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Research article

Interdependence of oil prices and exchange rates: Evidence from copula-based GARCH model

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Abstract: This paper aims to investigate the conditional dependence structure between crude oil prices and three US dollar exchange rates (China, India and South Korea) from a new perspective using a copula-GARCH approach. Various kinds of copulas both time-invariant and time-varying dependence dynamics are fitted. Over the 2008–2018 period, the findings provide evidence of significant dependence in terms of symmetric structure between the oil prices and the exchange rate returns. Further, the tail dependence and dynamic dependence between two variables add a supplement to the explanatory ability of the model. Empirical results indicate the intercorrelation between crude oil and exchange rate movements, and provide benefits in risk diversification and inflation targeting. The findings also have significant implications for risk management, monetary policies to determine the behavior of fiscal policy in oil-exporting countries.

Keywords: oil; exchange rate; copula; GARCH

1. Introduction

Crude oil (WTI) is one of the most crucial commodities of the real economy and financial markets. The high volatility of oil prices has been taken into account responsible for economic recessions, high inflation, trade deficits and low values for stocks and bonds because the US dollar is the major invoicing and settlement currency in international oil markets [1]. The suggestions and causes of the fluctuations in oil have attracted attention from academic researchers and practitioners, especially in the aftermath of the oil price shocks of the 1970s. Past studies reveal that oil price movements considerably impact economic activity and equity markets [2]. For instance, oil price shocks negatively influence GDP [3], oil prices Granger- cause economic growth in Japan, South Korea, and Thailand [4], both asymmetric and nonlinear linkages between oil price shocks and macroeconomic variables [5]. Furthermore, Beckmann and Czudaj [6] confirm that a weak US dollar exchange raises the purchasing power of oil-importing nations, while negatively impacting oil exporting countries. The oil prices have been dramatically affected by countless elements, such as nation policy, seasonal aspects, geopolitics, supply and demand [7]. As a result, research of how the oil prices and exchange rate movements is of great interest for policymakers and international investors since it has significant implications for policy design and investment management.

As regards theory, the interrelation between the oil market and the exchange rate market is firmly established. Krugman [8] points out that an oil-exporting (oil-importing) country may experience exchange rate appreciation (depreciation) when oil prices rise, and depreciation (appreciation) when oil prices fall. Golub [9] documents the potential importance of oil prices in explaining exchange rate movements. Bloomberg and Harris [10] explore the considerable influence of currency markets on oil price movements. Over the last few years, several studies show that there is a negative relationship between two variables, which results in portfolio diversification and hedging strategy between commodities crude oil (WTI) and the US dollar [11].

There are several reasons why the present study selecting three main currencies of countries (China, South Korea and India) in Asian as a case study is that the diplomatic history of Asia has lacked correspondence rather than an association between different parts of the continent, especially between Northeast Asia and South Asia. According to Brewster [11], China, South Korea and India's size and power have served to divide the region rather than unite it strategically. Additionally, these countries are better examples of the political, economic, and strategic interrelatedness than the disconnection among China, South Korea and India. Further, three countries are emerging economies and in terms of economic power, the World Bank ranks China 4th, South Korea 5th and India 77th by the ease of doing business. Finally, the development of these countries has been gradually sustainable and stable in terms of the objective of cooperation in trade and investment, agriculture, climate, culture, defense, education, energy, health, science, technology, poverty alleviations and social development. Explicitly, their oil-dependent economies depend on foreign labor, so their foreign exchange markets illustrate themselves as a good comparative case study for investigating sudden changes or intercorrelations in variance and the existence of relatedness in comparison to markets in other regions [12].

Although voluminous empirical studies have employed a wide range of econometric techniques to highlight the interaction of oil price and exchange rate, and its influence on macroeconomic and currency policy, little is known about oil price–exchange rate co-movements using Copula-GARCH approach. Several outstanding past studies, for example, Wu et al. [7] apply copula-based GARCH models to capture the economic value of co-movement between oil price (WTI) and exchange rate (US dollar index). Aloui et al. [2] also use a copula-GARCH approach to study the conditional dependence structure between crude oil prices and US dollar exchange rates. Exchange rates correspond to the amount of US per each five major currencies (the Euro, the Canadian Dollar, the British Pound Sterling, the Swiss Franc and Japanese Yen). In a same vein, Reboredo [1] considers the exchange rate data referred to European Union countries (Germany, France, Italy, Netherlands, Belgium/Luxembourg, Ireland, Spain, Austria, Finland, Portugal, Greece, Slovenia, Cyprus, Slovakia and Malta), Australia, Canada, United Kingdom, Japan, Norway and Mexico when implementing to examine the links between crude oil and these currency markets. Sebai and Naoui [13] study the connectedness between oil prices and the US dollar exchange rate using a copula approach and the DCC-MGARCH model. Our empirical work attempts to fill this gap by reexamining the oil-exchange rate dependence structure in three major countries in Asia (China, South Korea and India) through static and time-varying copulas. We believe that the results of this study will improve understanding of the oil price-exchange rate connectedness in the selected countries.

