2-2^{\frac{1}{\theta}}, 0\right)$
Rotate Joe 180°	$1+\frac{4}{\theta^2}\int_0^1 t\log(t)(1-t)^{2(1-\theta)/\theta}dt$	$\left(2-2^{\frac{1}{\theta}}, 0\right)$
Rotated BB1 180°	$1-\frac{2}{\delta(\theta+2)}$	$\left(2-2^{\frac{1}{\delta}}, 2^{-\frac{1}{\theta\delta}}\right)$

Note: $D_1(\theta) = \int_0^{\theta} \frac{c/\theta}{\exp(x)-1}dx$ is the Debye function [7].

2.3 Vine copula modeling

Modeling dependencies in high dimension by the standard multivariate copulas are inflexible because they do not allow for different dependency structures between pairs of variables [21]. Vine copulas can cross over this restriction; vine copulas are a flexible tool for illustrating the multivariate copulas through graphical models. The multivariate copulas are constructed from a cascade of bivariate copulas (called pair-copulas), as a result of which we are able to select bivariate copulas from a wide range of families.

The principles of vine copulas were propounded by Joe [22] and extended by Bedford and Cooke [23, 24]. Brechmann and Schepsmeier [7] stated that a vine structure can be chosen manually or through expert knowledge, or be given by the data itself.

This study used D-vine copula modeling to analyze the dependence between the crude oil futures prices of the NYMEX, ICE, and DME. D-vine copula is a special class of regular vine, and it gives us a specific way of decomposing the density function. The D-vine model can be specified in the form of a nested set of trees, of which each tree is a path, as shown in Figure 2. The modeling of the D-vine copula is as follows: first an appropriate D-vine tree structure has to be specified; next, adequate copula families have to be selected and estimated [7].

2.3.1 Structure of D-vine

We let the structure of D-vine be given by the data itself. To construct a D-vine structure, we need to select the order of the variables in the first tree, as the first step. There are many approaches to ordering the sequences of variables, such as the empirical Kendall's tau, the Spearman's rho, the distance measure [21], and the degree of freedom parameters of the Student's T copula [25]. This paper used the empirical Kendall's tau and the distance measure, and compared the results from these two approaches.

Empirical Kendall's tau

The Kendall's rank correlation, or the empirical Kendall's tau ($\bar{\tau}_n$), as in equation (7), is used to measure the degree of dependence in each pair of the transformed standardized residuals of the data set. A high value of $\bar{\tau}_n$ means that there is high dependency between the two variables. The strongest dependencies, in terms of absolute empirical values of pairwise Kendall's tau, are used as the first pair in the first, and is subsequently followed by the next. The selection of the D-vine structure is based on the one that maximizes the sum of the corresponding absolute value of $\bar{\tau}_n$ in the first tree.

$$\bar{\tau}_n = \frac{P_n - Q_n}{\binom{n}{2}} = \frac{4}{n(n-1)} P_n - 1, \tag{7}$$

where P_n and Q_n are the number of concordant and discordant pairs, respectively. The two pairs, (X_i, Y_i) and (X_j, Y_j), can be said to be concordant when $(X_i - X_j)(Y_i - Y_j) > 0$, and discordant when $(X_i - X_j)(Y_i - Y_j) < 0$ [26].

Distance Measure

There are many approaches to measuring the distance between probability distributions or data set. This study used the approach to distance measure which is closely related to divergence measures based on the idea of information-theoretic entropy first presented by Shannon [27]. This divergence measure is symmetric and is referred to as the non-directional divergence measure. It qualifies as distance measure [28]. The formula can be written as given in equation (8).

$$I(f_1, f_2) = K(f_1, f_2) = \int (f_1 - f_2) \log \frac{f_1}{f_2} dy, \tag{8}$$

where $I(f_1, f_2)$ is the distance measure between the probability functions f_1 and f_2 of the standardized residual. A low value of $I(f_1, f_2)$ means that there is high association, or high affinity between f_1 and f_2. For ordering variables, the lowest $I(f_1, f_2)$ is used as the first pair in the first tree, and is subsequently followed by the next. The selection of the D-vine structure is based on the one that minimizes the sum of the corresponding absolute value of $I(f_1, f_2)$ in the first tree.

D-vine tree

Thereafter, we order the sequences of the variables in the first tree by the empirical Kendall's tau and the distance measure. We can construct the D-vine structure for three variables as shown in Figure 2.

