Structure Dependence between Oil and Agricultural Commodities Returns: The Role of Geopolitical Risks

Aviral Kumar Tiwari[a,e], Micheal Kofi Boachie[b], Muhammed Tahir Suleman[c], Rangan Gupta[d]

[a]Rajagiri Business School, Rajagiri Valley Campus, Kochi, Kerala, India
[b]School of Economics, University of Cape Town, Rondebosch, 7701, South Africa
[c]Department of Accounting and Finance, University of Otago, Dunedin, New Zealand
[d]Department of Economics, University of Pretoria, Pretoria, 0002, South Africa
[e]South Ural State University, Lenin Prospect 76, Chelyabinsk 454080, Russian Federation, Russia

Highlights

- Analyze structural dependence between energy and agricultural markets by accounting for Geopolitical risks.
- Employ copula-based methods to study the co-movement.
- Strong co-movements between energy markets and agricultural markets.
- Geopolitical risks negatively impact the correlation between oil and a specific agricultural commodity.

Abstract

The link between energy and agricultural markets have been studied extensively in the last two decades. Nonetheless, the literature fails to consider the effects of geopolitical risks (GPRs), geopolitical risks due to acts and GPRs due to threats in studying the link between the two markets. Addressing these issues, we examine the dependence between crude oil prices and agricultural commodities (oats, corn, wheat and soybean) for a period starting from April 4, 1990, to February 15, 2019. Our study used copula-based techniques to study the co-movement. We find that strong co-movements between energy markets and agricultural markets, which are negatively influenced by GPRs. Hence, suggest the ability of agricultural commodities, particularly corn, oats and wheat, to act as a hedge against oil returns downturn resulting from geopolitical unrest. This evidence of hedging is further vindicated, when we observe that agricultural and oil markets are negatively correlated when the former is bullish and the latter bearish.

JEL Codes: C22, Q02, Q10

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1. Introduction

Conventionally, there is a relationship between energy and agricultural markets. This link may be direct or indirect. Directly, energy (e.g., natural gas, petrol, diesel and gasoline) is a major input for agricultural production [1-2]. Indeed, the increased use of corn as ethanol feedstock exposes the agricultural market to both input-related supply shocks stemming from rising energy prices and demand-side shifts based on biofuel's role as a petroleum substitute. At the same time, high crude oil prices make ethanol production relatively more profitable, which increases the demand for corn [1]. In the US, for example, the Renewable Fuel Programme further connected the crude oil and agricultural commodities such as corn and soybeans on the demand side [3-4].

Higher energy prices lead to a rise in the input cost (e.g., fertilizers and chemicals) and create higher transportation costs. Besides, high oil prices lead to a higher demand for biofuels, which in turn raises the need for agricultural inputs for producing biofuels [2, 5-6]. The indirect link between energy and agriculture works through exchange rate effects. Since energy or oil is mainly traded in US dollars, changes in oil prices cause appreciation/depreciation of local currencies and influences the prices of agricultural commodities [6, 7].

Recent studies show a strong correlation between crude oil returns and energy crops or co-movements [3, 8-9]. These co-movements of prices in energy and agricultural markets have rejuvenated the empirical research on market integration to assist investors and policymakers make informed decisions [9]. In periods where the performance of conventional assets is poor, investors become more interested in commodities that offer counter-cyclic returns, and this has led to growth in the commodity derivatives market. However, prices of commodities, such as oil and agricultural commodities fluctuate randomly [10]. Prices of commodities like cereals, oilseed products, dairy products, and wheat have become more volatile in recent years, and there is a growing demand for renewable energy such as bio-fuels, which can result in higher food prices [11].

Nonetheless, returns from investment in energy and agricultural commodities usually carry low correlation with financial assets and plausible interdependence among these commodities may enlarge the common stochastic discount factor [3]. The link between agricultural and energy markets suggest possible spillover effects. In circumstances where investors view agricultural commodities as a single class of asset, according to Tang and Xiong [12] shocks in the energy market is expected to transmit to the feed stocks of bioenergy and even to food commodities. In the literature, we find that shocks in macroeconomic variables such as those affecting business cycles and aggregate demand transmit to agricultural commodity returns through price shocks in the energy market [3, 13]. Thus, while shocks in one market enhance the correlations of returns, the same shocks may spillover to other markets, and can cause the return-volatility nexus to persist for a long time [3].

Some reasons have been given to use agricultural commodities to hedge against crude oil by [3]. The differences in fundamental causes behind price movement of agricultural commodities and crude oil prices provide scope for investors to hedge crude oil with agricultural commodities. For instance, fundamentally, weather fluctuations and availability of land affect the production of crops and therefore commodity prices, while economic activity influences energy prices. Further, the rapid expansion of the cultivation of energy crops (corn and soybean) has the potential to limit the allocation of land to other commodities such as wheat and oats, and these changes may push up the price of food wheat and oats. This interconnection among the prices of oil and the underlying agricultural commodities makes a strong case for exploring the hedging potential of agricultural commodities [3].

Over the last two decades, the link between energy and agricultural commodities has become one of the most controversial and has been widely researched [3, 9, 11, 14]. The aim has been to find the causes of this market integration in commodities to help policymakers and investors understand these linkages and their potential adverse effects on the broader economy and provide hedging opportunities in the agricultural markets. In doing this, several econometric techniques such as GARCH and copula-based models capable of capturing dependence or spillover effects related to extreme price observations have been useful in understanding the link between energy and agricultural markets.

To this point, very few empirical researches have analyzed the dependence among agricultural commodities and energy integration using a switching copula model. The copula method has been used to study the spillover or dependence structure of commodities in the literature [9, 16-19]. So, we study the dependence structure of the copula model since it's better to capture tail dependence, especially during extreme market conditions and can better mimic real-world situations [9, 16]. The *first* contribution of this study is the use of dependence structure using the copula method since it better captures tail dependence, especially during extreme market conditions and can better mimic real-world situations [9, 19]. The copula method has been used to study spillover or dependence structure of commodities in the literature [9, 16-19].

Furthermore, several studies on the energy-agricultural market nexus fail to explain other factors such as geopolitical risks, geopolitical risks due to acts (GPRA) and GPRs due to threats (GPRT), which are essential to comprehend the link between energy and agricultural markets [3, 8-9]. Note that, geopolitical risks are global in nature and hence, are likely to be more critical for global commodities we are analyzing here (Economic Bulletin of April 2017 of the European Central Bank, and the World Economic Outlook of October 2017 of the International Monetary Fund). Moreover, unlike metrics of uncertainties, which are generally country-specific at high frequency and are likely to suffer from the problem of Endogeneity (Ludvigson et al., [20] to commodity market movements, geopolitical risks are exogenous, besides being considered as more important than uncertainty when affecting oil markets (Demirer et al., [21]). Therefore, we investigate the structural dependence between energy and agricultural markets by accounting for GPRD_ACT and GPRD_THREAT, and analyze hedging of the oil market via agricultural commodities. Incorporating GPRD, GPRD_ACT, and GPRD_THREAT allow better to understand the dynamics of the energy and agricultural markets. Thus, our *second* contribution is to investigate the structural dependence between energy and agricultural markets by accounting for GPRA and GPRT and analyze hedging aspect of oil. Incorporating GPRs, GPRA and GPRT allow better to understand the dynamics of the energy and agricultural markets.

Using the daily data on crude oil and five primary agricultural commodities (corn, oats, rice, soybean, and wheat), for a period of April 4, 1990, to February 15, 2019. We find that strong co-movements between energy markets and agricultural markets, which are negatively influenced by GPRs. It further suggests that the ability of agricultural commodities, act as a hedge against oil returns downturn resulting from geopolitical unrest. The rest of the paper proceeds as follows. Section 2 provides a review of the relevant literature, while we detail our methodology in section 3. In section 4, we present and discuss our empirical results. We conclude the study in section 5 with some policy recommendations.

2. Literature Review

Studying the link between energy and commodity markets is not relatively new. To analyze the structural dependence between returns of oil price and the agricultural commodities, this section presents a review of relevant literature on the theme. We acknowledge that many studies examined the spillovers between the two commodities. However, the review of literature is limited to studies dealing with volatility transmission, dynamic correlations, and hedging between crude oil and agriculture markets. Du et al. [22]

explored the correlation between oil and agricultural commodity markets in the US using a stochastic volatility approach and weekly future prices for November 1998 to January 2009. They find that oil price volatility spills over to wheat and corn prices. Thus, there is a volatility spillover from the energy market to agricultural markets.

Furthermore, using the data of the USA, Wu et al., [23] examined volatility spillover of oil prices to the corn market using weekly data for the period 01-1992 to 06-2009. The authors employed GARCH specification to analyze the data and found a significant volatility transmission from crude oil to the corn market after 2005. It suggests that dependence between energy markets and agricultural commodity markets. In another study, Serra et al., [24] examined the possible volatility transmission from oil to the ethanol market in Brazil. Using the BEKK model and weekly price data covering 07-2000 to 11-2009, they found a strong volatility linkage among the oil, sugar, and ethanol markets.