This paper significantly contributes to the existing literature in the following ways. First, we take a novel approach in studying the dollar exchange rate movements in three major countries in Asia (China, India and South Korea), which has not been investigated in the literature. This paper also remarkably contributes to the systematical understanding of intercorrelation between crude oil prices and exchange rate returns in the selected nations and could be best depicted by a time-varying Gaussian copula. Second, this study makes methodological advancements by introducing the copula-based GARCH models to comprehensively report the volatility and dependence structure of crude oil prices and dollar exchange rate returns. The copula-based GARCH models may also put on show asymmetric and tail dependence as well as skewness and leptokurtosis of oil and exchange rate returns [7]. This research has employed the copula-based GARCH models to get the better of the drawbacks of multivariate GARCH models and provide a more accurate result for the dependence structure [14].

The rest of this paper is structured as follows: Section 2 provides a review of past literature. Section 3 presents the methodology and data. Section 4 provides empirical results. Lastly, a conclusion is drawn in Section 5.

2. Literature review

This section briefly reviews several articles that investigate the connectedness between oil prices and exchange rates in Asian countries. In recent years, some methods have been used to address the issue of the relationship between two variables. For example, Nusair and Olson [15] investigate the effects of oil price shocks on Asian exchange rates using quantile regression analysis and verify that positive and negative oil price shocks have asymmetrical influences on exchange rate returns, which vary in significance, size, and sign throughout the distribution of exchange rate returns. Hussain et al. [16] employ a detrended cross-correlation approach to examine the co-movements of the oil price and exchange rate in 12 Asian countries (China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, Pakistan, the Philippines, Singapore, Sri Lanka, Taiwan). The findings demonstrate a weak negative cross-correlation between oil price and the exchange rate for most Asian countries included during the sample period. Chen et al. [17] present the impacts of oil price shocks on the bilateral exchange rates of the US dollar against currencies in 16 countries, and point out that the responses of dollar exchange rates to oil price shocks differ greatly depending on whether changes in oil prices are driven by aggregate demand. Nusair and Kisswani [18] use the Johansen cointegration test to determine the long-run relationship between Asian real exchange rates and oil prices in the presence of structural breaks, and provide evidence of a stable long-run relationship in all but Japan and the Philippines. Specifically, the results reveal unidirectional causality from exchange rates to oil prices in Korea, the Philippines, and Singapore. Turhan et al. [19] employ VAR models to examine the role of oil prices in explaining the dynamics of selected emerging countries' exchange rates using daily data. Authors show that a rise in oil prices results in the significant appreciation of emerging economies' currencies against the U.S. dollar. Further, this article recommends that oil price dynamics change significantly in the sample period and the relationship between oil prices and exchange rates became more apparent after the 2008 financial crisis including the case of South Korea, the Philippines and Indonesia. At the same time, Beckmann and Czudaj [6] deliver evidence for various causalities replying on the dataset including in nominal terms, effective depreciation of the dollar triggers an increase in oil prices when analyzing the connectedness between oil prices and the dollar exchange rate applying Markov-switching vector error correction model. Basher et al. [20] use a SVAR to model the dynamic linkages between real oil prices, an exchange rate index for major currencies, emerging market stock prices. Employing monthly data from 1972 to 2005, the authors find that positive shock to oil prices tend to depress emerging stock prices and the trade-weighted US. dollar index in the short run. Lizardo and Mollick [21] make a great contribution to the monetary model of exchange rates by adding oil price variable, and document that oil prices accurately describe movements in the value of the U.S. dollar (USD) against major currencies from the 1970s to 2008. Using Causality tests, cointegration and VECM approaches, Bénassy-Quéré et al. [22] study cointegration and causality between real oil prices and the dollar exchange rates using monthly data from 1974 to 2004, and point out that a 10 % increase in the oil price coincides with a 4.3% appreciation of the dollar in the long term, and that the causality runs from real oil prices to the dollar exchange rates. Chen and Chen [23] focus on the long-run relationship between real oil prices and real exchange rates using a monthly panel of G7 countries, and verify that real oil prices might have been the presiding source of real exchange rate movements and there exists a connectedness between real oil prices and real exchange rates.

As a short summary, despite the wealth of literature concerning the relationship between oil prices and exchange rates, especially in the Asian area, very limited research has been carried out in China, South Korea and India market context. Furthermore, the most often used methods for connectedness analysis between these variables do not implicate the fundamental time-varying changes in the dependence structure and are not relevant when marginal distributions are sophisticated. As a result, the aim and primary contribution of this current investigation are to fill this gap.

3. Methodology

The commodity market and exchange rate movements vary all the time and their dependencies might not be vividly depicted by static and linear models. As per Bai and Lam [14], asymmetric and time-varying correlations of the financial time series and volatility clustering are modelled by the copula function. We first start with the brief introduction to copula functions, then represent uniform marginals for return distributions, the alternative families of copula models of conditional dependence structure between the variables.

3.1. Copula function

A copula presents the cumulative distribution function of a multidimensional distribution with uniform marginal distributions [24]. Sklar [25] shows that a copula function illustrates the interaction between a bi-dimensional distribution and its two marginal distributions, apprehending the dependency structure [26]. They can state that a 2-dimensional joint distribution function F with continuous marginal F_1 and F_2 has been defined as follows

$$F(x_1, x_2) = C\left(F_1(x_1), F_2(x)\right) \tag{1}$$

where C is the copula function and F_1, F_2 are the marginal functions which have the uniform distributions. Copulas could be applied to measure rank dependence as well as tail dependence. Kendall's tau rank correlation is utilized to capture monotonic dependence structures:

$$\tau = (m-n)/(e+f) \tag{2}$$

where m and n are the numbers of concordant and discordant pairs respectively. The coefficient of Kendall's tau could be defined as below [26]:

