Conditional dependence between oil prices and CEE stock markets: a copula-GARCH approach

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Abstract

This study investigates both the constant and time-varying conditional dependency between crude oil and stock markets for the CEE countries (Hungary, Poland, Czech Republic, Romania, and Croatia) by using the conditional copula-GARCH model with both constant and time-varying dependence parameters in the field of energy economics. Through different copula functions, the proposed models allow specifying the joint distribution of the crude oil and CEE stock returns with full flexibility. First, from the copula models, we find that all series show fat-tail, leverage effects, and volatilities tend to cluster. Second, in both constant and time-varying copula models, we find that conditional dependence is similar for most countries, which means that a significant conditional dependence exists in all oil-stock price pairs. Our findings have important implications for both policymakers and investors by contributing to a better understanding of oil-stock relationships. A significant interdependence between crude oil price and stock markets suggests that enterprises and governments in CEE regions should pay attention to the stock market performance when the oil price fluctuates.

Keywords: oil price, CEE, stock market, dependence, Copula model

Introduction

The conditional dependency structure between global commodities and stock markets are exceedingly crucial for the cross-asset diversification of investment portfolios since fluctuations in the oil price have shown an unpredictable influence on the trajectory of global oil pricing and, in turn, on financial markets (Yu *et al.*, 2019; Boako *et al*. 2019; Cai *et al*. 2020; Mensi, 2019; Boubaker and Raza, 2017; Park and Ratti, 2008). This is why studies that look into this relationship have been increasing during the last decades, i.e. to systematically understand the dynamics of oil prices and the links between them and other macroeconomic and financial indicators. Besides, according to Boako *et al*. (2019), the conditional dependency

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structure between country-specific stock markets and international oil prices is mild when stock markets do not have large, sectoral composition weightings of a particular commodity in India, Russia, Brazil, China, Mexico, Indonesia, South Korea, and Turkey. In this context, the dependence between oil and stock markets was occasionally investigated in the literature because the majority of previous articles centre on the contemporaneous interaction and pay little attention to the specific cross-interdependence structure or lead-lagged dependence (Mokni and Youssef, 2019; Polat, 2020; Hamdi *et al*., 2019; Wen *et al*., 2019).

With the rapid growth of world economy and financial markets, alongside the development of emerging market economies, fluctuations in world oil prices and stock market co-movements would properly have greater endogenous and exogenous consequences for the associations between the oil and stock markets (Yu *et al*., 2019). In fact, spillovers of oil price innovations to the stock market cannot only be contemporaneous, but also, they would exist and change across different time investment horizons. In this scenario, Mokni and Youssef (2019) affirm that the influence of crude oil movement on stock markets can be explained by their impact on present and future real cash flows. Moreover, many papers demonstrate that an increase in oil prices result in a decrease on stock markets (Cai *et al*., 2020; Polat, 2020; Wen *et al*. 2019; Boubaker and Raza, 2017). As a result, oil and stock investors must pay a lot of attention to the oil-stock nexus under various time scales and market conditions.

Interestingly, developing markets in emerging economies with a relatively high and stable growth rate in Central and Eastern European countries such as Hungary, Poland, the Czech Republic, Romania and Croatia in recent years is especially considerable, and they are usually good choices for market participants looking to diversify their portfolios internationally (Hung, 2018; Hung, 2019b; Williams and Bezeredi, 2018). This is the case because these stock markets have achieved a substantial development level, the same in size and institutional characteristics. Besides, according to numerous authors, such as Živkov et al. (2020), Akhvlediani and Sledziewska (2017), Cunado and Gracia (2014), Tóth (2019), Apostoaie and Bilan (2019), Stošić-Mihajlović and Jović (2017), Miklaszewska et al. (2012), these countries are fast growing but are highly dependent on crude oil import. Therefore, the primary purpose of this paper is to implement an in-depth analysis of the dynamic interrelatedness that exists between crude oil and stock markets and taking into consideration the empirical research of time-varying connectedness between CEE stock markets and global oil prices has become necessary from the particular perspective of portfolio diversification and hedging strategies.

In this study, we examine the conditional dependence between crude oil prices and CEE stock markets by using the copula-GARCH approach. In the existing literature, the economic theory shows that oil price shocks have a dramatic impact on the stock market activity (Wang *et al.* 2019; Tiwari *et al*. 2019; Yu *et al*. 2019;

Boubaker and Raza, 2017; Salisu and Mobolaji, 2013; Wu *et al*., 2012). In addition, many papers have documented that an increase in oil prices results in a decrease in stock markets in developed countries (Park and Ratti, 2008; Asteriou and Bashmakova, 2013). In another dimension, from both developed and developing countries, Sukcharoen *et al*. (2014) argue that there is a weak dependence between oil prices and stock indices. Recently, Tiwari *et al*. (2020) report that oil price co-movements contribute more to stock market indices of G7 economies during turmoil periods than during tranquil times. Yu *et al*. (2019) show that the effect of oil price changes on the stock markets of the US and China is stronger under extreme circumstances than under normal circumstances.

Such empirical results may have several practical implications for investors, portfolio managers, and policymakers. It can be useful for investors in explaining the flow of information between oil and stock markets in the CEE countries and thus, make more informed decisions on predicting portfolio market risk exposures and determining the persistence of diversification benefits in the markets under study. The results might also be significant for evaluating the informational efficiency of emerging and frontier stock markets. More specifically, results might provide straightforward insight into how oil volatility shocks are transmitted to stock markets and estimate the degree and persistence of these shocks over time. For portfolio hedgers, it is vital to reveal how markets are connected in time to build an effective hedging strategy. From a financial stability perspective, the price spillover across oil and CEE stock markets is also a crucial consideration for policymakers, enabling them to make better decisions about the regulation of the stock sector markets and oil price policies.

While acknowledging the valuable contribution produced by prior research examining the oil-stock relationship, we would believe that shortcomings remain because the majority of them centred mainly on the contemporaneous interaction and paid little attention to the specific cross-dependence structure for various time horizons. Moreover, examining the delayed dependence indicates a significant importance for investment and risk management (Mokni and Youssef, 2019). For example, if the oil-stock relationship persists for a given period, investors must consider this scenario in each decision they make. In contrast, if they ignore this, it might lead to erroneous decisions on investment activity. Further, to the best of our knowledge, most existing studies looking into dependence between oil-stock relationships have not taken into consideration the emerging stock markets in the CEE region. Our study investigates the conditional dependency structure between oil price and stock markets in selected CEE countries by using a conditional copula-GARCH model. More precisely, our main research questions are: 1) Are there any price spillovers between crude oil price and stock markets? Is the influence of crude oil market volatility on the stock market long lasting? Are there asymmetric, tail dependence, or even time-varying dependency structures across oil price and stock markets?