Commodity futures are a popular asset class, as the total value of various commodity index-related instruments increased from $15 billion in 2003 to $200 billion in mid-2008. The raising concerns that index investment as a form of financial speculation may cause unwarranted increases in energy and food prices through induced excessive price volatility [12]. Indeed, studies have shown that oil price shocks contributed more than demand-side shocks to the volatilities in agricultural commodity prices post-2008 crisis. Reboredo [25] examined the co-movements between oil prices and that of soybean, wheat and corn. In their bivariate copulas with time-varying dependence parameters on weekly data covering 01-1998 to 04-2011 and found no evidence of dependence between oil and agricultural prices.

Using Double Smooth Transition Conditional Correlation DSTCC-GARCH model and weekly price data, Silvennoinen and Thorp [26] studied the dynamics of oil-agriculture correlation for the period 2005–2007. They find a strong correlation between the prices of these commodities. On the other hand, Lucotte [27] used VAR forecast errors to find co-movement between oil and agricultural commodity prices. Similarly, Ghorbel et al., [28] also used time-varying Archimedean copulas to study dependence between oil and commodities markets such as wheat, rice, cotton and coffee were examined alongside that of oil. They found that there is structure dependence between oil and agricultural commodities.

Koirala et al. [17] investigated the dependence between agricultural commodity futures prices and energy futures prices using daily data covering 03-2011 to 09-2012. After employing the copula method for estimation, they find that agricultural commodity and energy futures prices are highly correlated and exhibit a positive and significant relationship. Similar results reported earlier by Mensi et al. [18]. They used VAR-BEKK-GARCH and VARDCC-GARCH models for daily spot prices of WTI oil, Europe Brent oil, gasoline, heating oil, barley, corn, sorghum, and wheat between 04-01-2000 and 29-01-2013. Their estimations showed evidence of dependence between these energy and agricultural markets.

The dependence between the implied volatility indices of crude oil and two agricultural commodities (wheat and corn) has been examined using wavelets copula methods [16, 19]. The authors find evidence of time-varying asymmetric tail dependence in most of the cases. It implies that the dependence structure between the commodities is sensitive to time horizon under consideration. In a similar work, Jiang et al. [29] combined copula and wavelets methods to analyze the dynamic dependence among oil, agricultural raw material and metal markets. They find that oil market lags behind agricultural markets but leads metal markets.

Ji et al. [9] used a time-varying copula with a switching dependence to examine the conditional dependence between energy and agricultural commodity markets. They find that the lower tail dependence is much stronger in a bearish regime than in a bullish regime, highlighting the importance of systematic risk spillovers during extreme downward movements. They also found a significant risk spillover from energy to agricultural commodities markets. On the other hand, Eissa and Al Refai [8] used linear and nonlinear Autoregressive Distributed Lag (ARDL) models to investigate the dynamic linkages between oil prices and agricultural commodities. They use seasonally adjusted monthly price series for crude oil and agricultural commodities (i.e., barley, rapeseed oil and corn) for the period 01-1990 to 12-2018. Their nonlinear analysis showed that the prices of agricultural commodities and oil prices co-move in the long run. They also found that prices of agricultural commodities respond rapidly and strongly to cyclical movements in oil prices, but adjustments towards equilibrium take relatively longer. Liu et al. [30] used Markov-switching GRG copula to analyze the dependence structure between crude oil futures price and 12 Chinese agricultural commodity futures prices. They find that there is a dependence between oil futures prices and the majority of agricultural commodity futures prices, although the strength of dependence depends on the regime.

There are several other studies have examined the structure dependence between agricultural commodities and energy markets and spillover effects (see, for example, Fowowe, [14]; Nazlioglu et al., [31]; Pal and Mitra, [3]; Teterin et al., [32]). Similarly, most recent studies Mostashari-Rad et al., [33] examine the optimize energy usage and determine the justification of greenhouse emissions in crops of Guilan Province, Iran. Their results display that the highest energy consumption was related to tea and lowest with kiwifruit production. In another study, Kaab et al., [34] used optimization techniques for environmental effect decline and energy usage optimization in planted and ratoon farms of sugarcane production at Imam Khomeini Sugarcane Agro-Industrial Company. They concluded that a rise of energy consumption efficiency was mostly ascribed to electricity, diesel fuel, human labour and nitrogen fertilizer in sugarcane production.

Many recent studies linked the environmental and climates issues related to energy consumption with agricultural commodities. For example, Ghasemi-Mobtaker et al., [35] implemented an application of the photovoltaic system as a substitute clean energy energy-environmental sustainability using irrigation methods. They determined that cumulative exergy demand findings show that shares of Non-renewable, fossil for barley production mainly result from electricity and diesel fuel. Likewise, Hosseini-Fashami et al., [36] analyzed energy-environmental life cycle valuation of greenhouse strawberry production in Iran. They concluded that energy-environmental indices improve greenhouse strawberry production and help to move toward higher sustainability. In another study Saber et al., [37] examine the exergoenvironmental aspects across rice production systems, including conventional, low external input, and organic structures in Iran. They determined that the cumulative exergy demand analysis indicated that Non-renewable, fossil fuel was the primary energy consumption.

Mostashari-Rad et al., [38] evaluated environmental damages of horticultural crops under different cropping systems including citrus, hazelnut, kiwifruit, tea, and watermelon in Guilan province of Iran. They found that among all horticultural crops studied, and hazelnut production involves greater energy consumption. When compared for environmental impacts and energy forms, the citrus production was the best, due to the low emissions across all horticultural productions. We can conclude from the literature that a lot of literature analyzed the relationship between energy and agricultural commodities using a variety of different models. However, none has accounted for considering geopolitical risk and threats, which could also influence the dependence structure of energy and agricultural markets. We believe GPRs and GPRTS in modelling the dependence between energy and agricultural commodity markets.

3. Methodology

3.1. Data

For the empirical analysis, we used daily futures prices traded on the New York Mercantile Exchange (NYMEX) during April 4, 1990, to February 15, 2019, for oil and agricultural commodities. The data agrarian commodities, as well as energy, was obtained from the DataStream. We used crude oil as a proxy of energy. While for agricultural commodities, we used five commodities, i.e., corn, oats, rice, soybean, and wheat. Since corn, rice, and soybean are oil (ethanol and biodiesel) producing agricultural commodities. Following Pal and Mitra [3], we classify corn, rice and soybean as energy crops and wheat and oats as food crops. In this respect, higher prices for energy crops will increase the price of energy, such as ethanol and biodiesel. Conversely, since energy is a key input in the production of agricultural commodities, high energy prices commonly increase the agriculture commodity prices (for details, please refer to Esmaeili and Shokoohi [11]; Mensi et al., [16, 19]).

Besides, since we want to relate the dependence of oil and the other agricultural commodities with geopolitical risks (GPRD), we use the associated daily index developed by Caldara and Iacoviello [39]. They calculate the index by counting the number of articles related to geopolitical risk in 11 newspapers (as a share of the total number of news articles)[1]. The index is then normalized to average a value of 100 in the 2000-2009 decade. The search identifies articles containing references to six groups of words: Group 1 includes words associated with explicit mentions of geopolitical risk, as well as mentions of military-related tensions involving large regions of the world and a US involvement; Group 2 includes words directly related to nuclear tensions; Groups 3 and 4 include mentions related to war threats and terrorist threats, respectively, and; finally, Groups 5 and 6 aim at capturing press coverage of

[1] The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post

actual adverse geopolitical events (as opposed to just risks) which can be reasonably expected to lead to increases in geopolitical uncertainty, such as terrorist acts or the beginning of a war. Based on the search groups above, Caldara and Iacoviello [39] further disentangle the direct effect of adverse geopolitical events from the impact of pure geopolitical risks by constructing two indexes. The Geopolitical Risks associated with Threats (GPRD_THREAT) index only includes words belonging to Search groups 1 to 4 above. The Geopolitical Risks due to actual Acts (GPRD_ACT) index only includes words belonging to Search groups 5 and 6[2].