$$\tau\left(X_1, X_2\right) = 4E\left[C\left(F_1(X_1), F_2(X_2)\right)\right] - 1 = \int_0^1\int_0^1 C(u_1, u_2)dC(u_1, u_2) - 1 \tag{3}$$

where u_1 and u_2 are the cumulative distribution functions. Further, copulas also could measure the tail dependence. The lower tail dependence is referred to as the probability of having an utmost small value of one variable given an extremely small value of another variable. The upper tail dependence $(\lambda_u \in [0,1])$ can be written as

$$\lambda_u\left(X_1, X_2\right) \equiv \lim_{q\to 1^-} P\left(X_2 > F_2^{-1}(q) \mid X_1 > F_1^{-1}(q)\right) \tag{4}$$

where X_1, X_2 are continuous variables. F_i^{-1} is the quantile function and the lower tail dependence is defined symmetrically.

3.2. Marginal specifications

We look in the interdependence between crude oil and each of the three US dollar exchange rate returns. We combine the copula functions with the AR-GARCH model of conditional heteroscedasticity because many financial time series have been shown to have problems of leptokurtosis, volatility clustering, long memory and leverage effect [14]. BIC criterion is determined the amount of AR lag terms. Given a time series y_t, the GARCH (1,1) model can be written as

$$y_t = \mu + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \varepsilon_t,\ \varepsilon_{i,t} \mid \psi_{t-1} = \sigma_{i,t} z_{i,t} \tag{5}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

$$z_{i,t} \sim skewed - t(z_i \mid \upsilon_i, \lambda_i) \tag{7}$$

where (5) is the conditional mean equation and (6) presents the conditional variance equation. σ_t^2 is the conditional variance of return series at time t, with the following conditions: $\omega > 0, \alpha > 0, \beta > 0$ and $\alpha + \beta < 1$ to confirm a stationary GARCH process. The skewed Student-t distributions are fitted for the shocks with υ degree of freedom and λ being the skewness parameter in order to successful capture the possibly asymmetric and heavy-tailed characteristics of oil price and exchange rate returns.

3.3. Copula models of conditional dependence structure

A diversity of copula models was adopted in this study, which allowed us to capture the both symmetric and asymmetric structure of extreme dependence between variables, including Gaussian, Student-t, Clayton (survival), Gumbel (survival), Frank, Joe, Clayton-Gumbel survival and Joe-Clayton.

The bivariate Gaussian copula is defined as

$$C(u,v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \left(1/2\pi|R|^{1/2}\right)\exp\left\{-(u,v)' R^{-1}(u,v)/2\right\} dudv \tag{8}$$

where ϕ presents the univariate standard normal distribution function u and v and R refers to as the correlation matrix.

The bivariate Student-t copula is defined as

$$C_t\left(u,v;R,n\right) = \int_{-\infty}^{t_n^{-1}(u)} \int_{-\infty}^{t_n^{-1}} \left(\Gamma\left(n+2\right)/2|R|^{-1/2}\right)/\left(\Gamma\left(n/2\right)\left(n\pi\right)\right)\left(1+1/n\left(u,v\right)' R^{-1}\left(u,v\right)\right)^{-(n+2)/2} dudv \tag{9}$$

where $t_n^{-1}(u)$ is the inverse of the CDF of the standard univariate Student-t distribution with v degree of freedom. R is also the correlation matrix.

The Clayton copula function proposed by Clayton [27] is defined as

$$C(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta}, \theta > 0 \tag{10}$$

where θ is copula parameter.

Gumbel copula (Gumbel [28]) is defined as

$$C(u,v) = \exp\left\{-\left[\left(-\ln u\right)^{\theta} + \left(-\ln v\right)^{\theta}\right]^{1/\theta}\right\}, \theta \geq 1 \tag{11}$$

Frank copula (Genest [29]) is defined as

$$C\left(u,v\right) = -1/\theta \ln\left[1+\exp\left(-\theta u\right)\left(\exp\left(-\theta v\right)-1\right)/\left(\exp\left(-\theta\right)-1\right)\right], \theta \in R \setminus \{0\} \tag{12}$$

The Joe copula (Joe [30]) is given by

$$C\left(u,v\right) = 1-\left[\left(1-u\right)^{\theta} + \left(1-v\right) - \left(1-u\right)^{\theta}\left(1-v\right)^{\theta}\right]^{1/\theta}, \theta \geq 1 \tag{13}$$

The Clayton-Gumbel and Joe-Clayton copulas (Joe and Hu [31]), which are known as BB1 and BB7.

BB1 model is defined as

$$C(u,v)=\left(1+\left[\left(u^{-\theta}-1\right)^{\delta}+\left(v^{-\theta}-1\right)^{\delta}\right]^{1/\delta}\right)^{-1/\theta} \tag{14}$$

BB7 model is defined as

$$C(u,v)=1-\left(1-\left[1-\left(1-u^{\theta}\right)\right]^{-\delta}\right)+\left(1-\left[1-\left(1-v^{\theta}\right)^{-\delta}-1\right]^{-1/\delta}\right)^{1/\theta} \tag{15}$$

where $\delta>0$ and $\theta\geq 1$, $\tau^{L}=2^{-1/\delta},\tau^{U}=2-2^{1/\theta}$

Cech [32] defined the survival copulas as

$$C_{180}(u,v)=u+v-1+C(1-u,1-v) \tag{16}$$

3.4. The dependence parameters of the time-varying copula

In this paper, we also considered dynamic dependence for Gaussian copula by assuming the copula dependence. According to Tang et al. [26], parameters vary over time following to the lag-one dependence ρ_{t-1} and historical information $\left(u_{t-1}-0.5\right)\left(v_{t-1}-0.5\right)$. The process follows:

$$\rho_t=A\left(\alpha_c+\beta_c\rho_{t-1}+\gamma_c\left(u_{t-1}-0.5\right)\left(v_{t-1}-0.5\right)\right) \tag{17}$$

where $A=-\ln\left[(1-x_t)/(1+x_t)\right]$ is the logistic transformation, which is to make sure that the dependence parameter belongs to the interval (−1,1).