Therefore, in this study, by using copula theory, we seek to overcome the limitations of previous researches and contribute to the existing literature in many ways. To the best of our knowledge, this is the first time that the oil-CEE stock markets cross-dependence is investigated based on the copula-GARCH model. We extend the past studies by mentioning the relationship between the crude oil market and European stock returns (Park and Ratti, 2008; Asteriou and Bashmakova, 2013; Cunado and Gracia, 2014; Živkov *et al*. 2020) by modeling the cross-interdependence by using both constant and time-varying copula-GARCH models to measure the dependence between the two markets elastically. The copula functions could capture a wide array of dependence structures, including nonlinear, asymmetric, and tail dependence (Bai and Lam, 2019). We focus on stock market data from the CEE countries, which is a group of five emerging economies (Hungary, Poland, Czech Republic, Romania, and Croatia) to determine oil-CEE stock dependence structures. The empirical results may provide a better understanding of the existence and shape of the conditional dependence structure between crude oil and CEE stock markets. Such information will help investors make portfolio decisions and manage risk.

The remainder of this paper proceeds as follows. Section 1 presents the literature review. Section 2 introduces the empirical methodology and data. Section 3 discusses the empirical results. In the final section, we provide a conclusion.

1. Literature review

In recent years, numerous studies have been recorded concerning the association between crude oil price and stock markets in different regions. Cai *et al*. (2020) study the time-varying correlation between crude oil and East Asian stock markets at different frequencies by using wavelet-based copulas. The authors provide evidence of dynamic dependence and asymmetric tail dependence between crude oil and East Asian stock markets at multiple frequencies. Lamouchi and Alawi (2020) select Dubai to highlight the dynamic connectedness between prices on the oil spot, oil future, and energy stock markets using the multivariate GARCH model. The results indicate that the relationships among the three markets in Dubai are lower than in the US. Specifically, the paper illustrates the persistence of volatility spillovers between the oil market and the energy stock markets and shows a unidirectional correlation from energy stock market to the crude oil. Similarly, Peng *et al*. (2020) confirm that there is a bidirectional nonlinearity between the Shanghai stock index and the international oil market. However, the interrelatedness between them is a gradually strengthening trend. In Turkey, Polat (2020) provides evidence of time-varying propagations between crude oil shocks and the Borsa Istanbul Stock Exchange. Ferreira *et al*. (2019) examine the detrended cross-correlation coefficient between oil price and 20 various stock returns and provide some evidence that there is a strong relationship between oil and stock prices after the global financial crisis.

Mensi (2019) takes into account the dynamic relationship between crude oil and the Saudi sector stock markets and shows that stock markets have directly affected oil price movements. Hamdi *et al*. (2019) study returns and volatility spillovers between oil price and financial return series and confirm that the contagion and intercorrelation between oil price and stock markets are significant. Wen *et al*. (2019) examine the risk spillover effects between oil prices and stock markets. Their findings reveal the strong existence in VaRs of S&P 500 index and oil prices, and that the risk spillover effect between these markets is asymmetric.

Several studies have examined the nexus between the crude oil and stock markets on the particular case of BRICS. Wang *et al*. (2019) point out that the information about extreme movements in the oil market has impacts on stock return movements, and an increase or decrease in oil price changes have an asymmetric effect on the stock price changes. Tiwari *et al*. (2019) show a significant long-run dependence coherence between stock markets and oil shifts. In particular, the authors also report that there is a robust instantaneous dependence in both directions between oil price and stock returns in these countries. Yu *et al*. (2019) investigate the dynamic correlation between the oil market and stock returns of the US and China. The results indicate that the dependence between the pairs of US-WTI, China-WTI and US-China vary dynamically over time. Boubaker and Raza (2017) provide strong evidence of time-varying volatility in different time horizons and put forward that oil-BRICS stock markets are indirectly affected by the volatilities of other prices and wavelet scale.

In the European country context, Park and Ratti (2008) report that oil price shocks have a statistically significant influence on stock markets in the US and in 13 European countries. They also show that there is little evidence of asymmetric effects on stock returns of positive and negative oil price shocks for oil-importing European countries. Asteriou and Bashmakova (2013) focus on the CEE financial markets and suggest that oil prices have a negative impact on stock markets, while the stock returns have a positive interaction on upward and downward movements of the oil market. Cunado and Gracia (2014) show the influence of oil prices on stock markets in 12 oil-importing European economies. They report that the response of the European stock markets to oil price innovations would radically differ depending on the fundamental causes of the oil price change. In addition, there exists a negative and significant influence of oil markets on the European stock market series. More recently, Živkov *et al*. (2020) identify the strength of the interrelatedness between the Brent oil market and stock prices of Visegrad group countries in various time horizons by using the DCC-EGARCH model alongside wavelet transform approaches. The findings show that all conditional correlations between Brent oil and stock prices are low at low and medium frequencies, but that, in the long term, there is a strong relationship between them.

In terms of the copula method for dependence modelling, there has been very little work invested in studying the dependence or co-movement between the crude oil and stock market in the CEE region. The Copula-GARCH approach has been found to be helpful in examining the dependence or the dynamic nexus of different time series (Yuan *et al.*, 2020). Recent researchers have considered the copula-GARCH model to allow for a flexible depiction of the marginals. Boubaker and Raza (2016) explore the connectedness between the oil price and stock markets of different countries and provide evidence of a strong and asymmetric dependence between the USA equity markets and the CEE stock markets. The dependency between crude oil and foreign exchange rate and stock markets has also been extensively studied (He and Hamori, 2019; Hung, 2019a; Ji *et al*., 2019; Aloui *et al*. 2013; Sukcharoen *et al*. 2014; Tiwari *et al*. 2020; Mokni and Youssef, 2019; Yu *et al*., 2019). In addition, Bai and Lam (2019) model the weekly return market in the copula-based GARCH framework. Empirical evidence shows that the conditional dependency structure between liquefied petroleum gas freight rate, product price arbitrage and crude oil price is time-varying.

In the papers described above, there is little attention paid to the emerging stock market, particularly to these operating in the CEE region, as well as the application of the copula-GARCH approach. To bridge the gap in the literature, we apply the copula-GARCH approach to examine the dynamic conditional dependency structure between crude oil and CEE stock markets, which implies the underlying time-varying change in the dependency structure when marginal distributions are complicated. In this study, we employ both static and dynamic copula methods for dependency modeling. Further, our empirical findings highlight the dependence change overtime, which holds significant implications for investors, hedgers, and risk managers.

2. Methodology

The oil and financial market movements change all the time and their dependencies might not be vividly depicted by static and linear models. Applying the copula function, we can incorporate any set of univariate marginal distributions to generate a full joint distribution. In order to investigate the dynamic connectedness between each paired market, we adopt both the constant and time-vary copula models.