3.2. Methodologies

3.2.1 Copula specification

We examined the structure dependence between oil price return (X_1) and the returns on agricultural commodities (X_2). We apply the copula-based framework as its marginal distribution is similar in internal (0 1), and it is a multivariate distribution function. Besides, for the case of two arbitrary time series, the copula framework utilized to examine the bivariate combined distribution function $F_{X_1X_2}(x_1, x_2)$. According to Sklar [40], the combined distribution of two arbitrary time series could be explained in terms of a copula after converting uniform distributions from marginal distribution. Therefore, the combined distribution of the two-time series could be denoted by a copula function C represented as:

$$F\left(X_{1,t}, X_{2,t};\ \delta_1, \delta_{2;}\, \theta^c\right) = C\left(F_1\left(X_{1,t}, \delta_1\right), F_2\left(X_{2,t}, \delta_2\right); \theta^c\right). \tag{1}$$

In the above equation $F_K\left(X_{K,t};\ \delta_K\right)$, K = 1, 2 is the marginal aggregate distribution function of $X_{K,t}\ and\ \delta_K$ while θ^c are the parameter sets of $F_K\left(X_{K,t};\ \delta_K\right)$ and C, respectively. Considering all the aggregate distribution are distinguishable, we can write the bivariate joint density as follow;

$$f\left(X_{1,t}, X_{2,t};\ \delta_1, \delta_{2;}\, \theta^c\right) = c\left(u_{1,t}, u_{2,t};\ \theta^c\right) \prod_{K=1}^{2} f_k\left(X_{k,t};\ \delta_k\right), \tag{2}$$

[2] The GPR data is available from https://www.matteoiacoviello.com//gpr.htm.

where $f(X_{1,t}, X_{2,t};\ \delta_1, \delta_{2;}\ \theta^c) = \partial F^2\,(X_{1,t}, X_{2,t};\ \delta_1, \delta_{2;}\ \theta^c)/\partial X_{1,t}\partial X_{2,t}$ is the combined distribution of $X_{1,t}\ and\ X_{2,t}$. $u_{k,t}$ is the likelihood integral conversion of $X_{K,t}$ based on $F_K(X_{K,t};\ \delta_K)$, K = 1, 2; $C(u_{1,t}, u_{2,t};\ \theta^c) = \partial C^2(u_{1,t} - u_{2,t},\ \theta^c) = \partial C^2(u_{1,t}, u_{2,t};\ \theta^c)\Big/_{\partial}\, u_{1,t}\partial u_{2,t}$ is the copula distribution function and finally, $F_K(X_{K,t};\ \delta_K)$ is the marginal distribution of $X_{k,t,}$ where K= 1, 2. The bivariate combined distribution of $X_{1,t}$, and $X_{2,t}$ is the product of copula distribution and two marginal distributions.

As clarified before, the co-movement between oil price and agriculture commodities returns can be negative or positive. The positive co-movement can be due to return chasing effect, whereas a negative relationship could be due to portfolio rebalancing effect. These two impacts could rule on various occasions inside a similar retro. Consequently, the two variables switch between negative and positive dependence systems. With the utilization of Markov Switching copula model, we could capture the expressed switching dependence. For this situation, the latent variable influences both the copula capacity and minimal models (Wang et al. [41-42]). Consider the below state-varying copula:

$$C_{S,t}(u_{1,t}, u_{2,t};\ \theta_1^C\theta_0^C) = \begin{cases} C_1(u_{1,t}, u_{2,t};\ \theta_1^C), & if S_t = 1 \\ C_0(u_{1,t}, u_{2,t};\ \theta_0^C), & if S_t = 0 \end{cases}$$

In the above equation, S_t is a latent series whereas $C_1(u_{1,t}, u_{2,t};\ \theta_1^C)$ and $C_0(u_{1,t}, u_{2,t};\ \theta_0^C)$ are the negative and positive dependence structures, correspondingly. As explained previously, the copula model combines the Clayton Copula (C^c) with the Survival Clayton copula (C^{SC})[3].

$$C_1(u_{1,t}, u_{2,t};\ \theta_1^C) = C^C(u_{1,t}, u_{2,t};\ \alpha_1) + C^{SC}(u_{1,t}, u_{2,t};\ \alpha_2), \tag{3}$$

$$C_0(u_{1,t}, u_{2,t};\ \theta_0^C) = C^C(1 - u_{1,t}, u_{2,t};\ \alpha_3) + C^{SC}(1 - u_{1,t}, u_{2,t};\ \alpha_4), \tag{4}$$

[3] According to Wang et al. [42], Gumbel copula can be used as an alternative. Although, Gumbel copula model does not fit effectively using different selection criteria such the Akaike information criteria.

where $\theta_1^C = (\alpha_1, \alpha_2)'$,$\theta_0^C = (\alpha_3, \alpha_4)'$; $C^C(u, v, \alpha) = (u^{-\alpha} + v^{-\alpha} - 1)^{-1/\alpha}$, $C^{SC}(u, v, \alpha) = (u + v - 1) + C^c(1 - u, 1 - v, \alpha)$ and $\alpha \in (0, \infty)$. The predictable shape parameter, α_1, can be converted into Kendall's τ_i, the coefficient of the correlation ρ_1, the tail dependence φ_i with $\tau_i = {}^{\propto_i}/_{(2 + \propto_i)}$, $\rho_1 = \sin(\pi * \tau_i/2)$ and $\varphi_i = 0.5 * 2^{-1/\propto_i}$, for i = 1, 2, 3, 4.

ρ_2 (ρ_3) measures the dependence of soaring oil price and high (low) agricultural commodity prices and ρ_1 (ρ_4) measures the dependency of lower oil prices and lesser (higher) agricultural commodity prices. Therefore, $\varphi_2(\varphi_3)$ evaluates the dependability of very high oil prices with enormously high (low) agricultural commodity prices. Whereas $\varphi_1(\varphi_4)$ assess the dependency of low oil prices with enormously low (high) agricultural commodity prices.

The latent series S_t based on the modes of Markov Switching chain with a conversion likelihood matrix described as follows:

$$p = \begin{bmatrix} p_{00} & 1 - p_{00} \\ 1 - p_{11} & p_{11} \end{bmatrix}$$

In the above equation $p_{ij} = 1 - p_{11}\Pr[S_t = j|S_{t-1} = i|]$ for I, j = 0, 1. In this case, the variables change across two states, i.e., positive and negative states. So, we can define the bivariate density function as follow:

$$f(\eta_1, \eta_{2,} \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, \theta_c^1, \theta_c^0) = \{\textstyle\sum_{j=0}^1 \Pr(S_t = j)\, C^j(u_{1,t}, u_{2,t};\ \theta_c^j) \prod_{k=1}^2 \{\sum_{j=0}^1 \Pr(S_t = j)\, f_k(\eta_k, \delta_k^j,\ S_t = j)\}\} \tag{5}$$

By modifying equation five into log-likelihood, we get;

$$L(\vartheta) = L_c(\varphi_1) + \textstyle\sum_{K=1}^2 L_k(\varphi_{2,k}) \tag{6}$$

From equation 6, the log of the copula density and the marginal density of X_k, are $\vartheta = (\theta_c^1, \theta_c^0, \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, p_{11}, p_{00})$; $L_c(\varphi_1)\ and\ L_k(\varphi_{2,k})$ correspondingly. These are further explained as:

$$L_c(\varphi_1) = \log[\Pr(S_t = 1)\, c^1(u_1, u_2;\ \theta_c^1) + (1 - \Pr(S_t = 1)\, c^0((u_1, u_2;\ \theta_c^0)],$$

$$L_K(\varphi_{2,k}) = \log[\Pr(S_t = 1)\, f_k(\eta_k\colon \delta_k^1 . S_t = 1) + (1 - \Pr(S_t = 1)\, f_k(\eta_k, \delta_k^0 . S_t = 0)]$$

where $\varphi_1 = (\theta_c^1, \theta_c^0, p_{11}, p_{00})$.

3.2.2 Marginal models

We used an ARMA(*m,n*)-GJR-GARCH(*p,q*) model, developed by Glosten, Jagannathan, and Runkle [43], with skewed *t*-distribution to model the oil and agriculture returns. We started with a simple returns series as below:

$$r_t = \phi + \epsilon_t \ ,$$

In the above equation, ϕ is the expected returns, and ϵ_t is a white noise with a zero-mean. More specifically we say that $\epsilon_t \sim GJR - GARCH$ if we can write $\epsilon_t = \sigma_t z_t$, where z_t is standard Gaussian as follow;

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \epsilon_{t-\mathrm{i}}^2 + \gamma_i I_{t-i}\epsilon_{t-i}^2) + \sum_{j=1}^{p}\beta_j \sigma_{t-j}^2. \quad (7)$$

where ω is a constant, ϵ_{t-i} is the ARCH component and σ_{t-j}^2 is the GARCH component and

$$I_{t-i} = \begin{cases} 0 \ \ if, & r_{t-1} \geq \phi \\ 1 \ \ if, & r_{t-1} < \phi \end{cases}.$$

We selected the lags (p, q) based on the Akaike Information Criteria (AIC).

3.2.3 Estimation methodology

Following the Canonical Maximum Likelihood (CML) method, we converted the standardize residuals into a consistent distribution by employing the beneath marginal cumulative distribution function.

$$F_\iota(\omega) = \frac{1}{T+1}\dot{\sum}_{\iota=1}^{T} I(\upsilon_{\iota,t}^{S_t} \leq \omega), \quad (8)$$

In the above equation, I(·) is a dummy variable which equals one if $\upsilon_{i,t}^{S_t} \leq \omega$, otherwise 0. Following this, we calculated the cumulative distribution function for every observation of $\dot{\hat{\upsilon}}_{\iota,t}^{S_t}$and indicated by $\dot{\hat{\mu}}_{i,j}^{S_t} = \widehat{F_k}(\dot{\hat{\mu}}_{i,j}^{S_t}), i = 1,2; j = 1,2, \dots, T;\ S_t = 0, 1.$