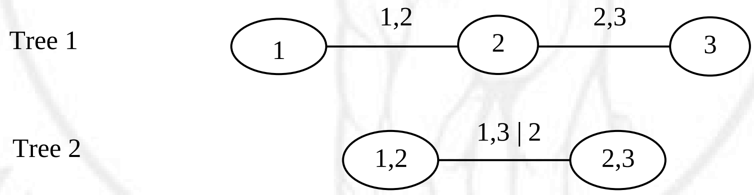

Figure 2. The pair-copulas of three-dimensional D-vine trees.

2.3.2 Density function of D-vine

We present the three dimensions, which are what we used in this paper. Let $X = (X_1, X_2, X_3) \sim F$ with marginal distribution functions F_1, F_2, F_3 and their density functions f_1, f_2, f_3, which have been proposed as follows (see [8]).

$$\begin{aligned} f(x_1, x_2, x_3) = {} & f(x_1) \cdot f(x_2) \cdot f(x_3) \\ & \cdot c_{1,2}\big(F_1(x_1), F_2(x_2)\big) \cdot c_{2,3}\big(F_2(x_2), F_3(x_3)\big) \\ & \cdot c_{1,3|2}\Big(F_{1|2}(x_1|x_2), F_{3|2}(x_3|x_2)\Big), \end{aligned} \tag{9}$$

where $c_{1,2}$, $c_{2,3}$, and $c_{1,3|2}$ denote the densities of bivariate copulas $C_{1,2}$, $C_{2,3}$, and $C_{1,3|2}$, respectively. $F_{1|2}$ and $F_{3|2}$ are the marginal conditional distributions that can be derived from formula (10).

The vine copulas involve marginal conditional distributions. The general form of a conditional distribution function is $F(x|v)$, given by

$$F(x|v) = \frac{\partial C_{xv_j|v_{-j}}(F(x|v_{-j}), F(v_j|v_{-j}))}{\partial F(v_j|v_{-j})}, \tag{10}$$

where v denotes all the conditional variables and $C_{xv_j|v_{-j}}$ is a bivariate copula distribution function. When v is univariate, the marginal condition distribution, for example, $F_{1|2}$ can be presented as

$$F_{1|2}(x_1 \mid x_2) = \frac{\partial C_{12}(F_1(x_1), F_2(x_2))}{\partial F_2(x_2)}. \tag{11}$$

2.4 D-vine copula estimation

In the R-package CDVines, the maximum likelihood was used to estimate the parameters of the copulas. The log-likelihood of the D-vine copula with three dimensions in equation (9) can be written as

$$\sum_{t=1}^{T} \log[c_{1,2}\left(F_1(x_{1,t}), F_2(x_{2,t})\right) \cdot c_{2,3}\left(F_2(x_{2,t}), F_3(x_{3,t})\right) \cdot c_{1,3|2}\left(F_{1|2}(x_{1,t}|x_{2,t}), F_{3|2}(x_{3,t}|x_{2,t})\right)] \tag{12}$$

3. Data and Empirical Results

This study used the oil prices from three major markets, the NYMEX, ICE, and DME, to analyze the dependence structure. The observations regarding the three data series were obtained from the EcoWin database during the period from 26 December 2008 to 28 June 2013.

We used the crude futures 1-Pos of daily closing prices and each data series was transformed into the log-difference $\ln\frac{P_t}{P_{t-1}}$, before it was used for analysis using the GARCH model and the vine copula.

Table 3 presents the descriptive statistics of the log-difference of three crude futures 1-Pos: the NYMEX, ICE, and DME. All of the three data series have a positive average growth rate, exhibiting positive skewness. If there is positive skewness, it means that the market has an upward trend, or that there is substantial probability of a big positive return. The kurtosis of these data is greater than 3. Hence, this kurtosis can be said to be super Gaussian and leptokurtic. This means that the growth rates of the empirical data have a typically spiky probability distribution function with heavy tails. The null hypotheses of normality of the Jarque–Bera tests are rejected in all the data series. The

Augmented Dickey-Fuller test shows that these data series are stationary at p-value less than 0.01.