Copula function

Sklar (1959) developed the definition of the copula, which is an n-dimensional function that can be decomposed into two parts: the marginal distribution and the copula. They can state that a 2-dimensional joint distribution function with continuous marginal and 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 (Nelson, 2006):

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

where u_1 and u_2 are the cumulative distribution functions. Further, copulas could also 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

$$\lambda_u\left(X_1, X_2\right) \equiv \lim_{q\to1^-} P\left(X_2 > F_2^{-1}(q) \mid X_1 > F_1^{-1}(q)\right) \tag{4}$$

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

Marginal specifications

This paper examines the interdependence between crude oil and the five CEE stock indexes. 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 (Hung, 2019a). BIC criterion is determined as the amount of AR lag terms. Given a time series y_t, the GARCH (1,1) model can be written as

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

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

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

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 successfully capture the possibly asymmetric and heavy-tailed characteristics of oil price and exchange rate returns.

Copula models of conditional dependence structure

A diversity of copula models allows us to capture both symmetric and asymmetric structures of extreme dependence between variables, including Gaussian, Student-t, Clayton (survival), Gumbel (survival), Frank, Joe, Clayton-Gumbel survival and Joe-Clayton (Bai and Lam, 2019).

The bivariate Gaussian copula is defined as

$$C(u,v)=\int_{-\infty}^{\phi^{-1}(u)}\int_{-\infty}^{\phi^{-1}(v)}\left(1/2\pi|R|^{1/2}\right)\exp\left\{-(u,v)'R^{-1}(u,v)/2\right\}dudv \qquad (7)$$

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

$$C_t(u,v;R,n)=\int_{-\infty}^{t_n^{-1}(u)}\int_{-\infty}^{t_n^{-1}}\left(\Gamma(n+2)/2|R|^{-1/2}\right)/\left(\Gamma(n/2)(n\pi)\right)\left(1+1/n(u,v)'R^{-1}(u,v)\right)^{-(n+2)/2}dudv \qquad (8)$$

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 (1978) is defined as

$$C(u,v)=\left(u^{-\theta}+v^{-\theta}-1\right)^{-1/\theta},\theta>0 \qquad (9)$$

where θ is copula parameter.

Gumbel copula (Gumbel, 1960) is defined as

$$C(u,v)=\exp\left\{-\left[(-\ln u)^{\theta}+(-\ln v)^{\theta}\right]^{1/\theta}\right\},\theta\geq 1 \qquad (10)$$

Frank copula (Genest, 1987) is defined as

$$C(u,v)=-1/\theta\ln\left[1+\exp(-\theta u)\left(\exp(-\theta v)-1\right)/\left(\exp(-\theta)-1\right)\right],\theta\in R\backslash\{0\} \qquad (11)$$

The Joe copula (Joe, 1993) is given by

$$C(u,v)=1-\left[(1-u)^{\theta}+(1-v)-(1-u)^{\theta}(1-v)^{\theta}\right]^{1/\theta},\theta\geq 1 \qquad (12)$$

The Clayton-Gumbel and Joe-Clayton copulas (Joe and Hu, 1996), which are known as BB1 and BB7.

BB1 model is defined as

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

BB7 model is defined as

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

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

Cech [11] defined the survival copulas as

$$C_{180}(u,v) = u + v - 1 + C(1-u, 1-v) \tag{15}$$

The dependence parameters of the time-varying copula

In this paper, we use time-varying Gaussian copula developed by Patton (2006). The parameter ρ of time-varying Gaussian copulas are defined as (Patton, 2006):

$$\rho_t = \overline{\Lambda}\left(\omega_\rho + \beta_\rho \rho_{t-1} + \alpha_\rho .1/10 \sum_{i=1}^{10} \Phi^{-1}(u_{t-i}) \Phi^{-1}(v_{t-1}) \right) \tag{16}$$

where Φ^{-1} is the inverse of the standard normal cumulative density functions and $\overline{\Lambda}(x) = \dfrac{1-e^{-x}}{1+e^{-x}}$ is the modified logistic transformation.

Symmetrized Joe-Clayton (SJC) copula model (Patton, 2006) can address the questions of tail dependence in the financial data. The SJC model is an extension of the BB7 copula model. It can be written as follows

$$C_{SJC}(u,v) = 0.5.(C_{BB7}(u,v) + C_{BB7}(1-u, 1-v) + u + v - 1 \tag{17}$$

$$\tau_t^U = \Lambda\left(\omega_U + \beta_U \tau_{t-1}^U + \alpha_U .1/10 \sum_{i=1}^{10} u_{t-i} - v_{t-i} \right) \tag{18}$$

$$\tau_t^L = \Lambda\left(\omega_L + \beta_L \tau_{t-1}^L + \alpha_L .1/10 \sum_{i=1}^{10} u_{t-i} - v_{t-i} \right) \tag{19}$$

where $\overline{\Lambda}(x) = (1+e^{-x})^{-1}$ is the modified logistic transformation.

Estimations of copula parameters

This study uses the two-step estimation method to estimate copula parameters, that is the Inference Functions for Margins (IFM) method developed by Shih and Louis (1995).

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

$$\hat{a}_i = \arg\max \sum_{t=1}^{T} \ln f_i(a_{ti}, b_i), \quad i = \overline{1,2} \tag{20}$$

We estimate unknown parameter θ_c of the copula as

$$\hat{\theta}_c = \arg\max \sum_{t=1}^{T} \ln c\left(F_1(a_{t1};\hat{b}_1), F_2(a_{t2},\hat{b}_2);\theta_c\right) \qquad (21)$$

Goodness-of-fit tests

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

$$S_n = \sum_{t-1}^{n} \left\{C_k\left(u_t, v_t;\hat{k}\right) - C_n\left(u_t, v_t\right)\right\}^2 \qquad (22)$$

Genest *et al*. (2009) provide a parametric bootstrap procedure to calculate the p-value of the test.

Data

Our dataset contains the daily crude oil prices of West Texas Intermediate OIL and five stock markets in CEE regions: Hungary, Poland, Czech Republic, Romania and Croatia, and their stock indexes are Budapest Stock Exchange BUX, Warsaw Stock Exchange WIG, Prague Stock Exchange PX, Bucharest Stock Exchange BET and Zagreb Stock Exchange CRO, respectively. We obtain the full range of datasets from Bloomberg at the time when this study is carried out. The dataset has 3031 observations spanning from February 2008 to September 2019, excluding holidays, weekends and any other non-trading days. We attempt to investigate the conditional interdependence between oil prices and CEE stock markets after the global financial crisis of 2008. The daily return data series are computed as R_t = 100 x ln (P_t/P_{t-1}), where P_t is the price level of the market at time t. The logarithmic stock returns are multiplied by 100 to approximate percentage changes and avoid convergence problems in estimation.

