Nonlinear and asymmetric interconnectedness of crude oil with financial and commodity markets

Yarema Okhrin[a,*], Gazi Salah Uddin[b], Muhammad Yahya[c]

[a] *Department of Statistics, Faculty of Business and Economics, University of Augsburg, Germany*
[b] *Department of Management and Engineering, Linköping University, Linköping, Sweden*
[c] *School of Economics and Business, Norwegian University of Life Sciences, Ås, Norway*

1. Introduction

This paper investigates the heterogeneous and asymmetrical effect of COVID-19 and the Russian–Ukrainian war on the crude oil, S&P 500 index, EUR/USD exchange rate, and the fear index of the U.S. stock market. In general, these assets reflect the overall health of the global financial and economic system. For instance, S&P 500 is the most liquid financial index and partly reflects the development of the global financial system. Crude oil plays a fundamental role in a country's development and economic activities. Elevated prices of energy commodities lead to higher inflation and production cost, resulting in declined demand, output, and trade in the economy. The COVID-19 pandemic has contributed significantly to demand and supply shocks that have led to an unprecedented decline in crude oil prices. In addition, the global geopolitical uncertainty primarily caused by the Russian–Ukrainian conflict has further increased the uncertainty in the crude oil market. The stability of the crude oil market is not only important for oil-exporting countries but also for oil-importing and industrialized countries to maintain the price stability of goods. EUR/USD exchange rate is utilized to reflect on the trade and investment patterns in the global economy. This study adds to the literature by examining the heterogeneous and asymmetric impact of COVID-19 and the Russian–Ukrainian conflict on these different asset classes. This would enable us to understand how different asset classes react to such unique shocks.

Crude oil, as being a dominant commodity and a source of economic prosperity, there is a significantly large number of studies examining the connectedness dynamics between crude oil and other asset classes (see, for example, Awartani et al., 2016; Bouri et al., 2020; Charfeddine and Benlagha, 2016; Dutta, 2018; Ji and Fan, 2012; Liu et al., 2017; Nakajima and Hamori, 2013, among others). Furthermore, several studies examined the connectedness dynamics among different asset classes during periods of financial and economic turmoil (see, for example, Aloui et al., 2011; Baruník et al., 2015; Berger and Uddin, 2016; Chuliá et al., 2019; Du and McPhail, 2012; Kyritsis and Serletis, 2019; Manera et al., 2013, among others). However, there is scarce evidence related to the development of interconnectedness dynamics during rare disaster risks.

Interconnectedness or dependence can be conveniently modeled using copulas. Any joint continuous distribution can be factored as a product of the corresponding copula and marginal distributions using Sklar's theorem. Relying on this idea copula modeling is particularly

* Corresponding author.
E-mail addresses: yarema.okhrin@wiwi.uni-augsburg.de (Y. Okhrin), gazi.salah.uddin@liu.se (G.S. Uddin), muhammad.yahya@nmbu.no (M. Yahya).

flexible for constructing new distributions since margins and dependence structure are specified independently. This method has, however, a severe practical limitation. Though there are numerous bivariate copulas, the majority of their higher-dimensional extensions are controlled by several parameters and are too restrictive. Pair copula constructions or vine copulas are designed to solve the problem of scarcity of flexible high-dimensional copulas. The idea is to construct a multivariate distribution by defining (conditional) copulas for pairs of variables. A recent and extensive review on vine-based modeling can be found in Czado and Nagler (2022). The selection of the proper vine copula family and hierarchy is an important issue with the maximum spanning tree suggested by Dißmann et al. (2013) being one of the most popular approaches. Additionally to pure dependence modeling, the vine copulas can be applied for modeling the causal dependence. However, in contrast to the classical linear regression, this approach allows to model the whole conditional distribution of the dependent variable. Thus, this can be seen as a nonlinear extension of the quantile regression, see Kraus and Czado (2017). For recent applications of vines to risk modeling (see, for example, Barthel et al., 2019; Czado et al., 2019; Kielmann et al., 2021, among others).