As the dependence structure follows the Markov-Switching process, so to rearrange the log-likelihood function, Hamilton's filtered system used as follow:

$$L(\theta) = \log\left(\hat{\xi}'_{t|t-1}\lambda_t\right)$$

$$\hat{\xi}'_{t|t} = \left(\hat{\xi}'_{t|t-1}\lambda_t\right)^{-1}\left(\hat{\xi}'_{t|t-1} o \lambda_t\right)$$

$$\hat{\xi}'_{t+1|t} = P'^{\hat{\xi}'}{}_{t|t},$$

$$\lambda_t = \begin{pmatrix} f_1(\eta_{1,t}: \delta_1^1) f_2(\eta_{2,t}: \delta_2^1) c^1\left(\hat{u}_{1,t}^1 ; \hat{u}_{2,t}^1 \theta_c^1\right) \\ f_1(\eta_{1,t}: \delta_1^0) f_2(\eta_{2,t}: \delta_2^0) c^0\left(\hat{u}_{1,t}^0 ; \hat{u}_{2,t}^0 \theta_c^0\right) \end{pmatrix}$$

In the above equation, the Hadamard product described as "o" and μ^{S_t}indicates density u=function for $S_t = 0, 1$. The vector of the parameters $\theta = (\theta_c^1, \theta_c^0, \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, p_{11}, p_{00})$ is then determined by maximizing $L(\theta)$[4]

$$\theta = arg \max_{\theta} \sum_{t=1}^{T} L(\theta) \tag{9}$$

The time-varying dependence between oil and agricultural commodities can be created to estimate the model's parameter. So, it is $E(c_1(u_1, u_2)) = \int_0^1 \int_0^1 c_1(u_1, u_2) d\, c_1(u_1, u_2)$, then, Kendall's τ of the mixed copula under the positive dependence regime is given as:

$$\tau^1 = \omega_1[\propto_1/2 + \propto_1] + (1 - \omega_1)[\propto_2/2 + \propto_2] \tag{10}$$

Likewise, Kendall's $\tau$of the diversified copular beneath the negative dependence regime is $\tau^0 = \omega_2[\propto_3/2 + \propto_3] + (1 - \omega_2)[\propto_4/2 + \propto_4]$[5] (11)

The correlation coefficient of the mixed copula under different dependence regimes is thus calculated as $\rho^j = \sin\left(\pi * \tau^j/2\right) for$j = 0, 1. Thus, the smoothing correlation ρ_{sm} is defined as:

$$\rho_{sm} = \rho_{1,sm}\rho^1 - \rho_{0,sm}\rho^0 = \rho_{1,sm} * \sin(A) - \rho_{0,sm} * \sin(B) \tag{12}$$

[4] According to Wang et al. [42], it is good to make use of the simplex search method in order to evade illogical value to obtain the $\theta(\hat{\theta}_0)$. Thus, we could start with the MLE estimates of $\theta(\hat{\theta}_0)$ as the basic value of h.

[5] For a rigorous and through derivation about the Kendall's correlation and smooth correlation of the mixed copular, please see Wang et al. [41-42]

Where A = 0.5, and $A = 0.5\pi X[\omega_1\tau_1 + (1-\omega_1)\tau_2]$, $B = 0.5\pi X[\omega_2\tau_3 + (1-\omega_2)\tau_4]$ and $\rho_{j,sm}$ is the smoothing probability in regime j for j = 0, 1 (for details, see Kim and Nelson [44]).

4. Empirical Findings

4.1. Descriptive statistics

For the empirical analysis, the data consisted of energy and four agricultural commodities prices. We used the oil prices and agriculture commodities (i.e., corn, oats, soybean, and wheat) futures prices traded on NYMEX from April 4, 1990, to February 15, 2019. Our choice of this data set is mainly directed because of the well-known cost-push impacts in the literature (for details see, Esmaeili and Shokoohi [11]; Mensi et al., [16, 19]). It states that high energy prices commonly increase the agriculture commodity prices as it is considered a key input for the production process. We use log returns for oil and agricultural commodities. The descriptive statistics are presented in Table 1.

Table 1 exhibits the basic statistics and essential diagnoses test for the commodity returns. The average returns throughout the period for all the commodities are positive. Amongst the agricultural commodities, corn has the lowest mean, whereas the highest standard deviation is for oats. Oil returns display quite a high standard deviation. It also has a large range between minimum and maximum values and exhibits higher uncertainty compared to agricultural commodities. All the series (except wheat) display negative skewness. Further, the series shows that kurtosis is quite high and rejects that the series are normally distributed. It is also confirmed by the significant statistics of Jarque–Bera.

We also presented the results of the ADF unit root test in Table 1. The significant test statistics imply that all the commodities series are stationary except rice. Further, we also presented the results of Ljung-Box statistics, Q and Q^2, and significant statistics confirm the presence of heteroscedasticity. The LM test for the presence ARCH impact also significant at 1% and justify to use GARCH-class models estimation.

Table 1: Descriptive Statistics

	Oil	Corn	Oats	Soybean	Wheat	Rice
Panel A						
Mean	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000
Std.Dev.	0.024	0.017	0.023	0.016	0.018	0.017
Minimum	-0.401	-0.276	-0.255	-0.234	-0.128	-0.245
Maximum	0.164	0.128	0.154	0.203	0.111	0.281
Skewness	-0.697*	-1.112*	-1.014*	-1.006*	0.059	0.0361
Kurtosis	17.872*	24.003*	14.691*	20.672*	5.901*	27.183*
Jarque-Bera	66719.7*	133374.8*	42093.9*	94586.6*	2519.7*	174863.2*
Panel B: diagnoses						
ADF	-26.78*	-24.79*	-27.69*	-24.99*	-25.24*	-19.152
L-B	42.00*	41.40*	64.60*	56.60*	36.83	43.0 *
L-B^2	906.00*	80.40*	117.10*	1189.60*	1084.50*	49.6 *
ARCH LM	475.40*	58.00*	90.70*	955.20*	408.10*	41.5 *
Observations	7176	7176	7176	7176	7176	7176

Note: Table reports the descriptive statistic along with diagnoses test results for Oil and agricultural commodities returns. Std.Dev. is the standard deviation. The residual-based diagnostics L-B is the Ljung-Box test for autocorrelation of returns and squared returns along with ARCH LM test is also presented in panel B. * denotes significance at 1% level.

Table 2 presents results of Nonlinearity tests, i.e., Teraesvirta neural network test, White neural network test, Tsay test, and likelihood ratio test for threshold nonlinearity. In the majority of the cases, the results are significant at 1% level. The results are stronger for the Tsay test as all the series (excluding rice) shows significant results.

Table 2: Nonlinearity test

	Oil	Corn	Oats	Soybean	Wheat	Rice
Teraesvirta NN Test	21.72*	1.89	15.83*	225.28*	3.52	14.987*
White NN Test	2.34	0.09	10.14*	31.72*	2.57	47.3185*
Tsay Test	4.70*	2.03*	1.98*	3.36*	2.673*	0.9574
Likelihood Ratio Test	26.53	52.47	138.99*	138.99*	48.89*	21.288*

Note: * denotes significance at 1% level.

4.2. Results from Marginal distribution models

The results of the estimation for the marginal distribution of ARMA (m, n)-GJR-GARCH (p, q) are presented in Table 3. From the table, looking at the mean equation, we conclude that each of the commodity return series has a different ARMA (m, n) and significant at 1%. Moving towards variance equation, we find volatility persistence (sum of ARCH and GARCH is near one) that in the minority of the cases, except oil and rice return series. Furthermore, the asymmetric parameter (gamma) is negative and statistically significant for the Oats, Soybeans, and wheat, which indicate that negative surprises end up with higher conditional volatility compared to positive surprises of the same size. So, we conclude that bad news impacts the volatility more compared to the good news.

Table 3 also reports the results of the Ljung-Box statistics on standardized residuals as well as standardized squared residuals for different lag structures: lag (1), lag (23), and lag (39). We conclude, from the significance of the results, that there is an absence of serial correlation in the standardized residuals as well as standardized squared residuals. Moreover, results from ARCH-LM test also confirms the nonexistence of conditional heteroscedasticity in the series for the different specification of ARCH lags (ARCH (3), ARCH (5), and ARCH (7)). Comparing these results with those in Table 1, we conclude that the ARMA (m, n)-GJR-GARCH (p, q) model is for the oil as well as agricultural commodities.

4.3. Results of single-copula

In this section, we present the empirical results from the single copula estimations between oil and agricultural commodities. Following Wang et al., [41], the results of the analysis for each pair of oil and five agricultural commodities returns for six single copula models are presented in Table 4. The six copula models consist of the normal copula, student-t copula, and four types of the Clayton copula (see Table 4).