Table 1. Descriptive statistics for return series

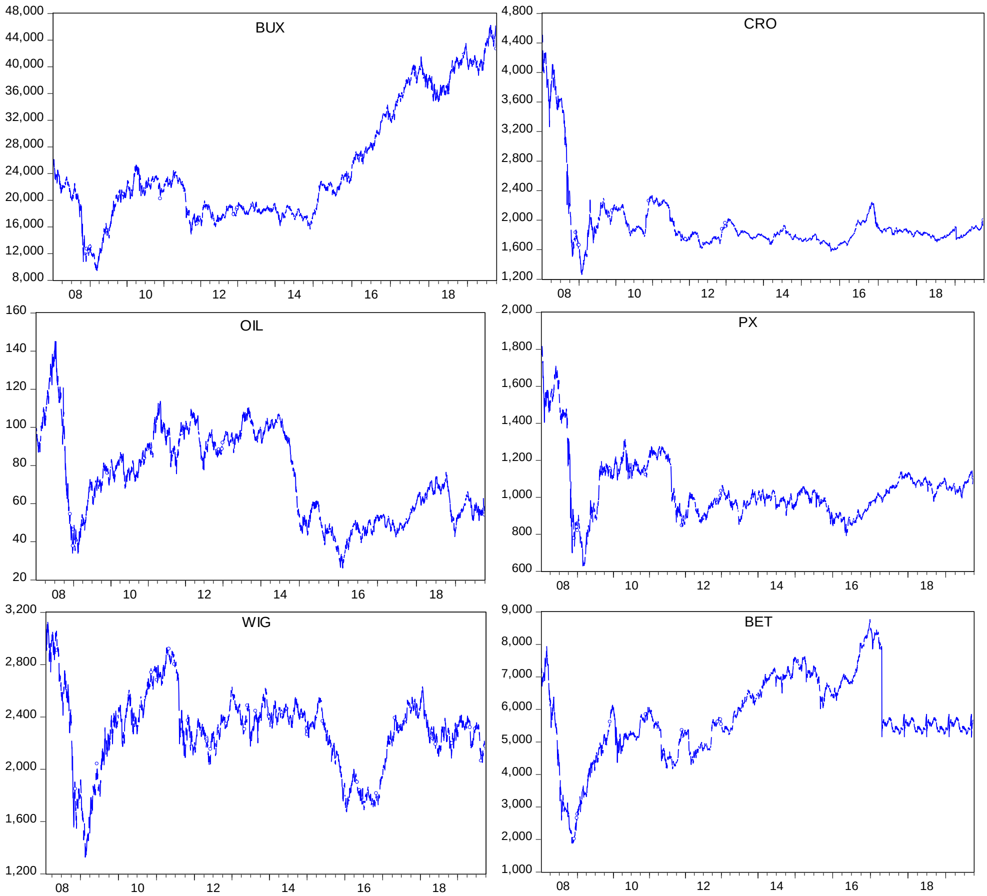
	OIL	BUX	CRO	PX	WIG	BET
Mean	-0.020168	0.016497	-0.026640	-0.015814	0.000537	-0.069475
Max.	16.40973	13.17775	14.77896	12.36405	19.29744	10.56451
Min.	-13.06537	-12.64895	-10.76363	-16.18547	-20.98936	-23.67794
Std.dev	2.395458	1.510821	1.114638	1.376712	5.318397	4.531757
Skewness	-0.173212	-0.090538	-0.193376	-0.559147	-4.531776	-4.707774
Kurtosis	7.834097	11.73846	28.42859	21.78009	13.73615	24.58514
Jarque-Bera	2965.424*	9644.671*	81653.80*	44685.21*	23765*	762000*
ARCH-LM	17.53076*	38.55281*	68.17641*	44.84995*	10.0579**	40.0004**
AR(p)	2	2	1	1	1	1

Notes: ARCH-LM test is the heteroscedasticity test. AR(p) represents the best AR lag selected by BIC criterion. * denotes significance at 1% level

Source: Author’s calculations.

Table 1 reports the descriptive statistics and ARCH-LM test statistics for all return series over the sample period 2008-2019. The mean values of all returns are close to zero. Coefficients of skewness are negative, which show that negative returns take place more often than positive returns. In addition, excess kurtosis demonstrates that all considered markets have high peaks and fat tails. This is confirmed by the Jarque-Bera test, which means that the returns do not follow the normal distribution. These findings show that there exists an ARCH effect in the oil prices and stock market returns. Therefore, it is appropriate to apply the AR-GARCH-Skew-t model. Finally, the optimal AR(p) lags are determined by the BIC criterion which plays a crucial part in the further analysis using copula methods. The graphs in Figure 1 illustrate the price movements of crude oil and five CEE stock market prices.

Figure 1. Daily price developments of the indices



Source: Author's representation.

3. Results

Prior to implementing the copula analysis, we provide the findings of the rank correlation and unconditional correlation in Table 2 for comparison. All coefficients are statistically significant at 1% level, revealing positive relationships between all oil-stock pairs, except in the case of the OIL-CRO pair. In general, the OIL-BUX and OIL-WIG pairs have the highest coefficient for both the rank and the unconditional correlations.

Table 2. Rank correlation and unconditional correlation

Pairs	OIL-BUX	OIL-CRO	OIL-PX	OIL-WIG	OIL-BET
Pearson	0.0681841*	-0.014026*	0.0147010*	0.0377666*	0.006245*
Spearman	0.0102542*	-0.018699*	0.0005187*	0.0720278*	0.002723*
Kendall	0.0263597*	-0.012875*	0.0002035*	0.0490212*	0.002209*

Note: * represents significance at 1% level
Source: Author's calculations.

3.1. Marginal distributions of market returns

It is important to note that oil and financial data is characterized by the fat tail and high kurtosis (Bai and Lam, 2019; Hung, 2019a). Additionally, all series exhibit autocorrelation and ARCH effect, and AR-GARCH model has the ability to match fat tail and high kurtosis characteristics of data. Thus, the GARCH model can be used directly to calculate marginal distribution so as to transform oil and stock price data to make it appropriate for carrying out the copula models. The corresponding skewed-t AR(p)-GARCH(1,1) parameters for each return series are computed in Table 3.

Table 3. Parameter estimates for the marginal models

	OIL	BUX	CRO	PX	WIG	BET
Mean equation						
μ	0.002884	0.047009*	0.015764	0.032805***	0.035880**	0.000904
	(0.030329)	(0.019914)	(0.015141)	(0.018809)	(0.015948)	(0.011104)
θ_1	-0.03604**	0.015054	0.008936	0.051925*	0.059973*	0.048462**
	(0.018272)	(0.018756)	(0.018923)	(0.018821)	(0.019572)	(0.018346)
θ_2	-0.000793	-0.051461**				
	(0.018325)	(0.017551)				
Variance equation						
ω	0.022523**	0.021809*	0.015379*	0.280076*	0.098053*	0.011058*
	(0.009922)	(0.006826)	(0.004407)	(0.049305)	(0.083592)	(0.002688)
α	0.060940*	0.079577*	0.108519*	0.285735*	0.329014*	0.105685*
	(0.009282)	(0.012174)	(0.015451)	(0.111882)	(0.043751)	(0.016537)