3.5. Estimations of copula parameters

We employ the two-step estimation method to capture copula parameters, that is the Inference Functions for Margins (IFM) method developed by Shih and Louis [33].

Let a_1,a_2 be two random variables, where a_i is cumulative distribution function (cdf) $F_i(a_i,b_i)$ and $f_i(a_i,b_i)$ is its destiny functions. b_1,b_2 and θ_c are the parameters to be estimated for the marginals and the copula respectively. The a_i of the marginal are measured by

$$\hat{a}_i=\arg\max\sum_{t=1}^{T}\ln\, f_i(a_{ti},b_i),\quad i=\overline{1,2} \tag{18}$$

We estimate unknown parameter θ_c of the copula as

$$\hat{\theta}_c = \arg\max \sum_{t=1}^{T} \ln c\left(F_1(a_{t1};\hat{b}_1), F_2(a_{t2},\hat{b}_2);\theta_c\right) \tag{19}$$

3.6. Goodness-of-fit tests

Crame-von Mises (CvM) statistic is applied to capture goodness-of-fit tests for the copula models which can be written as

$$S_n = \sum_{t-1}^{n} \left\{C_k\left(u_t, v_t; \hat{k}\right) - C_n\left(u_t, v_t\right)\right\}^2 \tag{20}$$

Genest et al. [34] provide a parametric bootstrap procedure to calculate the p-value of the test.

3.7. Data

Our dataset contains weekly West Texas Intermediate (WTI) crude oil prices and exchange rates correspond to the amount of USD per one unit of each of three major currency in Asian trade: the Chinese Yuan Renminbi (CNY), the Indian Rupee (INR) and the Korea (South) Won (KRW) for the period 1 June 2008 to 30 December 2018 (573 observations), which are obtained from Bloomberg database. The way we calculated the returns on crude oil price and exchange rates was to take the logarithm difference of the two successive weekly prices. The choice of the three countries is justified as those are the top countries in terms of exports of goods and services as well as emerging economy in Asia [26], and these nations have not been taken into account the questions of the interrelatedness between the oil price and exchange rate movements when we made a comparison with most previous investigations.

The graph in Figure 1 shows the time-paths of returns and the price developments of the crude oil (WTI), the US. Dollar against Chinese Yuan Renminbi (CNY), Indian Rupee (INR) and Korea (South) Won (KRW) over the study period. It is clear from the weekly return graphs that return of oil was highly volatile during the research period after completing the global financial crisis (2007) and less for currencies, while the weekly prices experienced a dramatical fluctuation.

The reason for this phenomenon because new investment or speculation opportunities might be derived by traders based on the connectedness between the oil and US dollar exchange rate markets [7]. As a result, there are volatility clustering effects for all selected variables, giving a justification for the manipulation of GARCH models.