Table 3. Data Descriptive Statistics for Log-difference of Crude Oil Futures Price 1-Pos

	NYMEX	**ICE**	**DME**
Mean	0.001	0.001	0.001
Median	0.001	0.001	0.001
Maximum	0.133	0.127	0.134
Minimum	-0.131	-0.097	-0.091
Std. Dev.	0.023	0.020	0.019
Skewness	0.188	0.006	0.088
Kurtosis	8.276	7.141	7.649
p-value of Jarque–Bera	(0.01)	(0.01)	(0.01)
p-value of Augmented-Dickey-Fuller test	(< 2.2e-16)	(< 2.2e-16)	(< 2.2e-16)
Number of observations	1135	1135	1135

Table 4. Results of ARMA(p,q)-GARCH(1,1) with Skewed Student-T Residual for Log-difference of Crude Oil Futures Price 1-Pos

	NYMEX	**Std. error (*p-value*)**	**ICE**	**Std. error (*p-value*)**	**DME**	**Std. error (*p-value*)**
mu	8.057e-06	4.271e-07 (< 2e-16 ***)	7.207e-05	8.820e-05 (0.414)	6.638e-05	8.219e-05 (0.419)
ar1	2.422e-01	2.404e-05 (< 2e-16 ***)	8.135e-01	9.690e-02 (< 2e-16 ***)	8.170e-01	9.367e-02 (< 2e-16 ***)
ar2	6.964e-01	2.475e-05 (< 2e-16 ***)	-	-	-	-
ar3	9.905e-03	2.561e-05 (< 2e-16 ***)	-	-	-	-
ma1	-3.066e-01	3.181e-05 (< 2e-16 ***)	-8.356e-01	9.270e-02 (< 2e-16 ***)	-8.436e-01	8.896e-02 (< 2e-16 ***)
ma2	-7.143e-01	3.193e-05 (< 2e-16 ***)	-	-	-	-
ω	5.640e-06	3.559e-06 (0.113)	2.963e-06	2.068e-06 (0.152)	2.536e-06	1.841e-06 (0.168)
α	7.266e-02	2.318e-02 (0.002 **)	5.642e-02	1.805e-02 (0.002 **)	4.873e-02	1.694e-02 (0.004 **)
β	9.138e-01	2.753e-02 (< 2e-16 ***)	9.359e-01	2.040e-02 (< 2e-16 ***)	9.456e-01	1.852e-02 (< 2e-16 ***)
ν (degree of freedom)	8.132	1.689e+00 (1.47e-06 ***)	6.789	1.335e+00 (3.66e-07 ***)	4.767	6.943e-01 (6.61e-12 ***)
λ (skewness)	8.554e-01	4.189e-02 (< 2e-16 ***)	9.003e-01	3.742e-02 (< 2e-16 ***)	9.055e-01	3.683e-02 (< 2e-16 ***)
Log-likelihood	2,888.761		2,986.977		3,042.667	

Note: Significant codes: 0 "***"; 0.001 "**"; 0.01 "*" 0.05.

Table 4 presents the appropriate marginal models for the log-difference of three crude futures 1-Pos data: The ARMA(3,2)-GARCH(1,1) with skewed student-T residual for the NYMEX data and the ARMA(1,1)-GARCH(1,1) with skewed student-T residual for the ICE and DME data. The models are selected by using the AIC criterion. For the NYMEX, the $\alpha + \beta$ is 0.986, for the ICE and the DME, the $\alpha + \beta$ are 0.992 and 0.994, respectively; this implies that their volatilities have a long-run persistence. For the short-run effect of the unexpected factors, we considered the event from the α parameters of the NYMEX, the ICE and the DME. The results showed that they have the values 0.073, 0.056 and 0.049, and that this has a small impact on volatility.

Next, we transformed the standardized residuals from the ARMA-GARCH model into the uniform [0,1] by using the empirical distribution function $F_n(x) = \frac{1}{n+1}\sum_{i=1}^{n} 1(X_i \leq x)$, where $X_i \leq x$ is the order statistics and 1 is the indicator function. The transformed data were used in the Kolmogorov–Smirnov (K–S) test for uniformity [0,1] and the Box–Ljung test for serial correlation. More details are available in Patton [29] and Manthos [30]. These tests are necessary to check for the marginal distribution models' misspecification before using the copula model.

The results of the K–S test and the Box–Ljung test are presented in Table 5. The K–S test showed that these marginal distributions are uniform, by accepting the null hypothesis at p-values equal to 1. The results of the Box–Ljung test provided that all of the four moments of all the marginal distributions are i.i.d., by accepting the null hypothesis that there is no serial correlation at p-values greater than 0.05. Therefore, our marginal distributions were not misspecified and can be used for the copula model.