Table 3: Parameter estimates for the marginal distribution models

	Oil	Corn	Oats	Soybean	Wheat	Rice
Panel A: Mean equation						
Constant	0.0000 (0.70)	0.0001 (0.37)	0.0002 (0.43)	0.0002 (0.12)	0.0001 (0.60)	0.0001 (0.50)
AR(1)	0.4514 (0.00)	0.0217 (0.08)	0.6427 (0.00)	1.1235 (0.00)	-0.7241 (0.00)	
AR(2)	-0.6874 (0.00)			-0.9457 (0.00)	-0.4433 (0.03)	
AR(3)	-0.2486 (0.02)				0.1839 (0.43)	
AR(4)					0.5326 (0.00)	0.0754 (0.00)
MA(1)	-0.4710 (0.00)		-0.5994 (0.01)	-1.1485 (0.00)	0.7364 (0.00)	
MA(2)	0.6832 (0.00)		-0.0443 (0.01)	0.9703 (0.00)	0.42963 (0.03)	
MA(3)	0.2230 (0.05)		0.0031 (0.81)	-0.0149 (0.01)	-0.2099 (0.36)	
MA(4)	0.0077 (0.57)		-0.0111 (0.36)	-0.0166 (0.04)	-0.56737 (0.00)	
MA(5)	-0.0299 (0.01)				-0.0075 (0.53)	0.0000 (0.09)
Panel B: Variance equation						
Constant	0.0000 (0.30)	0.0000 (0.15)	0.0000 (0.00)	0.0000 (0.00)	0.0000 (0.00)	0.0842 (0.00)
ARCH	0.0485 (0.00)	0.0702 (0.00)	0.0947 (0.00)	0.0818 (0.00)	0.0466 (0.00)	0.9106 (0.00)
GARCH(1)	0.7130 (0.00)	0.9150 (0.00)	0.8992 (0.00)	0.9371 (0.00)	0.9611 (0.00)	
GARCH(2)	0.2170 (0.00)					-0.0108 (0.37)
Asymmetry	0.0307 (0.00)	0.0114 (0.42)	-0.0428 (0.00)	-0.0520 (0.00)	-0.0296 (0.00)	1.0498 (0.00)
Skew	0.9263 (0.00)	1.0266 (0.00)	0.9996 (0.00)	0.9547 (0.00)	1.0798 (0.00)	4.4896 (0.00)
Shape	6.9087 (0.00)	5.0413 (0.00)	3.6456 (0.00)	5.4306 (0.00)	6.9376 (0.00)	0.0001 (0.46)
Log Likelihood	17749.96	20119.3	18024.29	20870.13	19440.89	20351.28
Akaike	-4.9426	-5.6052	-5.0201	-5.8130	-5.4138	-5.6698
Bayes	-4.9272	-5.5975	-5.0086	-5.8006	-5.3985	-5.6621
Shibata	-4.9426	-5.6052	-5.0202	-5.813	-5.4139	-5.6698
Hannan-Quinn	-4.9373	-5.6025	-5.0162	-5.8087	-5.4086	
Panel C: Diagnostic tests						
Ljung-Box Test on Standardized Residuals						
Lag[1]	2.134 (0.14)	0.694 (0.41)	6.786 (9.19E-03)	5.421 (0.02)	2.176 (0.14)	1.553 (0.21)
Lag[23]	6.355 (1.00)	2.116 (0.17)	12.184 (1.46E-11)	11.270 (0.00)	12.057 (0.99)	1.768 (0.30)
Lag[39]	10.608 (0.99)	3.228 (0.37)	18.595 (1.90E-02)	16.987 (0.23)	22.875 (0.44)	2.628 (0.53)
Ljung-Box Test on Standardized Squared Residuals						
Lag[1]	2.266 (0.13)	0.018 (0.00)	0.2537 (0.61)	8.158 (0.00)	0.02254 (0.88)	1.106 (0.29)
Lag[5]	7.66 (0.11)	0.66884 (0.85)	1.9134 (0.64)	9.843 (0.01)	0.27599 (0.98)	1.627 (0.71)
Lag[39]	12.968 (0.06)	1.39452 (1.71)	5.7974 (0.32)	11.143 (0.03)	1.2917 (0.97)	2.128 (0.88)
ARCH LM Tests						
ARCH (3)	0.041 (0.84)	0.736 (0.35)	0.407 (0.52)	1.147 (0.28)	0.048 (0.83)	0.220 (0.64)
ARCH (5)	0.074 (0.99)	1.029 (0.65)	3.117 (0.27)	2.291 (0.41)	0.394 (0.91)	0.277 (0.95)
ARCH (7)	2.016 (0.74)	1.529 (0.75)	5.926 (0.15)	2.596 (0.59)	0.9296 (0.92)	0.716 (0.95)

Note: This table presents the estimation for the marginal distribution of ARMA(m,n)-GJR-GARCH(p,q). The lags of the model (m,n,p,q) are selected based on AIC. The residual-based diagnostics L-B is the Ljung-Box test for autocorrelation of returns and squared returns along with ARCH LM test for the existence of ARCH effect is also presented in panel C. The p-values are reported in the parenthesis.

Table 4: Estimation of single-copula models: oil and agricultural commodity futures

	Corn	Oats	Soybean	Wheat	Rice
Normal copula					
ρ	0.1250***	0.0795***	0.1282***	0.1019***	0.0058***
SE	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
LL	56.54	22.77	59.44	37.52	0.12
AIC	-111.08	-43.53	-116.89	-73.04	-1.76
BIC	-104.20	-36.65	-110.01	-66.16	-8.640
Student-t copula					
ρ	0.1276***	0.0822***	0.1330***	0.1033***	0.0058***
SE	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
DoF	20.91***	14.96***	17.69***	13.19***	99.99***
SE	(5.590)	(2.989)	(4.019)	(2.602)	(104.856)
LL	64.35	37.19	70.61	58.48	0.30
AIC	-126.70	-72.38	-139.23	-114.96	-1.39
BIC	-119.83	-65.50	-132.35	-108.08	-8.27
Clayton(u, v)					
α	0.1286***	0.0839***	0.1345***	0.1024***	0.0033***
SE	(0.015)	(0.014)	(0.015)	(0.014)	(0.012)
LL	45.24	21.09	48.34	30.94	0.04
AIC	-88.48	-40.17	-94.68	-59.88	-1.92
BIC	-81.60	-33.29	-87.79	-53.01	-8.79
Rotated Clayton copula (with tail dependence in upper tail instead of lower): Clayton(1-u, 1- v)					
α	0.1241***	0.0795***	0.1277***	0.1115***	0.0082***
SE	(0.015)	(0.014)	(0.015)	(0.014)	(0.012)
LL	42.30	19.03	43.72	36.30	0.239
AIC	-82.61	-36.06	-85.44	-70.61	-1.52
BIC	-75.73	-29.18	-78.56	-63.73	-8.399
Rotated Clayton copula (half rotated): Clayton(1 - u, v)					
α	0.0001	0.0001	0.0001	0.0001	0.0051***
SE	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
LL	0.07	0.04	0.06	0.05	0.03
AIC	2.13	2.08	2.20	2.09	2.06
BIC	9.01	8.96	8.99	8.98	8.94
Rotated Clayton copula (half rotated): Clayton(u, 1 - v)					
α	0.0001	0.0001	0.0001	0.0001	0.0001
SE	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
LL	0.06	0.03	0.07	0.05	0.48
AIC	2.12	2.06	2.14	2.09	0.01
BIC	9.01	8.94	9.02	8.97	2.01

Note: SE, LL, AIC and BIC represent standard error, log-likelihood, the Akaike information criterion, and the Bayes information criterion, respectively. DoF shows the degrees of freedom for the Student-t distribution.
α is the shape parameter, ρ is the correlation coefficient of two series in the Normal or Student-t copula. The numbers in parentheses are standard errors. *** indicates significance 1% level, respectively.

Table 4 displays the estimated coefficient for oil and each of the agricultural commodities as well as the standard error (SE), log-likelihood (LL), the Akaike information criterion (AIC) and Bayes information criterion (BIC). The results exhibit significant parameters at 1% level for four of the copula models (normal, student-t, Clayton and 180-degree Clayton copula) for all the pairs of oil and agricultural commodities.[6] Our results are more significant compared to Ji et al., [9]. If we compare the copula models based on LL, AIC, and BIC, no copula model performed better than other copula models. It is argued in the literature that normal copula and student-t copula can elucidate symmetric negative and positive dependencies. Nonetheless, normal copula does not address tail dependence; whereas the student-t copula deals with symmetric tail dependence ((see Liu et al., [46])). To address the issue of asymmetric tail dependence, we use a dependence-switching copula model.

The results of the regular copula or single-copula model show there is structure dependence between the energy market and the agricultural market. In all the four copula models, the dependence measure is positive. Therefore, we conclude that there exists a positive structure dependence between crude oil prices and agricultural commodity returns. The results are in tandem with a recent study by Ji et al., [9].

4.4. Results of dependency switching copula

The estimation from the dependence-switching copula models with positive and negative correlation regime as well as regime switching are presented in Table 5. The results show the coefficients for the dependence-switching copula for each set of oil and agricultural commodities. The copula coefficients in the case of positive correlation regime (when both markets are bearish as well as when both markets are bullish, see panel A and B) are positive and significant at 1% for all pair of oil and commodities except oil-rice pair. These results are consistent with the results of Ji et al. [9]. However, the results from the negative correlation regimes (in case of bearish oil markets and bullish agricultural markets) are significantly negative at 5% level (at least) for oil-corn, oil-oats, and oil-wheat. No significant results were found in the case of oil-soybeans, oil-rice pair when the oil market is bullish and agricultural

[6] The mixture copula models proposed by Zimmer [45], as reported in Table A1 in the Appendix of the paper, yields a similar dependence pattern.

markets are bearish. These results suggest that corn, oats and wheat can serve as a hedge against oil returns, given that the correlation is negative and significant in these agricultural markets when the oil market is declining. Still, the same cannot be said for oil clearly.

Table 5: Estimation of the dependence-switching copula model.