β	0.936768* (0.009395)	0.909861* (0.013366)	0.883492* (0.015446)	0.573734* (0.040508)	0.661316* (0.173764)	0.879641* (0.016650)
ν	0.908126* (0.022981)	0.970521* (0.025124)	0.914044* (0.023869)	0.962029* (0.022731)	0.958101* (0.023767)	0.961596* (0.022754)
λ	7.536180* (0.949843)	9.144226* (1.331997)	7.129947* (0.864344)	3.736290* (0.269593)	3.997131* (0.294160)	5.119062* (0.454961)
ARCH-LM	0.74433 [0.9512]	1.484242 [0.8251]	4.892 [0.23569]	1.667 [0.9999]	0.0003664 [0.9847]	0.25481 [0.9949]
Q (10)	2.7421 [0.9258]	4.9405 [0.3857]	3.826 [0.25448]	0.001301 [0.9919]	0.05806 [0.9852]	4.647 [0.1400]
Q^2(10)	5.026 [0.4256]	3.468 [0.6539]	1.577 [0.20914]	0.001301 [0.9712]	0.0003456 [0.9852]	0.38442 [0.9994]

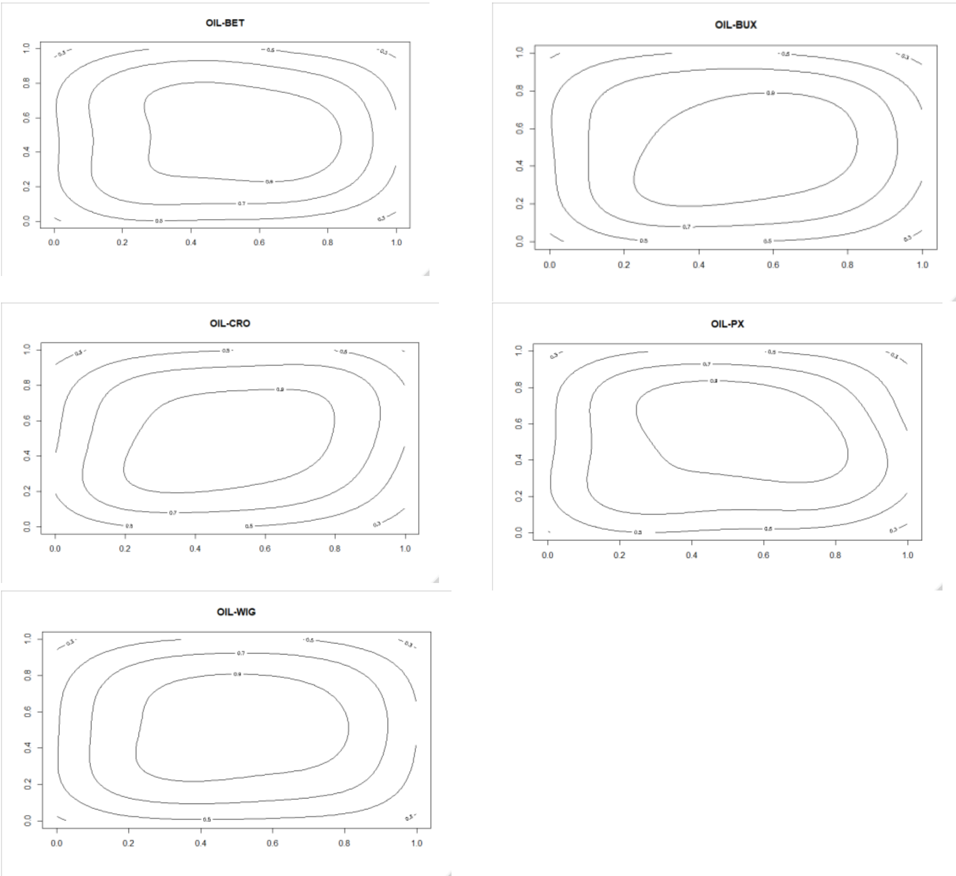
The numbers in parentheses are standard deviations, while the numbers in brackets are probability. ARCH-LM is heteroscedasticity test. * , **,*** represents significance at 1%, 5% and 10% respectively.
Source: Author's calculations.

As shown in Table 3, most of the parameters in the AR-GARCH models are statistically significant, justifying the skewed-t distribution of the error term. In the GARCH model, the coefficients of α and β are significant for all return series, which means that crude oil and CEE stock returns have volatility clustering effects. Furthermore, $\alpha + \beta$ is close to 1, this shows that innovations are quite an existence to all variables under investigation. The Liung-Bux Q, Q^2 and ARCH-LM tests are executed for the standardized residuals to check if the marginals are modelled correctly. It is obvious that these indicators are not significant, suggesting that there are no remaining autocorrelations and no ARCH effects unexplained by the model. Hence, the marginals are accurately identified. The findings imply that the copula model would be used to estimate the tail dependence and dependence for each oil-stock pair.

3.2. Copula results

First, we provide the contour plots of the distribution made by copula functions in Figure 3. The graphs show what the dependency structures would look like between various filtered series. At a first glance, the asymmetric tail dependence is quite clear for all the selected pairs. Next, both static and dynamic copulas are fitted to the residuals from marginals.

Figure 2. Copula contour plots



Source: Author's representation.

Table 4 exhibits the estimated parameters of constant copulas (Gaussian, Student-t, Clayton, Joe, Gumbel, Frank, Survival Clayton, Survival Gumbel, BB1, Survival BB1, and BB7) and time-varying copula (Gaussian, SJC) for five oil-stock price pairs (OIL-BUX, OIL-BET, OIL-CRO, OIL-PX, OIL-WIG), respectively. A simulation method for standard errors of the two-staged parameter estimator, as proposed by Patton (2013), can be employed. The parameters of each pair from the copula model are ranked based on both Log-likelihood (LL) and the AIC criterion. The Cramer-von Mises (CvM) test is the most robust test to get additional confirmation of goodness-of-fit of copula models (He and Hamori, 2019). The significant p-value demonstrates that the copula provides a better fit to the model (Bai and Lam, 2019; Hung, 2019a). Specifically, AIC and LL values are broadly consistent with CvM tests. In the time-varying copula context, SJC copula performs better for all oil-stock pairs based on the AIC criterion, which means that conditional time-varying characteristics of the dependency structure between five oil-stock pairs are statistically significant.