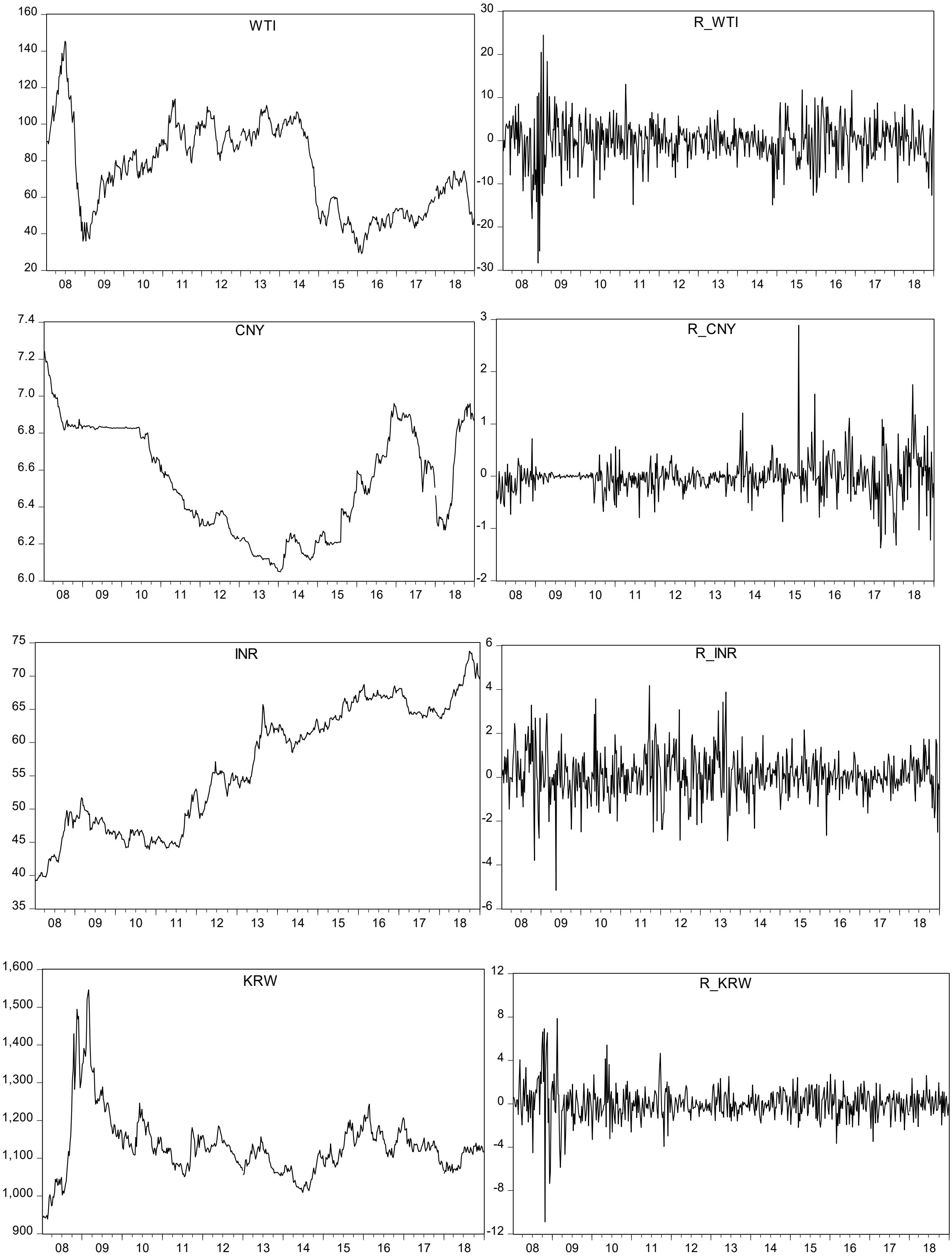

Figure 1. Weekly close prices and returns, June 1, 2008–December 30, 2018.

The descriptive statistics and distributional characteristics for crude oil and exchange rate returns are summarized during sample period 2008–2018 in Table 1, which reveals that the standard deviation of oil returns is higher than that of exchange rate returns, consistent with general results in the literature that commodities have higher volatilities. All four series illustrate negative skewness except CNY and kurtosis that is higher than normal, thereby implying that negative returns take place more often than large positive returns and the distribution of returns has larger, deeper tails than the normal distribution. Therefore, it is more plausible to apply skewed Student-t distributed error terms in the AR-GARCH models [14]. Similarly, the Jarque-Bera statistics are large and significant, so the assumption of skewed Student-t is more appropriate in our investigation. Ljung-Box (LB) Q statistics of order 10 show the persistence of autocorrelation in all the return series. Finally, results of the Lagrange Multiplier tests indicate the presence of ARCH effects in the return series, thus supporting to apply the GARCH-based approach.

Table 1. Descriptive statistics of return series.

	WTI	CNY	INR	KRW
Mean	−0.0011	0.0000975	0.001005	0.000306
Maximum	0.24472416	0.02890333	0.04179342	0.07867303
Minimum	−0.28381920	−0.01373338	−0.05160288	−0.10886315
Std.dev	0.051120527	0.003606234	0.010529856	0.015732963
Skewness	−0.44979824	1.15297540	−0.01116092	−0.21979474
Kurtosis	4.030170	9.977774	2.248166	7.894281
Jarque-Bera	410.54^{*}	2517.5^{*}	122.24^{*}	1501.7^{*}
Q(10)	39.99^{*}	55.42^{*}	11.00^{***}	48.70^{*}
ARCH	192.9^{*}	198^{*}	167.8^{*}	112.8^{*}
AR(p)	4	4	4	1

Notes: ARCH is the heteroscedasticity test. Liung-Box Q-statistic is the test for autocorrelation using 10 lags. *,**,*** deno te significance at 1%, 5% and 10% respectively. AR(p) represents the best AR lag selected by BIC criterion.

4. Empirical results

4.1. Results of the marginal models

In a preliminary step, we consider several limitations of the general marginal model before using copula methods for measuring the degree of interdependence among variables. The optimal AR(p) lags are determined by BIC criterion as indicated in Table 1. Table 2 reports the parameters of the corresponding skewed-t AR(p)-GARCH(1,1) parameters for each return series.

As we can see from Table 2, skewness and shape parameters are statistically significant, thereby implying that the skewed-t distribution of the errors term is appropriate for the four series. This is consistent with the evidence documented in Table 1**.** Additionally, the coefficients of α and β in the GARCH specifications are statistically significant and meaning that WTI, CNY, INR and KRW returns have volatility clustering effects. Meanwhile, $\alpha+\beta$ is close to 1, which thus shows that conditional volatility is past-dependent and quite persistent to all four series. Further, the Ljung-Box Q and ARCH-LM statistics are not statistically significant, which illustrates that there does not exist autocorrelation and GARCH effects under consideration. Hence, we can conclude that the marginals are clearly specified.

Table 2. Parameter estimates for the marginal models.