	Corn	Oats	Soybean	Wheat	Rice
A Positive correlation regime– Panel A and Panel B					
Panel A: Both markets are bearish					
α_1	0.8955***	0.6664***	0.6951***	0.5891***	-0.0254
	(0.24)	(0.12)	(0.09)	(0.08)	(0.02)
ρ_1	0.4669***	0.3825***	0.3941***	0.3498***	-0.0203
	(0.08)	(0.05)	(0.04)	(0.04)	(0.02)
φ_1	0.2306***	0.1767***	0.1845***	0.1541***	3.29E+11***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.23)
Panel B: Both markets are bullish					
α_2	0.5205***	0.2321***	0.3739***	0.2619***	0.0198
	(0.15)	(0.08)	(0.08)	(0.07)	(0.04)
ρ_2	0.3187***	0.1627***	0.2449***	0.1809***	0.0155
	(0.07)	(0.05)	(0.04)	(0.04)	(0.03)
φ_2	0.1321***	0.0252	0.0784***	0.0354	3.58E-16
	(0.05)	(0.03)	(0.03)	(0.03)	(2.63E-14)
Negative correlation regime – Panel C and Panel D					
Panel C: Oil markets are bearish, agricultural markets are bullish					
α_3	-0.1109***	-0.0692**	-0.0167	-0.08334***	0.0651
	(0.03)	(0.03)	(0.04)	(0.04)	(0.07)
ρ_3	-0.0921***	-0.0563**	-0.0132	-0.0683***	0.0495
	(0.03)	(0.03)	(0.03)	(0.03)	(0.0497)
φ_3	259.27	1.11E+04	4.88E+17**	2045.94	1.19E-05
	(497.59)	(5.18E+04)	(0.40)	(7347.52)	(0.000131)
Panel D: Oil markets are bullish, agricultural markets are bearish					
α_4	-0.0467	0.0382	-0.0028	0.0384	-0.1330
	(3.70E-02)	(3.26E-02)	(3.42E-02)	(3.68E-02)	(0.11)
ρ_4	-0.0376	0.0294	-0.0022	0.0296	-0.1117
	(3.04E-02)	(2.47E-02)	(2.70E-02)	(2.78E-02)	(0.09)
φ_4	1.37E+06	6.43E-09*	2.69E+107***	7.08E-09	91.638
	(1.61E+07)	(9.98E-08)	(0.41)	(1.23E-07)	(390.26)
Panel E: Regime Switching					
P_{11}	0.9977***	0.9989***	0.9989***	0.9978***	0.9984
P_{00}	0.9984***	0.9998***	0.9995***	0.9963***	0.9949
LL	15491.87	15517.53	15449.45	15511.41	15577.00
AIC	-31023.70	-31075.10	-30938.90	-31062.80	-31193.94
BIC	-31161.30	-31212.60	-31076.50	-31200.40	-31331.51

Note: α_i is the shape parameter of the dependence-switching copula, and ρ_i and φ_i are the measures of dependence and tail dependence, respectively. The numbers in parentheses are standard deviations. LL, AIC and BIC denote the estimated log-likelihood value based on equation (4), the Akaike information criterion, and the Bayes information criterion, respectively. P_{11} and P_{00} are two transition probabilities. Values are in the order of the first parameter and the standard error. ** and *** indicates significant at 5% and 1% level of significance, respectively.

Panel E of Table 5 presents the coefficients of the regime-switching model. The results conclude that probabilities P_{11} and P_{00} are positive and significant at level 1%. However, we did not find any significant results for rice. The coefficients of the probabilities are close to 1, which confirms a high persistence of the same dependence regime. In line with Ji et al., [9], we also reported the results of parameter ρ_i and φ_i which measures the dependencies and tail dependencies across oil and agricultural commodities, respectively. The tail dependencies, according to Ji et al., [9], measure the probability of large losses or profits occurring simultaneously in both energy and agricultural markets. Therefore, under any extreme market conditions, the tail dependencies serve as a good signal for systemic risks.

Consistent with the literature, we find that commodity markets co-move together and suffer from extreme shocks (Pindyck and Rotemberg, [47]; Ji and Fan [48]; Ji et al. [9]). It is because the coefficients for most of the dependence and tail dependence during the positive correlation regime are significantly positive, whereas the majority are insignificant under negative correlation regime.

As the results of dependence-switching copula model in the previous section are much stronger for positive correlation regime, so we focused more on their features. Therefore, we presented the smoothing probability of positive correlation regime among oil returns and agricultural commodities returns for the full sample in Figure 1. It is clear from the graphs that all the pairs of oil and agricultural commodities exhibit similar patterns (excluding rice) with the highest jump to the probability to 1 during the global financial crisis.

Figure 2 displayed the smoothing correlation coefficients of agricultural commodities with oil as time-varying structures over time. From the graphs, it is clear that the level of correlation during the normal states for most of the pair of oil–agricultural are pretty low and are below 0.1. However, all the pairs of oil-agricultural commodities (except rice) show similar patterns with jumps in correlations to the highest level to 0.4 during the global financial crisis period. It concluded that the tails dependencies are important for risk consideration, specifically during the financial crisis. However, for the pair of oil-rice, the values are very low (few times approach 0) compared to other oil and agriculture commodities pares.

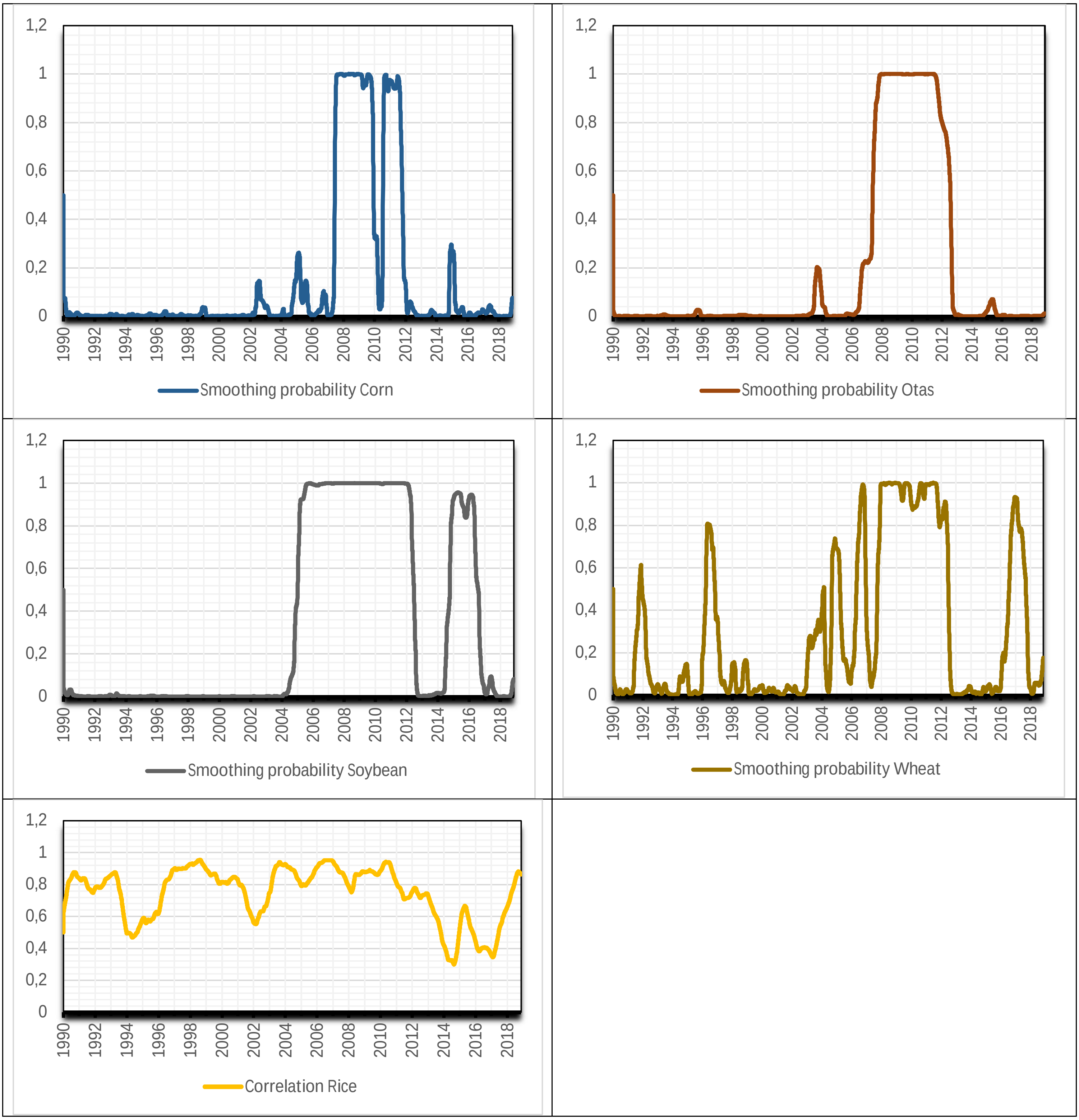

Figure 1: Smoothing probability of the positive correlation regime between the oil returns and agricultural commodity returns