Table 4. Estimates for constant and time-varying copula models

	OIL-BUX	**OIL-CRO**	**OIL-PX**	**OIL-WIG**	**OIL-BET**
Gaussian					
ρ	0.0253^{***}	0.0629^{*}	0.0141^{***}	0.00531^{***}	0.00752^{***}
	(0.0415)	(0.041)	(0.0416)	(0.0416)	(0.0416)
LL	0.456	2.83	0.142	0.0201	0.0562
AIC	1.09	-3.65	1.72	1.96	1.89
Student-t					
ρ	0.0219^{***}	0.0646^{*}	0.0121^{***}	0.00156^{***}	0.00752^{***}
	(0.0429)	(0.042)	(0.0426)	(0.0434)	(0.0445)
v^{-1}	0.00918	0.0707	0.00114	0.0069	0.00798
	(0.0343)	(0.101)	(0.0191)	(0.00244)	(0.0125)
LL	0.419	2.59	-0.0901	0.396	3.08
AIC	3.16	-1.18	4.18	3.21	-2.17
Clayton					
θ	0.00189^{***}	0.0452^{*}	0.0196^{***}	0.0101^{***}	0.0189^{***}
	(0.0406)	(0.0514)	(0.0464)	(0.0444)	(0.0448)
LL	0.00383	1.94	0.398	0.11	0.403
AIC	1.99	-1.89	1.20	1.78	1.19
Gumbel					
θ	0.0228^{***}	0.0455^{*}	0.0147^{***}	0.000169^{***}	0.0242^{***}
	(0.0247)	(0.0284)	(0.0173)	(0.0266)	(0.0199)
LL	0.619	1.65	0.624	-0.00371	1.44
AIC	0.761	-1.29	0.752	2.01	-0.876
Frank					
θ	0.00929^{***}	0.0701^{*}	0.00466^{***}	0.00753^{***}	0.0062^{***}
	(0.245)	(0.246)	(0.246)	(0.247)	(0.247)
LL	0.0594	3.35	0.0148	0.0385	0.0261
AIC	1.88	-4.70	1.97	1.92	1.95
Joe					
θ	0.00918^{***}	0.026^{*}	0.0102^{***}	0.00097^{***}	0.0188^{***}
	(0.0273)	(0.0402)	(0.0215)	(0.04)	(0.0271)
LL	-0.000653	0.788	0.637	0.00428	1.58
AIC	2.0	0.424	0.725	2.01	-1.15
Survival clayton					
θ	0.0361^{***}	0.043^{*}	0.00442^{***}	0.00731^{***}	0.012^{***}
	(0.0504)	(0.0514)	(0.0402)	(0.0497)	(0.0415)
LL	1.58	1.72	0.0253	-0.00288	0.187
AIC	-1.17	-1.44	1.95	2.01	1.63

Survival Gumbel					
θ	0.00561*** (0.0211)	0.0484* (0.0286)	0.00911*** (0.0253)	0.000314*** (0.0243)	0.0166*** (0.0415)
LL	0.0297	1.86	0.0681	0.0875	0.187
AIC	1.94	-1.72	1.86	2.0	1.63
BB1					
δ	0.023*** (0.00252)	0.0538* (0.0642)	0.0241*** (0.049)	0.0106*** (0.0571)	0.0288*** (0.0472)
θ	0.00918 (0.0227)	0.0518* (0.0342)	0.0232 (0.0164)	0.0101 (0.0349)	0.0154 (0.0207)
LL	0.608	2.21	0.779	0.0764	1.49
AIC	2.78	-0.418	2.44	3.85	1.01
Survival BB1					
δ	0.0366*** (0.0545)	0.0544* (0.0647)	0.00925*** (0.00762)	0.0015*** (0.0139)	0.0193*** (0.045)
θ	0.0353 (0.02890)	0.0524* (0.0357)	0.0089 (0.0254)	0.00144 (0.0248)	0.0186 (0.025)
LL	1.55	2.18	0.0684	-0.0207	0.355
AIC	0.90	-0.351	3.86	4.04	3.29
BB7					
δ	0.0211*** (0.0343)	0.0501* (0.0402)	0.0243*** (0.02)	0.0104*** (0.0444)	0.0289*** (0.0955)
θ	0.0192 (0.0468)	0.0476* (0.0556)	0.0228 (0.047)	0.01 (0.0482)	0.0268 (0.0748)
LL	0.788	2.06	0.891	0.0795	1.57
AIC	2.42	-0.125	2.22	3.84	0.854
			Time-varying copula model		
Gaussian					
ω	0.254* (0.0766)	0.0128* (0.208)	0.0123** (0.0284)	0.0327** (0.0623)	0.0115* (0.057)
α	0.0158** (0.0416)	0.0119* (0.0794)	0.00918** (0.0855)	0.0309*** (0.342)	0.0107* (0.575)
β	0.0069* (0.000111)	0.0167*** (0.00752)	0.0308 (0.318)	0.0707 (0.271)	0.00964 (0.101)
LL	4.0	2.03	3.28	2.08	3.82
AIC	-12.8	-0.89	-66.01	-42.1	-12.5
SJC					
ω_U	-21.054** (0.2013)	-14.727* (0.002)	-5.642 (0.103)	-0.783* (0.538)	-8.974*** (0.035)
α_U	-6.064* (0.004)	-3.001** (0.0038)	-1.0907 (0.0166)	3.2104* (0.028)	-0.8312*** (0.0010)
β_U	0.9058 (0.254)	2.758* (0.014)	0.0878* (0.0241)	1.8170** (0.0051)	-1.9830 (0.0141)
ω_L	-13.021** (0.000)	-0.4502*** (0.0018)	-14.025** (0.0147)	-1.8540 (0.201)	0.875 (0.404)

α_L	-5.0126* (0.1010)	0.9065 (0.0301)	1.2045 (0.098)	8.3601*** (0.2100)	20.120** (0.097)
β_L	0.647*** (0.043)	1.258* (0.001)	17.0250* (0.035)	23.014 (0.023)	14.078* (0.002)
LL	2.23	-4.11	25.14	1.14	3.21
AIC	-5.69	5.24	-120.12	-6.05	-5.68

Notes: Standard errors of parameters are reported in parentheses. ***, ** and * indicate significance at 1%, 5% and 10% respectively.
Source: Author's calculations.

Overall, the parameters of dependence for the eleven copulas are positive and significant for all the five pairs of the crude oil and stock markets during the research period. This finding indicates that a strong dependence exists between any pair of the selected variables. It implies that there is a strong contagion effect between crude oil prices and CEE stock returns, such as an increase in volatility in the crude oil market which is likely to result in a rise in volatility in the CEE stock prices. Additionally, the results of the constant copula models studied in this paper illustrate that the static dependence is highest between OIL and CRO, followed by OIL and BUX, OIL and PX, OIL and BET, and then OIL and WIG. For oil-importing countries like Hungary, Poland, Czech Republic, Romania, and Croatia, the positive oil-stock dependence is in line with the theoretical method, which shows that the stock market of an oil-importing country would increase when the oil price goes up. The high dependence is between crude oil and CRO, BUX, PX, which reveals that there is a strong connectedness and a strong spillover effect between them. By contrast, the weak dependence between crude oil and WIG, BET shows that there is little relationship and a weak transmission effect among them. This finding is also in accordance with other studies, such as Tiwari *et al*. (2019) and Boubaker and Raza (2017).

The smallest values of the AIC among all of the pairs are those of the Gaussian copula, which implies that the Gaussian copula is the best model for estimating the dependence, which is also confirmed by the CvM test in Table 5. This finding reveals that the dependence between crude oil and CEE stock markets is governed by symmetry, which means that the oil-stock relationship appears to co-move symmetrically.