	WTI	CNY	INR	KRW
Mean equation				
μ	−0.000814	−0.000053	0.000693	−0.000428
	(0.001731)	(0.000041)	(0.000451)	(0.000498)
θ_1	0.048516	0.056369	0.069738**	0.052243
	(0.042782)	(0.043765)	(0.042719)	(0.044742)
θ_2	−0.027193	0.078344	0.031599	−0.067292***
				(0.043430)
Variance equation				
ω	0.000040***	0.0000001	0.000002	0.000007
	(0.000027)	(0.000001)	(0.000011)	(0.000014)
α	0.091130*	0.157551*	0.095571	0.136854**
	(0.026328)	(0.034526)	(0.130006)	(0.079289)
β	0.895217*	0.841449*	0.891268*	0.831484*
	(0.029140)	(0.029802)	(0.136581)	(0.044155)
υ	8.078940**	3.863446*	5.893756**	8.110733**
	(2.556187)	(0.404775)	(3.130839)	(3.599319)
λ	0.832369*	1.000965*	1.045379*	1.061891*
	(0.050615)	(0.046719)	(0.072858)	(0.063671)
Q(5) p-value	0.9562	0.9998	0.9998	0.9636
ARCH p-value	0.5916	0.9978	0.5233	0.9596

Notes: Ljung-Box is the test for autocorrelation using 5 lags. ARCH is heteroscedasticity test. The numbers in parenthese s are standard errors. *,**,*** denote significance at 1%, 5% and 10% respectively.

4.2. Copula results

Figure 2 demonstrates several copula contour plots under skewed-t marginal distribution to monitor how the dependency structures would be among divergent filtered series before fitting into various kinds of the copula. These plots illustrate that the marginal difference causes great dissimilarly when using the same copula. As such, this paper employs the copula model to provide an adaptable approach of constructing bivariate distributions given the marginal distributions, and the dependence structures separately. Next section, we document the static copulas and time-varying copula fitted to the residuals from marginals.

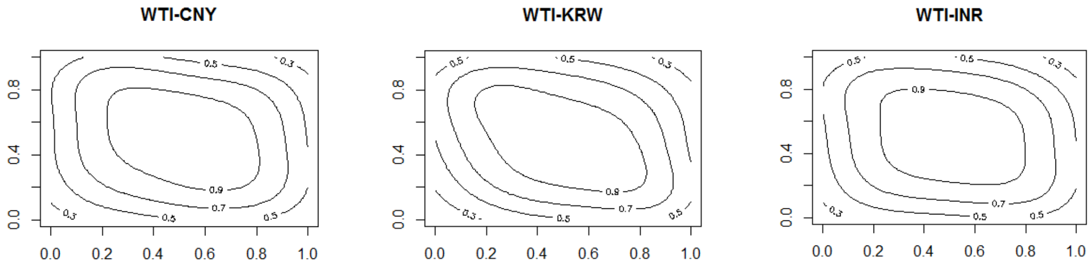

Figure 2. Contour plots based on Student-t copula.

Table 3 represents the copulas parameters of static and time-varying dependence between various returns series. We employ the method of simulation for standard errors of the two-staged parameter estimator proposed by Patton [35]. For each pair under consideration, the copulas are classified based on both AIC and Log-likelihood (LL) criterion. According to Bai and Lam [14], Cramer-von Mises tests can be applied to get extra evidence of good-of-fit of models as indicated in Table 4**.** The large p-value demonstrates that the copula provides a better fit to the model [26,14]. The following sections elaborate the various dependence structures between each of pair.

The estimations for the static copulas document in panel A of Table 3 show that the dependence parameters for 10 copula functions (Gaussian, Student-t, Gumbel, Frank, Clayton, Joe, BB1, BB7, Survival Clayton, Survival BB1, Survival Gumbel) are, as expected, highly significant and positive for almost all the pairs under consideration. The dependence somewhat varies across pairs of the crude oil and exchange rate. These findings properly support the hypothesis of significant dependence between oil and exchange rate returns over the research period.

For the dependence between WTI and CNY could be adequately explained by Survival Gumbel copula based on the AIC criterion, which is also found out by the CvM test. The finding suggests that the connection between WTI and CNY is symmetric and similar during sample period. The conditional linear correlation picked up from time-varying copulas is also plotted in Figure 3, which simply get a systematical understanding of the dependence structure. The linear correlation from time-varying Gaussian copula provides strong evidence of interrelatedness between WTI and CNY since 2008. The correlation coefficients fluctuate around zero prior to 2009, then gradually decreases to about 0.09 and stay below zero ever since. The findings from the copula could draw the conclusion that the crude oil WTI and CNY exchange rate are weak negatively correlated, which implies that the volatility of crude oil causes the extreme movements of China currency. The findings are in line with Hussain et al. [16] and Chen et al. [17].