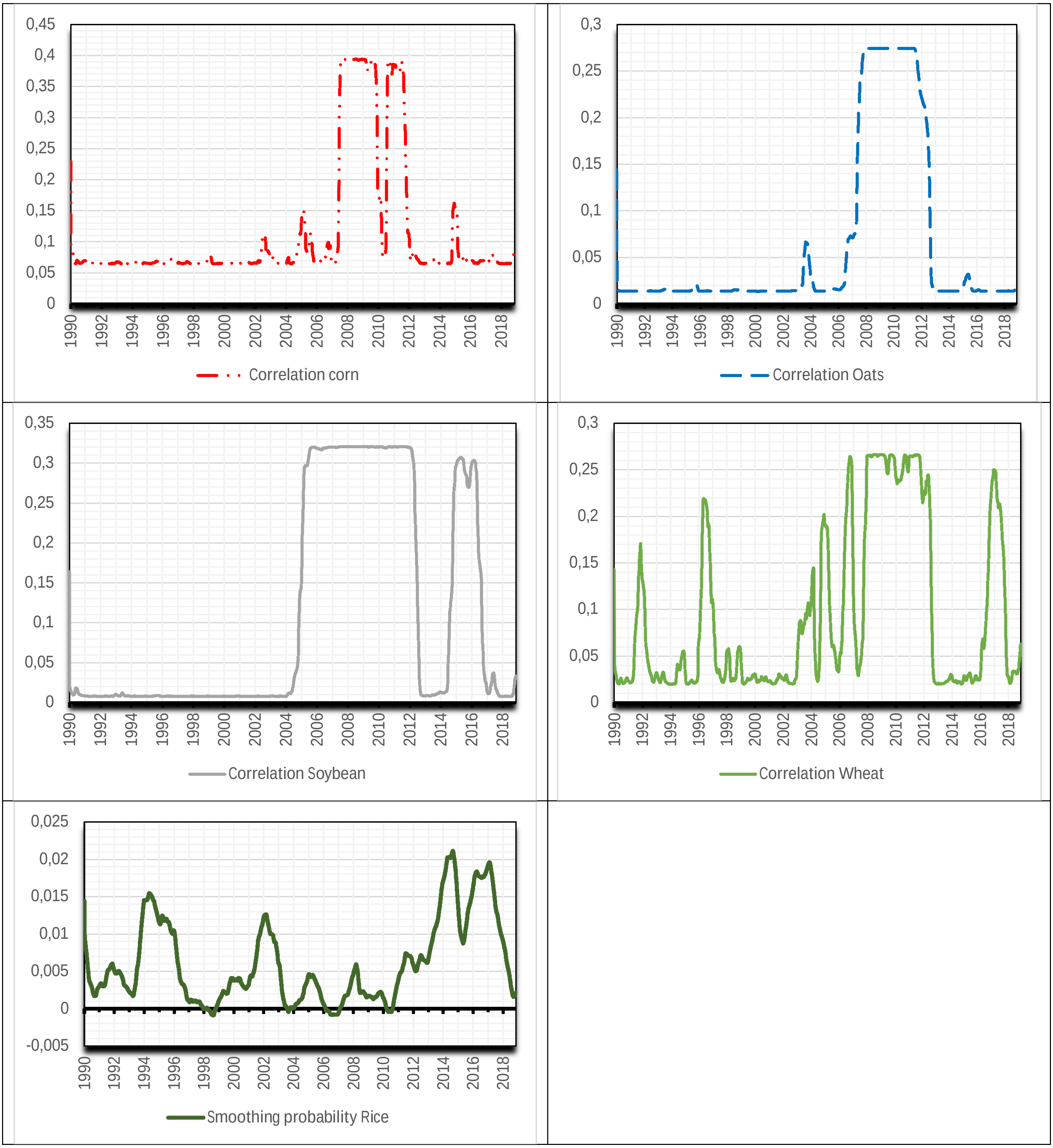

Figure 2: Smoothing correlation coefficients of the positive correlation regime between the oil returns and agricultural commodity returns

4.5. Geopolitical Risks and dependence between energy and agricultural markets.

The correlations for the agricultural commodities with oil under the positive correlation regime were also used as dependent variables to assess the effect of geopolitical risks, and hence the hedging ability of agricultural commodities in the wake of heightened geopolitical risks. Almost all the GPRs recorded a negative coefficient and were statistically significant at 1%. The only exception is GPRD_ACT and correlation for soybeans and rice. It suggests the existence of diversification benefits for investors by moving from oil to the agricultural commodities during periods of heightened risks associated with geopolitical factors.

Overall, these results on geopolitical risks and threats suggest that the GPRs influence the co-movement between energy and agricultural markets, and more importantly agricultural markets can hedge the risks of the oil market since geopolitical risks negatively affect the oil market (Cunado et al. [49]). The result in terms of the hedging ability of agricultural commodities, particularly corn, oats and wheat, for the oil market is also in line with the dependence results obtained earlier for bearish oil and bullish agricultural market, whereby we saw a negative correlation. Now, geopolitical risks can be used as a source for the bearish oil market.

Table 6: Geopolitical Risks and the Correlations for all Commodities with Oil

Variable	Correlations corn	Correlations oats	Correlations soybeanns	Correlations wheat	Correlations Rice
Part A					
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
GPRD	-0.00011***	-0.00013***	-7.61E-05***	-8.40E-05***	-0.000326***
	(1.54E-05)	(1.38E-05)	(2.04E-05)	(1.32E-05)	(2.43E-05)
C	0.122937***	0.073157***	0.116992***	0.101898***	0.773388***
	(0.001806)	(0.001619)	(0.002382)	(0.00155)	(0.002839)
Part B					
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
GPRD_ACT	-2.14E-05*	-3.06E-05***	6.31E-06	-2.02E-05**	1.77E-05
	(1.21E-05)	(1.08E-05)	(1.59E-05)	(1.04E-05)	(1.90E-05)
GPRD_THREAT	-8.61E-05***	-9.80E-05***	-7.98E-05***	-6.78E-05***	-0.000312***
	(1.49E-05)	(1.33E-05)	(1.96E-05)	(1.28E-05)	(2.34E-05)
C	0.123085***	0.0734***	0.116963***	0.102183***	0.771417***
	(0.001814)	(0.001626)	(0.002392)	(0.001557)	(0.002849)

Standard errors in parenthesis. ***, **, * denote significance at 1%, 5% and 10% respectively.

5. Conclusion

This study has investigated the structure dependence between energy and agricultural markets using copula method and prices on crude oil, corn, soybean, wheat and oats from April 4, 1990, to February 15, 2019. We used copula methods to investigate the dependence structure. Similar to Ji et al. [9], we used a dependence-switching copula approach while analyzing the dependence between oil and the four agricultural commodity markets.

Overall, our study shows that there is positive co-movement between energy and agricultural commodities. In particular, during the positive correlation regime, i.e., when oil and any specific agricultural commodity markets are in either bull or bear markets together. Dependence and tail dependence is stronger in the bearish markets under the positive correlation regime, suggesting that if oil and a specific agricultural commodity is in the downturn, their co-movements is stronger then, than when both markets are in the upturn. At the same time, in the negative correlation regime, dependence is only significant when agricultural markets are bullish, while oil market is bearish, suggesting that agricultural markets, especially, corn, oats and wheat, can hedge downturns in oil returns. This line of reasoning is further confirmed when we show that in the positive correlation regime, the correlation between oil and a specific agricultural commodity is negatively impacted by geopolitical risks.

Our results have financial implications. The significant tail dependence parameters indicate that traders or investors in one commodity market (say corn) should not overlook risks in other commodity markets (say crude oil) as well as geopolitical risks. Thus, commodity traders should pay equal attention to all commodity markets and geopolitical risks. To insulate oneself from the dual risks from the energy and agricultural markets, traders to carefully optimize their investments in these markets. Similarly, our results from the tail dependence, which measure extreme risk co-movement provide valuable evidence that can help to make a timely decision about risk management decisions as well as suitable portfolio approaches to protect investors. Specifically, we find the existence of a systematic risk during large market movements as well as with switching tail-risk interdependence, which could affect the portfolio managers or investors who often used commodities to diversify the risk.