Table 5. p-Value for CvM goodness-of-fit test

	OIL-BUX	**OIL-CRO**	**OIL-PX**	**OIL-WIG**	**OIL-BET**
Gaussian	**0.1519394**	**0.04420024**	**0.2374781**	**0.08315194**	**0.1059072**
Student-t	**0.6937356**	**0.08499564**	0.196116	**0.05395222**	**0.05592801**
Clayton	**0.08044851**	0.118346	**0.118346**	**0.07844641**	**0.0870521**
Gumbel	**0.09426639**	**0.02816065**	0.2763204	**0.06253427**	0.09966677

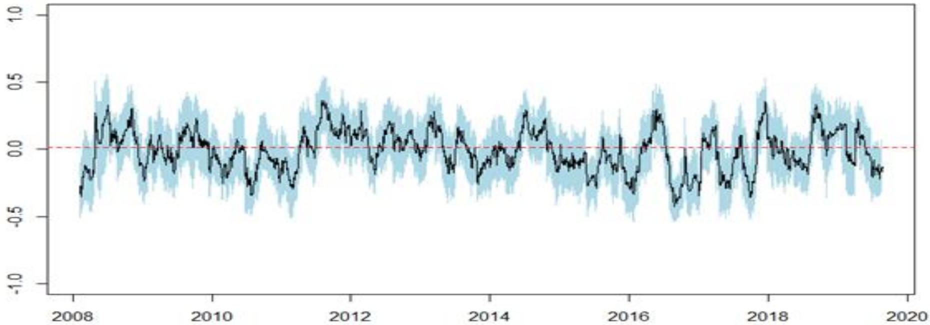
Frank	**0.08039778**	**0.06458319**	**0.2167135**	**0.07775813**	**0.1933195**
Joe	**0.0800961**	**0.1189614**	0.2141971	**0.05389952**	**0.05389952**
Survival clayton	**0.07987452**	**0.07293802**	0.2787797	**0.07599121**	**0.1015191**
Survival gumbel	**0.08026847**	**0.07880659**	0.2131636	**0.05393774**	**0.07419179**
BB1	**0.08053135**	**0.02931699**	0.293138	**0.07878642**	0.1175949
Survival BB1	**0.06099605**	**0.6581804**	0.1768229	**0.06674875**	**0.05411608**
BB7	**0.0609374**	0.1051191	**0.1761775**	**0.06654547**	**0.04665119**

Note: Insignificant p-values are presented in bold
Source: Author's calculations.

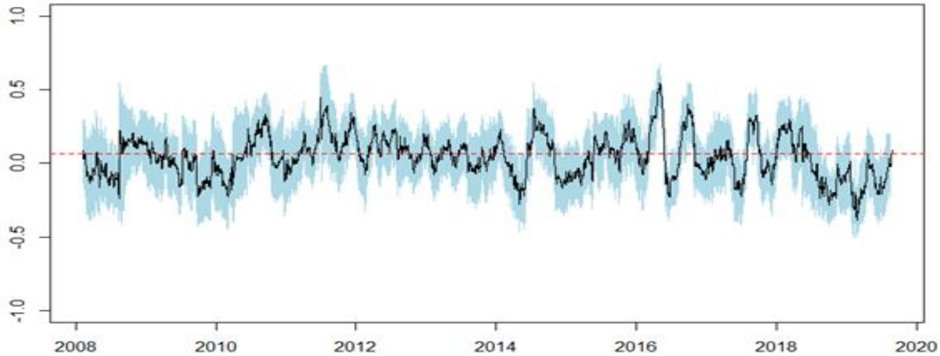
It is important to note that the dependence structure between crude oil and stock markets in the CEE region varies over time and is more likely to be impacted by different macroeconomic situations. Therefore, a static copula correlation model or constant dependence copula model would not be suitable for identifying an interdependence between the variables under consideration. To circumvent this limitation, we use time-varying Gaussian and SJC copulas to capture the variation in the dynamics of the dependence structure of the different market pairs (Bai and Lam, 2019; Hung, 2019a; Yuan *et al*. 2020). The β coefficient of the time-varying SJC copula shows what the impact on the other time series in the pair would be if there were an upward change in return series. The upper tail dependence parameter of the dynamic SJC copula is positive for all pair markets with the exception of the OIL-BET pair, which indicates that if the crude oil price increased, it would rise in CEE stock markets. By contrast, if this coefficient is negative, the oil price might decrease in CEE stock prices. In the dynamic of Gaussian copula coefficients, that is to say, the degree of persistence is measured by β, while α presents the adjustment that is generated in the dependence process. The significant values of α show variations over time for all oil-stock pairs. The bigger variation in the dependence structure has been found for the pairs of OIL and BUX, WIG since values of α are higher than other pairs. The values of LL and AIC reveal that the dynamic SJC copula comparatively better captures the time-varying dependence in all markets under consideration.

Figure 3 represents the plot of the dynamically estimated parameters from time-varying SJC copula for all five pairs. The red line shows the average of the estimated time-varying parameters. As the findings demonstrated in static copula models, time-varying results are somewhat similar to the findings from constant copula models. We can see that the time-varying dependence structure changes remarkably over the period shown. Overall, the dependence structure is less volatile, and we can infer similar results from the plots for the five pairs under examination. Our analyses shed light on the oil-stock relationship prevailing in each period change in step with static and dynamic dependence as well as associations between crude oil and stock markets in the CEE region.

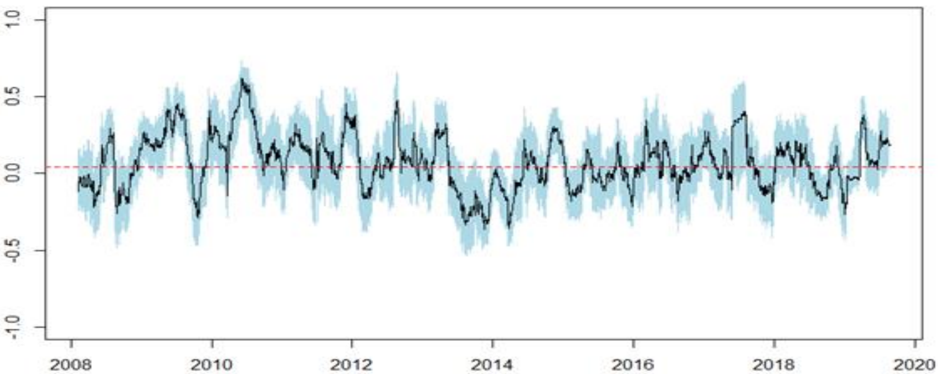
Figure 3. Dependence estimates for five oil-stock pairs based on time-varying SJC copula model.