Table 5. P-values of K–S Test and Box–Ljung Test for Marginal Distributions

	NYMEX **(*p-value*)**	**ICE** **(*p-value*)**	**DME** **(*p-value*)**
K–S test (*p-value*)	(1)	(1)	(1)
Box–Ljung test (*p-value*)			
1st moment	(0.853)	(0.944)	(0.160)
2nd moment	(0.856)	(0.651)	(0.766)
3rd moment	(0.990)	(0.999)	(0.693)
4th moment	(0.545)	(0.284)	(0.494)

Figure 3 illustrates the scatter plots of the three bivariate margins, NYMEX–ICE, NYMEX–DME, and ICE–DME. The data show the clustering in both the upper and the lower tail dependences. The pair-copula of ICE–DME shows stronger dependence in both the upper and the lower tails, compared to the other pairs.

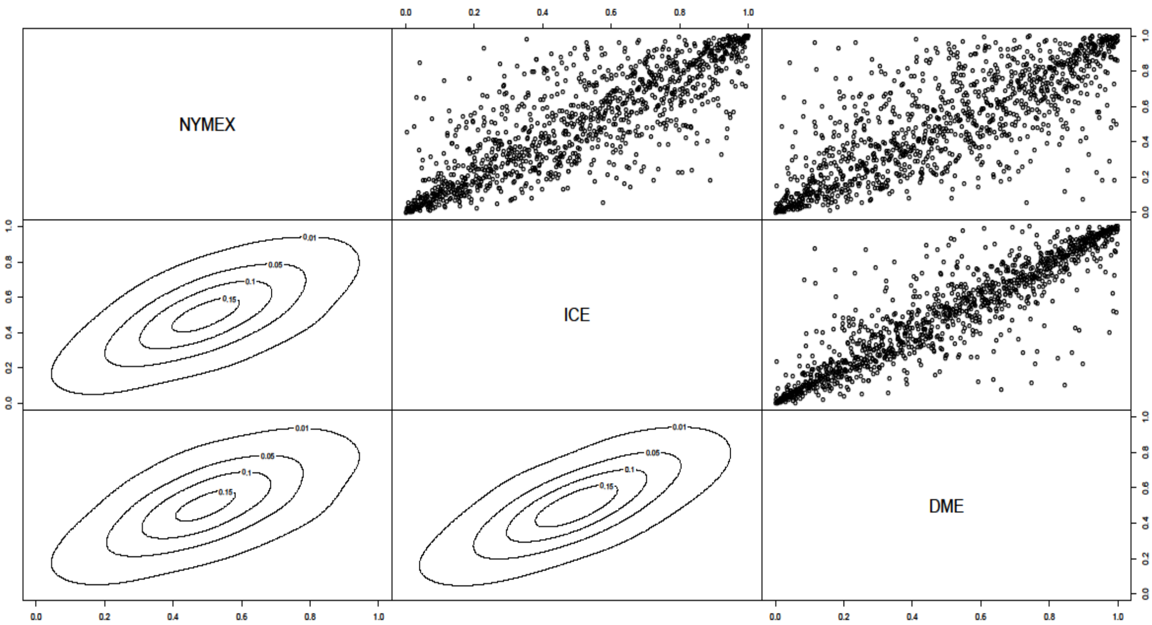

Figure 3. The scatter plots of NYMEX–ICE, ICE–DME, and NYMEX–DME.

In order to better understand the relationship between these pair copulas, the results of the dependence structure were analyzed by using the bivariate copula model, as presented in Table 6. We used various copula families, as presented in Table 1, to find out an appropriate dependence structure. The AIC and the BIC criteria are used to appraise as to which copula is the best fit and also used a goodness-of-fit test based on Kendall's tau. This goodness-of-fit test provides the Cram´er-von Mises (CvM) and the Kolmogorov–Smirnov (K–S) test statistics as well as the estimated p-values by bootstrapping [7] to test the appropriateness of the copula model under the null hypothesis that the empirical copula C belongs to a parametric class C_0 of any of the copulas, $H_0 : C \in C_0$. Kendall's tau correlation which was transformed from the copula parameter was used because each family of copula has a different range of copula parameters; hence we inverse a copula parameter into a Kendall's tau correlation, and it is bound on the interval [-1, 1]. Kendall's tau is a measure of concordance which is a function of copula; as a result, we can use it to assess the range of dependence covered by the families of copula.

The analysis is performed by taking into consideration the results of the AIC, the BIC, and the goodness-of-fit tests of the Cramer-von Mises (CvM) and the Kolmogorov-Smirnov (K–S) tests. As for the first pair-copula, NYMEX–ICE, the Rotated BB1 180° copula is appropriate to explain the dependence structure of this pair-copula. The Kendall's tau correlation is 0.646, and the lower and upper tail dependences are 0.680 and 0.758.