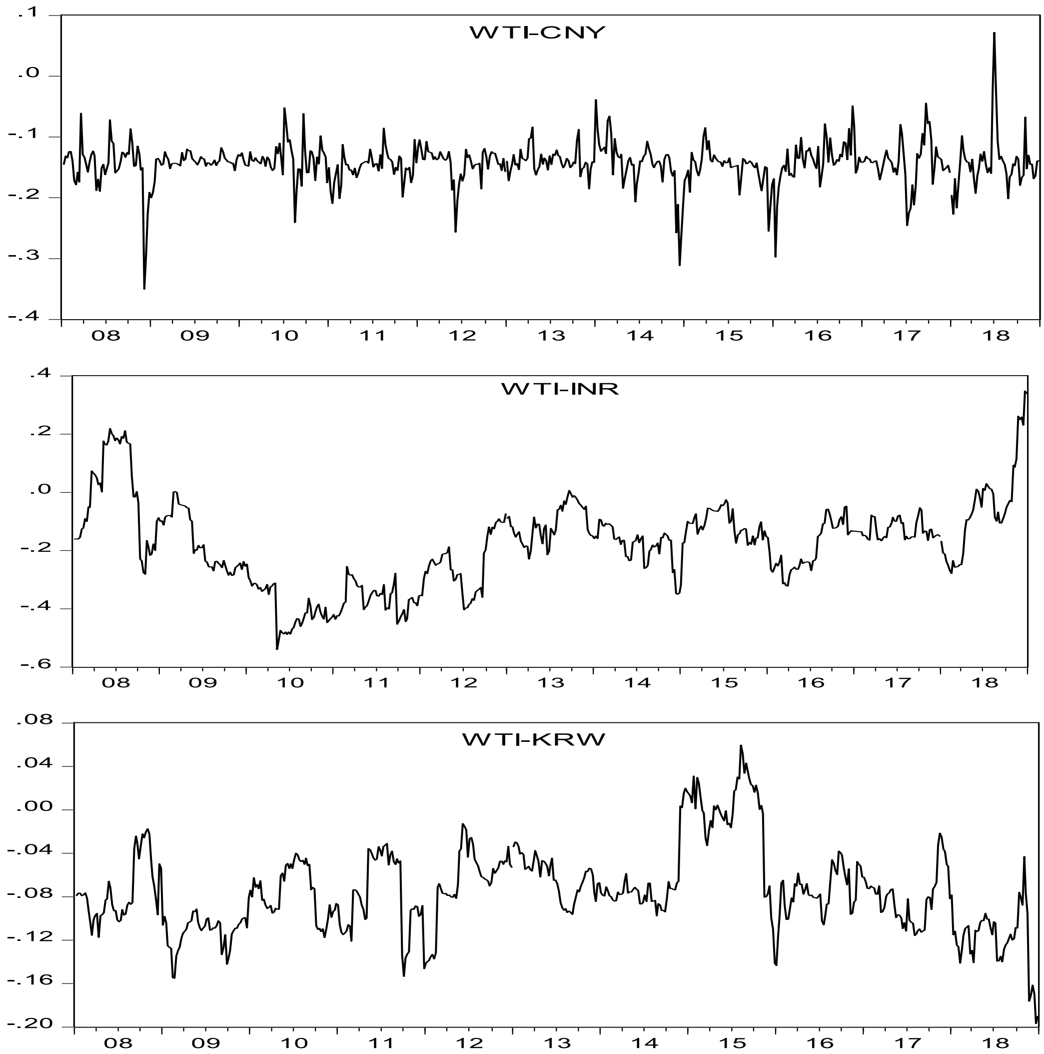

Figure 3. Conditional dynamic dependence estimates with critical value of 10% between crude oil and exchange rates from China, India and Korea.

Survival Gumbel copula also provides the best fit for the case of WTI and INR, while Student-t copula fully explains for the dependence between WTI and KRB based on AIC criterion. Additionally, LL differences between survival Gumbel and Student-t copula for this case are quite small. WTI-INR has systematic tail dependence with Student-t copula selected for the static case. As we can see from the average linear correlation, the dependencies between WTI and KRW, CNY are all very strong. Namely, KRW has the highest correlation with the crude oil price (0.24) followed by CNY (0.166) and INR (0.15).

In order to capture a better picture of the time-varying evolution, we plot the dynamic dependence parameter estimates between the crude oil and exchange rate movements over the sample period from the GARCH-copula model in Figure 3. It can be seen that the crude oil and the selected exchange rate have a different conditional dependence structure. We can summarize some interesting results from the figures of the dynamic copula as follows: First, the conditional correlation of the selected exchange rate with crude oil varies overtimes. Second, overall, it is significantly negative in all periods and positive in some periods. Specifically, the dependence structure between crude oil and exchange rate returns maintains a lower level or zero dependence during the research period. This result supports for the studies of Lizardo and Mollick [21]; Bénassy-Quéré et al. [22]; Nusair and Kisswani [15]. This would be because US government policy caused the US dollar to decrease dramatically in value in connection with most other countries' currencies so as to assist its exports as well as reduce the international trade deficit [7].

The goodness-of-fit test results to prove that the copula can fit well to the variables except for several cases. The paper follows the approach suggested by Aloui et al. [2]; Bai and Lam [14] using Cramer-von Mises tests to estimate p-value of the bivariate goodness-of-fit for different copulas. The test indicates that all market pairs are significant for all copulas used in the paper at the 5% level, providing that all the copulas can fit all the pair very well.

Briefly, the findings from the copulas could shed light on some key features. Firstly, the results point out the negative interconnectedness between crude oil prices and the selected exchange rate returns. The reasonable explanation for this negative relationship might be (i) oil-exporting countries wish to stabilize the purchasing power of their export revenues to keep away from losses they may take on currencies pegged to the US dollar. (ii) the depreciation of the US dollar creates oil more inexpensive for consumers in non-US dollar regions, to change their crude oil demand. (iii) a falling US dollar reduces the return on the US dollar denominated financial assets, increasing the attractiveness of oil and other commodities to international investors [7]. Furthermore, the dependency between WTI and CNY has been higher than the rest of pairs, which is attributed to the high volume of traded currencies in terms of neither net exporters nor significant importers of oil relative to their total trade in China. These dependences also exist significant time-varying correlations between the crude oil price and the exchange rate returns (CNY, INR and KRW). Finally, the dependence structure is asymmetric (tail dependence) for almost all market pairs, meaning that joint extreme co-movements are more likely to occur during the study period.