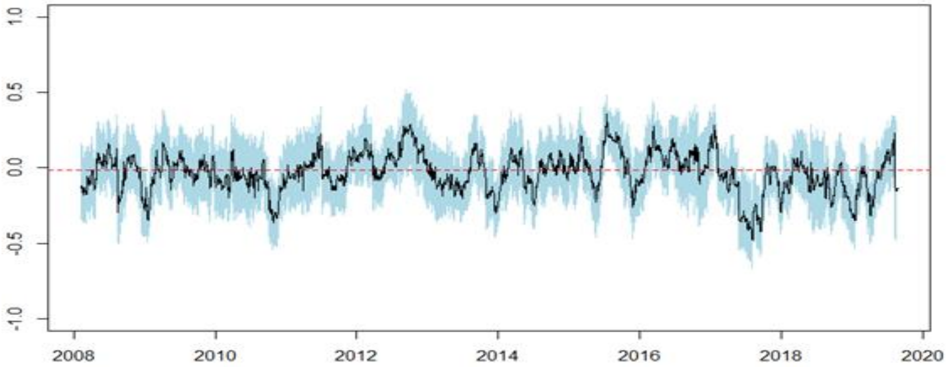
A1. Time-varying conditional correlation between OIL and CRO



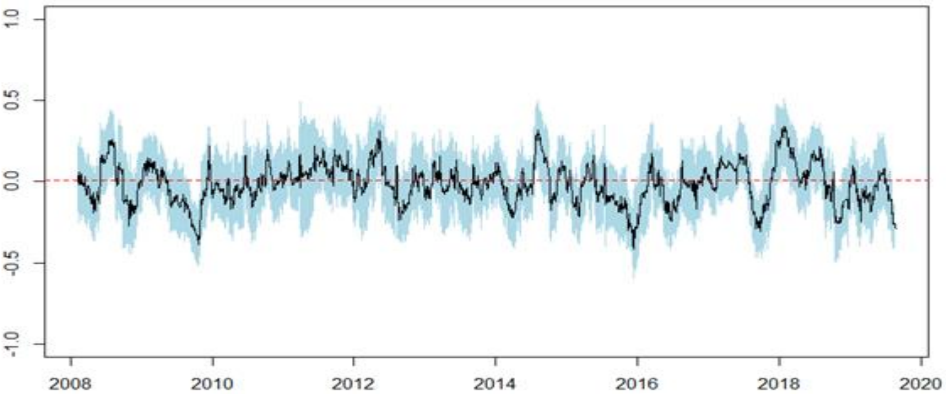
A2. Time-varying conditional correlation between OIL and BUX



A3. Time-varying conditional correlation between OIL and WIG



A4. Time-varying conditional correlation between OIL and PX



A5. Time-varying conditional correlation between OIL and BET

Source: Author's representation

These changes respond to the impact of fundamental economic and political situations, giving rise to market uncertainty and variations to spread and intensify. More importantly, our study aims to detect a change in the effect of crude oil prices on the CEE stock markets because shocks to oil prices have evolved both in time and in space, which influences both developing and industrial countries (Yu *et al*. 2019). These results are consistent with the argument by Park and Ratti (2008) that an increase in the volatility of oil prices significantly depresses stock markets contemporaneously in European countries. Also, Živkov *et al*. (2020) confirm that dynamic correlations between Brent oil and the selected stock indices (Visegrad group) are low at the daily-frequency level.

3.3. Policy implications

A better understanding of the influences of crude oil prices on financial markets plays a prominent role for investors, risk managers, and policymakers. Global investors are heavily involved in knowing how oil price innovations considerably impact stock prices and whether this influence has similar strength in the short or medium term in comparison with long investment horizons. More precisely, the spillover mechanism of oil shocks to financial markets would carry on a period, given that crude oil and stock investors operate according to different investment horizons. For that reason, oil and stock investors should systematically understand that oil-stock nexus might differ radically from various time horizons and under various market situations, and thus pay a lot of attention to portfolio design and risk management (Mokni and Youssef, 2019). In addition, such a time-varying interconnection reveals a risk synergy effect between the stock and oil markets when encountering market uncertainty. Hence, combining stock markets with oil assets in a diversified portfolio might not significantly reduce the foreseeable risks. Investors should automatically adjust their portfolio strategies based on the time-varying connectedness between oil and stock market to minimize risks and maximize profits.

The shock spillover running from oil market to CEE stock markets represents evidence of several predictability degrees in the CEE stock markets. In fact, the variations in oil price can be forecasted based on expectations of demand and supply in the oil market and, thus, their impact on stock markets in CEE countries can be anticipated. As a result, investors may be able to build profitable and exact speculation and arbitrage strategies, and diversify their portfolios based on the findings of this article which allow a systematically understanding of the connectedness of the CEE stock markets vis-à-vis the international oil market. Further, the CEE stock markets would introduce financial derivatives such as options and swaps allowing to hedge against high fluctuations in stock prices. These derivatives can be applied to lower the risk or increase the earnings of the investors operating in the CEE markets at times of increased oil volatility.

The significant implications of this paper are crucial, innovative and useful for global investors, portfolio managers, risk managers, and policymakers. They can use this study to formulate the optimal oil-CEE stock portfolios and estimate more exact predictions of price spillovers patterns in developing their hedging strategies (Živkov *et al*. 2020). Moreover, investors would not benefit from the oil-CEE stock portfolio to hedge themselves and to build more effective investment strategies because crude oil prices tend to induce more market co-movements in European stock markets (Park and Ratti, 2008).

In terms of investment, determining price spillover between oil and stock markets in the CEE region stresses that oil and stock markets can be considered as integrated. This indicates that the expected advantages of diversification from holding oil and stock sectors in the CEE market are declining. Hence, CEE investors should look elsewhere and most developed nations can benefit by investing a proportion of their wealth in the CEE market to reduce the influence of oil price shocks on their profitability. Government can use stock market volatility information to make appropriate and informed energy purchases and storage decisions, especially for the large oil importing CEE countries.

Conclusion

This study investigates both the constant and time-varying conditional dependency between crude oil and stock markets for the CEE countries from February 2008 to September 2019 by a conditional dependence copula-GARCH model. Through different copula functions, the proposed models allow specifying the joint distribution of the crude oil and CEE stock returns with full flexibility.

The empirical results highlight, first, that based on the marginal analysis, all series show fat-tail, leverage effects and volatilities tend to cluster. Second, in both constant and time-varying copula models, we find that the conditional dependence is similar for most of the countries, which means that a significant conditional dependence exists in all oil-stock price pairs, in particular, OIL-CRO pair has the strongest dependence since Croatia is a large oil importer. Third, from the CvM test and values of LL and AIC, the Gaussian copula model has the best performance among all the constant copula models, while the time-varying SJC copula model is the best model under consideration.

Our results have several economic and financial management implications. Firstly, portfolio managers and hedgers may be better able to understand the dynamic connectedness between crude oil prices and stock markets. More importantly, they might be able to adopt appropriate hedging strategies to better guard against oil volatility shocks that may occur in CEE countries. Secondly, such results might be useful for policymakers from a financial stability perspective, providing governments with insight into the conditional dependency structure and risk transmission between oil price and stock markets. Finally, our findings may also enable one to evaluate the level of emerging stock market information efficiency.

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