As far as the second pair-copula, NYMEX–DME, is concerned, the Rotated BB1 180° copula is appropriate for explaining the dependence structure of this pair-copula. The Kendall's tau correlation is 0.594, and the lower and upper tail dependences are 0.644 and 0.737.

As for the last pair-copula, ICE–DME, the BB1 copula is appropriate to explain the dependence structure of this pair-copula. The Kendall's tau correlation is 0.741, and the lower and upper tail dependences are 0.767 and 0.688.

The results demonstrate that the NYMEX, ICE, and DME have relatively strong dependence. Hence, we can safely infer that these crude oil futures prices move closely together, especially the ICE and the DME.

Table 6. Bivariate Copula Analysis of NYMEX–ICE, NYMEX–DME, and ICE–DME

Pair copula	**Copula family**	**Parameter**	**Std. error *(p-value)***	**Kendall's tau**	**Tail dependence**		**AIC**	**BIC**	***p-value***	
					Lower (τ^L)	**Upper** (τ^U)			**CvM**	**K–S**
NYMEX–ICE	Rotated BB1 180°	θ =0.264	0.062 (0.000)	0.646	0.680	0.758	-1,478.90	-1,468.80	0.64	0.39
		δ =2.496	0.090 (0.000)							
NYMEX–DME	Rotated BB1 180°	θ =0.165	0.058 (0.002)	0.594	0.644	0.737	-1,205.20	-1,195.10	0.73	0.77
		δ =2.276	0.079 (0.000)							
ICE–DME	BB1	θ =1.023	0.104 (0.000)	0.741	0.767	0.688	-2,074.50	-2,064.40	0.09	0.16
		δ =2.552	0.111 (0.000)							

Note: For the CvM and K–S tests, the critical value α = 5%. If p-value > 0.05, it means that the dependence structure of the data series is appropriate for the chosen family of copulas.

Next, we used the D-vine copula model to analyze the dependence structure between the crude oil futures prices and especially to examine which oil market is a key variable that governs the interactions within these three markets.

3.1 D-vine Structure

The empirical Kendall's tau $\bar{\tau}_n$ and the distance measure $I(f_1, f_2)$ were used to select the order of the variables in the first tree. Table 7 shows the empirical Kendall's tau matrix, which was computed from the transformed standardized residuals of the NYMEX, ICE, and DME. A high value of $\bar{\tau}_n$ means that there is "high dependency." The strongest dependencies in terms of absolute empirical values of τ_n are used as the first pair in the first tree, which is subsequently followed by the next. The selection of the D-vine structure is based on the one that maximizes the sum of the corresponding absolute value of $\bar{\tau}_n$ in the first tree, as can be understood from Figure 4.

Table 7. Empirical Kendall's tau Matrix

	NYMEX	ICE	DME
NYMEX	1	0.643	0.597
ICE	0.643	1	0.752
DME	0.597	0.752	1

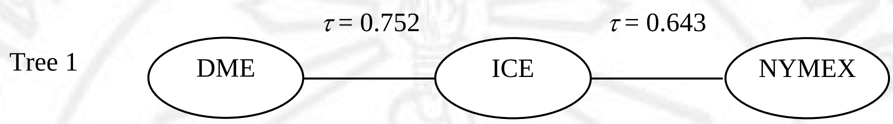

Figure 4. The order of the variables in the first tree of the D-vine structure by the empirical Kendall's tau.

Table 8 presents the distance measure matrix, which was computed from the skewed student-T distribution of the standardized residuals of the NYMEX, ICE, and DME. A low value of $I(f_1, f_2)$ means that there is "high association," or "high affinity" between f_1 and f_2. The lowest $I(f_1, f_2)$ is used as the first pair in the first tree, which is subsequently followed by the next. The selection of the D-vine structure is based on the one that minimizes the sum of the corresponding absolute value of $I(f_1, f_2)$ in the first tree, as can be seen from Figure 5.

Table 8. Symmetric Distance Measure Matrix

	NYMEX	ICE	DME
NYMEX	0	0.006	0.021
ICE	0.006	0	0.007
DME	0.021	0.007	0

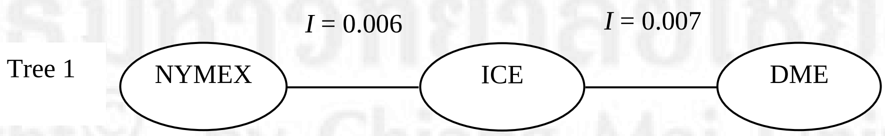

Figure 5. The order of the variables in the first tree of the D-vine structure by the symmetric distance measure.