Table 3. Estimates for copula models.

	WTI-CNY	WTI-INR	WTI-KRW
Panel A: static copula			
Gaussian			
ρ	0.168^{*}(0.0408)	0.16^{*}(0.041)	0.234^{*}(0.0392)
LL	7.84	7.05	15.5
AIC	−13.7	−12.1	−29.1
Student-t			
ρ	0.166^{*}(0.0434)	0.15^{*}(0.0448)	0.24^{*}(0.042)
v^{-1}	0.103(0.0402)	0.0983(0.0403)	0.155(0.016)
LL	8.95	10.3	17.9
AIC	−13.9	−16.5	−31.9
Clayton			
θ	0.96^{*}(0.0504)	0.202^{*}(0.0516)	0.218^{*}(0.0825)
LL	7.17	8.47	7.91
AIC	−12.3	−14.9	−13.8
Gumbel			
θ	1.10^{*}(0.0292)	1.09^{*}(0.0281)	1.18^{*}(0.0341)

Continued on next page

	WTI-CNY	WTI-INR	WTI-KRW
Panel A: static copula			
LL	6.25	5.41	21.2
AIC	−10.5	−8.81	−40.5
Frank			
θ	0.96*(0.256)	0.897*(0.256)	1.43*(0.258)
LL	7.01	6.11	15.5
AIC	−12	−10.2	−28.9
Joe			
θ	1.12*(0.0384)	1.1*(0.0361)	1.26*(0.047)
LL	4.04	3.09	19.7
AIC	−6.07	−4.17	−37.4
Survival Clayton			
θ	0.173*(0.0639)	0.151*(0.0647)	0.329*(0.0543)
LL	5.72	4.48	18.3
AIC	−9.45	−6.96	−34.7
BB1			
δ	0.12(0.0684)	0.162(0.069)	0.001(0.000434)
θ	1.05*(0.0384)	1.03*(0.036)	1.18*(0.0355)
LL	8.23	8.89	21.2
AIC	−12.5	−13.8	−38.4
Survival BB1			
δ	0.123(0.0368)	0.04(0.131)	0.29(0.0844)
θ	1.05*(0.0649)	1.09*(0.0374)	1.03*(0.0412)
LL	9.88	9.73	18.6
AIC	−15.8	−15.5	−33.1
BB7			
δ	1.06(0.0609)	1.04(0.0466)	1.22(0.0575)
θ	0.154*(0.0498)	0.181*(0.0602)	0.0871*(0.0645)
LL	8.08	8.87	20.7
AIC	−12.2	−13.7	−37.4
Survival Gumbel			
θ	1.11*(0.03)	1.101*(0.0307)	1.15*(0.0299)
LL	9.27	9.5	10.8
AIC	−16.5	−17	−19.5
Panel B: dynamic copula			
Dynamic Gaussian copula			
α_c	0.0031*(0.044)	0.0180*(0.0124)	0.0541*(0.0201)
β_c	0.801(0.1320)	0.380***(0.0730)	0.1260(0.0910)
γ_c	−0.501(0.3001)	0.228(0.1045)	1.360(0.1722)
LL	3.24	1.20	3.01
AIC	−7.1	−0.12	−4.7

Notes: Standard errors are in parenthesis. LL and AIC value for different specifications are presented. *,**,*** denote signif icance at 1%, 5% and 10% respectively. LL stands for Log-Likelihood.

Table 4. CvM goodness-of-fit test.

	WTI-CNY	WTI-INR	WTI-KRW
Gaussian	0.11454	0.10711	0.18075
Student-t	0.44233	0.32518	0.24887
Clayton	0.98201	0.86547	0.16709
Gumbel	0.72832	0.55810	0.90412
Frank	0.50043	0.50834	0.96106
Joe	0.40014	0.49200	0.29606
Survival Clayton	0.62061	0.41903	0.18085
Survival Gumbel	0.62421	0.45076	0.18029
BB1	0.62110	0.30753	0.17999
Survival BB1	0.60097	0.17753	0.20166
BB7	0.0001	0.04775	0.78007

Notes: p-values report from the goodness-of-fit tests. Insignificant p-values are highlighted in bold.

5. Conclusion

This study intended to investigate both the static and time-varying conditional dependence between weekly crude oil prices and three US dollar exchange rates by a conditional copula-GARCH model. To account for tail dependence time-invariant and time-variant dependence, a range of copulas are employed to model the interconnectedness between the crude oil price and exchange rate returns from the three leading countries, including South Korea, China and India with the sample size of 573 observations from 1 June 2008 to 30 December 2018.

Overall, the findings show that oil price and exchange rate returns are skewed and leptokurtic. The interrelatedness structure between crude oil and exchange rate returns also demonstrates an asymmetric or tail dependence structure. The GARCH model with the survival Gumbel copula possesses the better explanatory ability for correlation for oil-exchange rate market pairs during the research period. The results of the copula-based GARCH models provide evidence of the negative correlation between two variables. Put differently, the increase in crude oil prices are found to coincide with the depreciation of the dollar.

In addition, our findings clearly show that the oil market affects the exchange rates of the three Asian countries, this can be beneficial to investors by conducting a strategic asset-allocation decision, and more importantly, policymakers need to be cautious because the influence of oil price innovations varies by countries, whether the oil price innovation is positive or negative.

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Conflict of interest

The author declares no conflict of interest in this paper.

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