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Appendix

Table A1: Mix Copulas results with Oil

	Corn	Oats	Soybean	Wheat	Rice
Mix 1: Gumbel copula + Clayton copula					
parameter1	0.213855	0.072976	0.115712	0.884045	0.021017
	0.109236	0.035544	0.049198	0.044201	0.076052
parameter2	1.274734	1.856058	1.741313	1.042595	1.223303
	0.176217	0.540894	0.412464	0.00924	0.937646
parameter3	0.083957	0.040609	0.075004	0.746758	0.004197
	0.025087	0.018275	0.019605	0.305931	0.013465
LV	59.32278	27.41203	63.47673	51.36329	0.554206
AIC	-112.646	-48.8241	-120.953	-96.7266	4.891588
BIC	-100.889	-37.0671	-109.196	-84.9696	16.64858
Observations	7176	7176	7176	7176	7176
Mix2: Rotated Gumbel copula + rotated Clayton copula					
parameter1	0.200647	0.124271	0.189708	0.149401	0.256547
	0.081702	0.03725	0.056313	0.05718	NaN
parameter2	1.349377	1.638232	1.494507	1.425069	1.01
	0.179337	0.226457	0.182384	0.215358	0.002834
parameter3	0.067952	0.018783	0.053222	0.060408	1.01
	0.022113	0.01865	0.020596	0.020076	0.005512
LV	60.05545	33.33949	67.23685	51.31047	0.004637
AIC	-114.111	-60.679	-128.474	-96.6209	5.990725
BIC	-102.354	-48.922	-116.717	-84.8639	17.74772
Observations	7176	7176	7176	7176	7176
Mix3: Gumbel copula + rotated Gumbel copula					
parameter1	0.194973	0.876229	0.094203	0.854792	0.0001
	0.110352	0.038594	0.049824	0.059893	0.32467
parameter2	1.261838	1.01	1.737651	1.032816	0.0001
	0.181184	0.010425	0.483701	0.010776	NaN
parameter3	1.048718	1.624281	1.0492	1.398643	0.008189
	0.014255	0.224951	0.011787	0.208866	0.012199
LV	60.14103	33.10197	65.09481	52.32301	0.239798
AIC	-114.282	-60.2039	-124.19	-98.646	5.520403
BIC	-102.525	-48.4469	-112.433	-86.889	17.2774
Observations	7176	7176	7176	7176	7176
Mix4: Clayton copula + rotated Clayton copula					
parameter1	0.185666	0.110198	0.155744	0.135974	0.0001
	0.080511	0.034189	0.045811	0.047613	0.32467
parameter2	0.592692	1.002529	0.933522	0.679532	0.0001
	0.297491	0.346699	0.320282	0.264863	NaN
parameter3	0.091964	0.042457	0.081695	0.082827	0.008189
	0.019734	0.016082	0.018048	0.01705	0.012199
LV	59.79565	31.46876	65.86922	50.26681	0.239798
AIC	-113.591	-56.9375	-125.738	-94.5336	5.520403

BIC	-101.834	-45.1805	-113.981	-82.7766	17.2774
Observations	7176	7176	7176	7176	7176
Mix5: t copula + Gumbel copula					
parameter1	0.9999	0.9999	0.9999	0.701088	0.9999
	0.005352	0.001858	0.002731	0.427361	NaN
parameter2	0.126889	0.080669	0.132571	0.13507	0.0058
	0.012026	0.01236	0.012101	0.079404	0.011946
parameter3	20.70039	15.39561	17.24521	9.883718	100
	5.512978	3.16291	3.845704	5.314288	133.0658
parameter4	1.01	1.01	1.01	1.016637	1.01E+00
	NaN	NaN	NaN	0.044889	NaN
LV	63.62593	35.14036	**70.49914**	**58.41253**	**0.30334**
AIC	-119.252	-62.2807	**-132.998**	**-108.825**	**7.393319**
BIC	-109.495	-52.5237	**-123.241**	**-99.0681**	**17.15031**
Observations	7176	7176	**7176**	**7176**	**7176**
Mix 6: t copula + rotated Gumbel copula					
parameter1	0.942616	0.942519	0.9999	0.73272	0.612118
	0.218049	0.049514	0.031728	0.47357	NaN
parameter2	0.133632	0.046096	0.13257	0.134087	0.0001
	NaN	0.026073	0.012481	0.09041	0.026064
parameter3	19.84606	21.06665	17.24515	10.15411	100
	4.822382	7.368059	3.864101	5.879173	55.68405
parameter4	1.01	1.832023	1.01	1.01	1.01E+00
	NaN	0.578307	NaN	0.057821	NaN
LV	63.62847	**36.88593**	**70.49923**	58.33552	0.490272
AIC	-119.257	**-65.7719**	**-132.998**	-108.671	7.019457
BIC	-109.5	**-56.0149**	**-123.241**	-98.914	16.77645
Observations	7176	**7176**	**7176**	7176	7176
Mix 7: t copula + Clayton copula					
parameter1	0.82294	0.908261	0.9999	0.739837	0.053434
	0.804488	NaN	NaN	0.816211	NaN
parameter2	0.153597	0.088959	0.132572	0.138541	0.055908
	0.145825	NaN	0.008506	0.203739	NaN
parameter3	17.85981	14.08094	17.24479	10.11084	6.286447
	13.54104	NaN	3.767572	9.474166	NaN
parameter4	0.003506	0.0001	0.002888	0.0001	1.00E-04
	0.1142	NaN	NaN	0.218651	NaN
LV	**63.64393**	35.14278	**70.49924**	58.33703	0.406109
AIC	**-119.288**	-62.2856	**-132.998**	-108.674	7.187781
BIC	**-109.531**	-52.5286	**-123.241**	-98.9171	16.94478
Observations	**7176**	7176	**7176**	7176	7176
Mix 8: Frank copula + rotated Gumbel copula					
parameter1	0.90713	0.873238	0.907347	0.84722	0.001001
	0.050967	0.047939	0.048818	0.056206	NaN
parameter2	0.492512	0.058919	0.48134	0.140371	0.001

	0.121444	0.142023	0.130507	0.136191	NaN
parameter3	1.600576	1.658528	1.825396	1.541124	1.004247
	0.322849	0.236605	0.443216	0.208136	0.004915
LV	61.11721	32.92319	69.27932	47.31611	0.451922
AIC	-116.234	-59.8464	-132.559	-88.6322	5.096157
BIC	-104.477	-48.0894	-120.802	-76.8752	16.85315
Observations	7176	7176	7176	7176	7176
Mix9: Clayton–Frank					
parameter1	0.060801	0.091129	0.057932	0.111312	0.011037
	0.039894	0.041241	0.040566	0.047914	0.022703
parameter2	1.097897	1.151281	1.763781	0.795083	0.879429
	0.703	0.478515	1.39012	0.334389	1.415341
parameter3	0.598013	0.210768	0.598391	0.339174	0.021811
	0.10109	0.119695	0.109453	0.112517	0.083932
LV	59.1719	29.30924	**67.13719**	41.43151	0.544013
AIC	-112.344	-52.6185	-128.274	-76.863	4.911975
BIC	-100.587	-40.8615	-116.517	-65.106	16.66897
Observations	7176	7176	7176	7176	7176
Mix10: Frank–Gumbel					
parameter1	0.91435	0.963337	0.968223	0.817119	0.011037
	0.055225	0.026552	0.016644	0.097212	0.022703
parameter2	0.537561	0.308283	0.635404	0.211559	0.879429
	0.119015	0.121789	0.102729	0.142444	1.415341
parameter3	1.523385	2.850389	3.880913	1.343664	0.021811
	0.321094	1.548384	1.809636	0.198394	0.083932
LV	59.37259	27.45844	68.14281	44.38301	0.544013
AIC	-112.745	-48.9169	-130.286	-82.766	4.911975
BIC	-100.988	-37.1599	-118.529	-71.009	16.66897
Observations	7176	7176	7176	7176	7176
Mix11: Clayton–Joe					
parameter1	0.237893	0.123442	0.191346	0.159704	0.011037
	0.0985	0.034631	0.052948	0.050838	0.022703
parameter2	0.517693	0.965312	0.830731	0.653967	0.879429
	0.254709	0.313411	0.279835	0.237338	1.415341
parameter3	1.061577	1.025707	1.051522	1.0552	0.021811
	0.016527	0.011159	0.014354	0.012714	0.083932
LV	58.53503	31.12587	63.16957	51.79664	0.544013
AIC	-111.07	-56.2517	-120.339	-97.5933	4.911975
BIC	-99.3131	-44.4947	-108.582	-85.8363	16.66897
Observations	7176	7176	7176	7176	7176
Mix12: Gumbel–Joe					
parameter1	0.237893	0.123442	0.191346	0.159704	0.011037
	0.0985	0.034631	0.052948	0.050838	0.022703
parameter2	0.517693	0.965312	0.830731	0.653967	0.879429
	0.254709	0.313411	0.279835	0.237338	1.415341
parameter3	1.061577	1.025707	1.051522	1.0552	0.021811

	0	0.016527	0.02277	0.012714	0.083932
LV	58.53503	31.12587	63.16957	51.79664	0.544013
AIC	-111.07	-56.2517	-120.339	-97.5933	4.911975
BIC	-99.3131	-44.4947	-108.582	-85.8363	16.66897
Observations	7176	7176	7176	7176	7176
Mix13: Frank–Joe					
parameter1	0.93111	0.123442	0.981374	0.115407	0.893668
	0.084045	0.034631	0.009249	0.041777	3.850856
parameter2	0.682706	0.965312	0.704671	4.784168	0.054942
	0.109252	0.313411	0.084313	1.8505	0.237912
parameter3	1.40694	1.025707	6.846663	1.032303	1.003023
	0.610329	0.011159	2.887671	0.012395	0.101569
LV	57.49036	31.12587	65.39433	44.80067	0.260427
AIC	-108.981	-56.2517	-124.789	-83.6013	5.479145
BIC	-97.2237	-44.4947	-113.032	-71.8443	17.23614
Observations	7176	7176	7176	7176	7176

Note: * denotes statistical significant at 5% level. The value in parenthesis is the standard error. The highlighted copulas are the copula with the best goodness-of-fit for the respective countries.