The findings as displayed in Figure 4 and Figure 5 demonstrate that for the three variables of the crude oil prices chosen for this study, the order of variables in the first tree of D-vine by the empirical Kendall's tau approach is different from that by the distance measure approach, in reversed direction. In addition, the NYMEX and the DME were linked by ICE in both the structures.

3.2 Results of D-vine models

As the next step, the appropriate D-vine tree structures were specified by the empirical Kendall's tau (Figure 4) and the distance measure (Figure 5). Then, adequate copula families were selected and estimated. For the estimation of the copula parameters, we followed the process as presented in Aas et al. [8] and Brechmann and Schepsmeier [7]. First, we estimated the parameters of the three copulas involved by a sequential procedure that involved only the bivariate estimation for each individual pair-copula. Next, we used the parameters from the sequential estimation as the starting value to maximize the full log-likelihood procedure, or what is called a joint MLE estimation. Thereafter, the copula parameters of each pair can be obtained from the joint MLE estimation.

Table 9. Comparison between Parameters from Sequential Estimation and Joint MLE Estimation of Model 1: D-vine Model by Empirical Kendall's tau Sequencing

Pair	Family	Parameter	Seq. Est. (start)	Joint MLE (final)
1. DME–ICE	BB1	θ	1.023	1.083
		δ	2.552	2.505
		τ	0.741	0.741
		τ^L	0.767	0.775
		τ^U	0.688	0.681
2. ICE–NYMEX	Rotated BB1 180°	θ	0.264	0.267
		δ	2.496	2.530
		τ	0.646	0.651
		τ^L	0.680	0.685
		τ^U	0.758	0.760
3. DME–NYMEX | ICE	BB1	θ	0.070	0.069
		δ	1.053	1.053
		τ	0.083	0.082
		τ^L	0.000	0.000
		τ^U	0.069	0.069
AIC model	-	-	-3,589.489	-3,590.140

For example, in Table 9 is presented the comparison between the parameters from the sequential estimation and the joint MLE estimation of Model 1: D-vine model by the empirical Kendall's tau sequencing. It can be seen that the AIC value is slightly better when estimating all the parameters simultaneously. Thus, we are convinced that this model would be more appropriate than the bivariate model because the multivariate model can take all the considered variables into account.

Figure 6 presents the results of Model 1: D-vine model by the empirical Kendall's tau sequencing. Each pair-copula consists of the copula families and their Kendall's tau correlations that are transformed from the copula parameters by a joint MLE estimation.

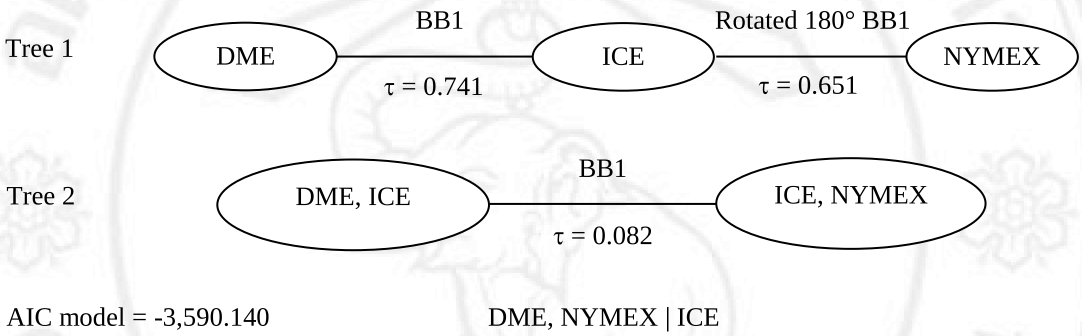

Figure 6. The Model 1: D-vine model by the empirical Kendall's tau sequencing.

Figure 7 presents the results of Model 2: D-vine model by the distance measure sequencing. When we compare these results with the results from the empirical Kendall's tau, it can be seen that this three dimensional model provides the same estimates of the parameters of interest and the value of AIC.

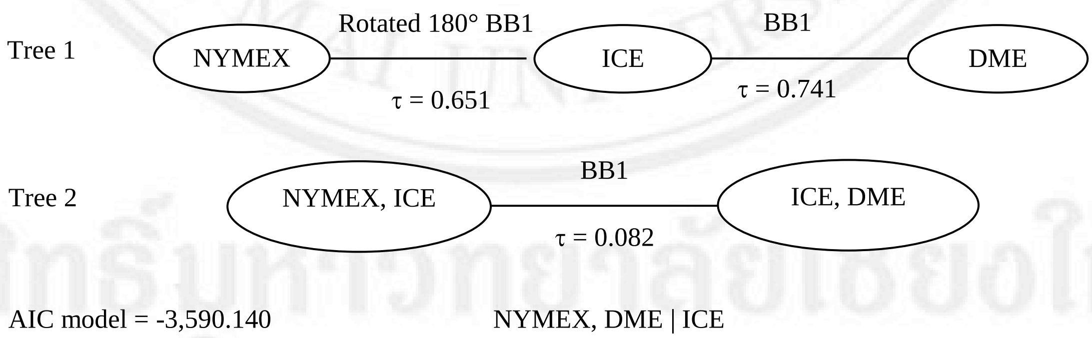

Figure 7. The Model 2: D-vine model by the distance measure sequencing.

In addition, we also fitted Model 3 and Model 4, the D-vine models with different orders of the variables to determine the better appropriate structure of the D-vine model for our data, and the results from the joint MLE estimation are shown in Figure 8 and Figure 9.

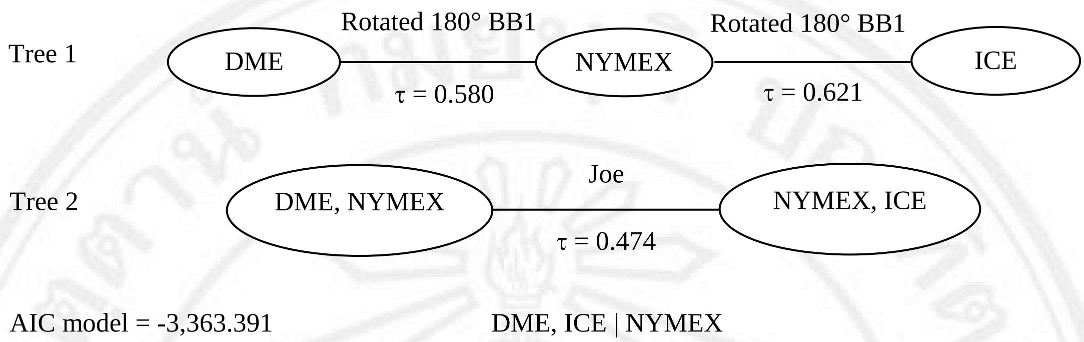

Figure 8. The Model 3: D-vine model with different orders of the variables: the DME, NYMEX, and ICE.

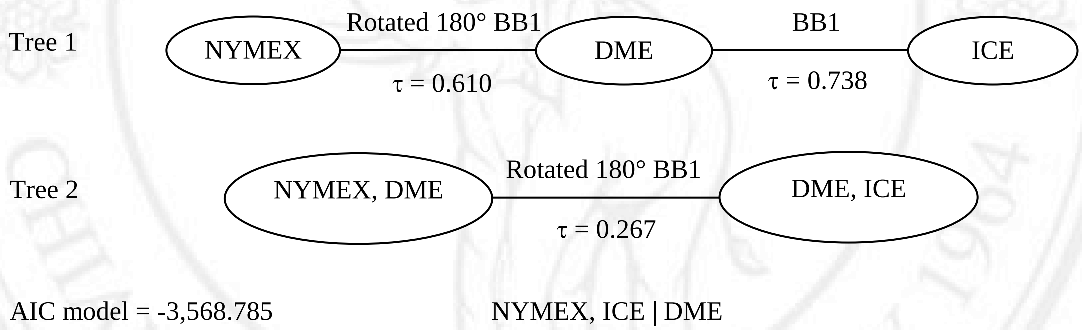

Figure 9. The Model 4: D-vine model with different orders of the variables: the NYMEX, DME, and ICE.

By taking into consideration the Akaike Information Criterion (AIC) value of each model, we found that Model 1 and Model 2, the D-vine models by the empirical Kendall's tau and by the distance measure sequencing, provide better fit than Model 3 and Model 4.

Model 1 and Model 2 provide the same estimates of the parameters of interest, which is that the DME and the NYMEX are linked by the ICE, as demonstrated in Figure 6 and Figure 7. For this reason, we will explain the results of only one model.

Model 2: D-vine copula model, which is modeled by the distance measure, reveals that there exists a positive dependence for each pair-copula, which estimated by a joint MLE. The first pair is the NYMEX–ICE, for which the rotated BB1 180°copula is the best fit, with two copula parameters, 0.267 and 2.530, a Kendall's tau correlation of 0.651, and the lower and upper tail dependences of 0.685 and 0.760, respectively.

The second pair is the ICE–DME, and the BB1 copula is chosen to explain the dependence structure of this pair-copula with two copula parameters, 1.083 and 2.505, a

Kendall’s tau correlation of 0.741, and the lower and upper tail dependences of 0.775 and 0.681, respectively.

The last conditional pair-copula of NYMEX–DME given ICE in Tree 2 provides that the BB1 copula is its best fit with two copula parameters, 0.069 and 1.053, a Kendall’s tau correlation of 0.082, and the lower and upper tail dependences of 0.000 and 0.069, respectively. This Kendall’s tau correlation by the conditional pair-copula of NYMEX–DME given ICE is less than those that are obtained by using the bivariate copula analysis of NYMEX–DME, which is 0.594, as presented in Table 6. This implies that the ICE has an influence on the dependence between the NYMEX and the DME, and that it is an important variable that governs the interactions within these variables.

4. Conclusions

This study used the GARCH model and the D-vine copula model to analyze the relationships between three random variables which we used to represent the crude oil prices of three different continents: Light crude futures 1-Pos of the New York Mercantile Exchange (NYMEX) for North America, Brent crude futures 1-Pos of the Intercontinental Exchange (ICE) for Europe, and Oman crude futures 1-Pos of the Dubai Mercantile Exchange (DME) for Asia. The daily closing prices during the period from 26 December 2008 to 28 June 2013 of three crude futures 1-Pos were used to conduct the analysis.

We found that the log-difference of the crude futures 1-Pos of the NYMEX data was appropriate with the ARMA(3,2)-GARCH(1,1) with skewed student-T residual. As for the log-differences of the crude futures 1-Pos of the ICE and the DME data, they were appropriate with the ARMA(1,1)-GARCH(1,1) with skewed student-T residuals. Moreover, it was observed that the three data series had long-run persistence.

The results from the bivariate copula analysis of and comparison between the crude futures 1-Pos of these three markets revealed that the relationships between the NYMEX–ICE pair, the NYMEX–DME pair, and the ICE–DME pair had co-movement. These findings correspond to the findings obtained in a previous study conducted by Reboredo [5]. In addition, we discovered evidences of asymmetric tail dependence in each pair. The NYMEX–ICE and NYMEX–DME pairs showed that the upper tail dependence was greater than the lower tail dependence, with the rotated BB1 copula families. As for the ICE–DME pair, it presented that the lower tail dependence was greater than the upper tail dependence, with the BB1 copula family. However, the values of the upper tail and the lower tail dependences of the three pair-copulas were quite close to each other. Furthermore, these findings support the “one great pool” hypothesis propounded in Adelman [1, 2], which, again, corresponds to the research studies of Hammoudeh et al. [4], Reboredo [5], and AlMadi and Zhang [6].

As far as specifying the D-vine structures in the cases of the three variables are concerned, we found that the D-vine models by the empirical Kendall's tau and the distance measure provided the best fit by giving better AIC values. In addition, these two models with the three dimensional copula provided the same estimates of the parameters of interest as well as the AIC values. The results of the bivariate and the D-vine copula models indicated that the ICE had an influence on the dependence between the crude oil prices of the NYMEX and the DME, and that it was an important variable that governs the interactions within these crude oil markets.

From the findings, it can be concluded that the crude oil prices of North America, Europe, and Asia in the case of crude futures 1-Pos have relatively strong dependence, and that regardless of whether it is an upward or a downward trend, their prices tend to move together. This finding is useful for decision planning of energy security in many countries in each of these regions. In addition, the evidence of the upper and the lower tail dependences between these three markets can be useful in risk management for investment in the commodity market. This information can tell us about the probability of joint occurrence of extreme events in crude oil prices.

Moreover, the best and the most advantageous finding of this study is it has given us the knowledge that among the three crude oil markets, the ICE is a crude oil market that has much influence. In other words, the change in oil prices in the ICE will impact quite significantly the oil prices in the NYMEX and the DME, in the same direction. Therefore, the price of the crude futures 1-Pos of the ICE is the appropriate information, or should be used as the indicator for monitoring the change in the oil prices of the NYMEX and the DME.

Regarding further studies in this field, we recommend that they include more of the related variables that represent the oil price movements in other crude oil markets also in the different regions of the world for a better understanding of the "one great pool" hypothesis.

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