We aim to extend the previous literature by evaluating the heterogeneous and asymmetric connectedness of different asset classes during the period of COVID-19 and the Russian–Ukrainian conflict. Specifically, we seek to answer the following questions. First, what is the temporal contribution of shock in crude oil prices to the other asset classes? Second, whether the dynamic connectedness among these different asset classes behaves homogeneously or heterogeneously? and third, does the magnitude of extreme connectedness behave asymmetrically across different asset classes? Answering these questions is of fundamental importance for market participants and policymakers as investors continuously seek alternative investment opportunities for portfolio diversification and risk management decisions and policymakers seek to disentangle the negative spillovers from such rare events to other asset classes.

Our contribution to the existing literature is four-fold. First, we evaluated the impact of the COVID crisis and Russian–Ukrainian conflict on the interconnectedness of the financial and commodity markets with a special focus on the risk dynamics. Therefore, we consider not a single snapshot of the dependence as is typically done in the literature (see, for example, Nazlioglu, 2011; Sun et al., 2021, among others), but analyze the temporal dynamics and causality of the risks. This is of particular interest as the uncertainty and connectedness dynamics tend to significantly alter with the additional observations in the sample.

Second, in contrast to the previous studies, we consider high-frequency intraday data. This allows us to have a deeper insight into the dependencies compared to the daily level. Several prior studies, Albulescu and Ajmi (see, for example, 2021), Batten et al. (see, for example, 2017), Berger and Uddin (see, for example, 2016), Brigida (see, for example, 2014), Dai et al. (see, for example, 2020, among others), utilize daily or weekly frequency data to examine the relationship among crude oil and other asset classes. However, these data frequencies fail to capture the intraday fluctuations in the prices of the underlying assets, which may result in a significant alteration in the connectedness dynamics in extreme events. Therefore, the utilization of high-frequency data entails us shedding more light on the extreme dependence among crude oil and other asset classes during extreme events. Avdulaj and Barunik (2015) utilize the high-frequency data and incorporate standard copula frameworks to examine the connectedness among only two assets (crude oil and S&P 500 futures). Therefore, our paper extends this study by incorporating several asset classes in our analysis and by utilizing vine copulas. Thus, we exploit the available data more efficiently without an unnecessary temporal aggregation.

Third, we quantify the dependence and its dynamics using paired vine copulas. This class of copulas is highly flexible and allows for a convenient visualization and quantification of nonlinear dependencies (Dai et al., 2020; Reboredo and Ugolini, 2018). Dai et al. (2020) and Reboredo and Ugolini (2018) utilize the vine copulas on daily data frequencies to examine the connectedness dynamics between crude oil and other asset classes. Our study adds to these studies by utilizing high-frequency data and by undertaking the extreme event sample in our analysis. This is of particular interest as the traditional approaches fail to capture the underlying dynamics among the series during extreme market conditions (Dai et al., 2020; Reboredo and Ugolini, 2018). Therefore, we add to the literature by utilizing a flexible approach to quantify nonlinear and asymmetric connectedness by utilizing vine copulas on high-frequency data over extreme market conditions.

Fourth, unlike previous studies, we put a particular focus on the crude oil returns as a function of several financial covariates using D-Vines. This is important as the literature emphasizes on the linkage between crude oil and other asset classes. Therefore, by utilizing crude oil returns as a function of several financial covariates, we are able to provide a more comprehensive overview of the nonlinear and asymmetric connectedness dynamics among the series. Furthermore, with this approach, we can model the whole conditional distribution within a single day. Thus, we capture the causal dependence in tails or at particular quantiles of the return distribution.

To summarize, the way we use the intraday data is unique. There are papers that use copulas and vine copulas to model crude oil prices, but these papers used daily data and could not model the time dynamics. Furthermore, there are also papers that use intraday data on crude oil but do not use copulas for these data. The unique feature that we employed is to model the dependence within a single day using vine copulas for intraday returns within this day. In addition, we do not rely on historical data and thus measure the momentum dependence. This approach is also used for approaches such as quantilograms, etc. Another uniqueness is the employment of D-vines. This means we do not just model dependence, but also the causal impact of other assets on the crude oil in a non-linear way.

The rest of the paper is structured as follows. Section 2 presents a review of the literature. Data, preliminary statistics, and the employed frameworks are presented in Section 3. Section 4 presents the empirical findings and a discussion of the results. And, Section 5 concludes the paper.

2. Related literature review

With the outbreak of the global financial crisis during 2007/08, numerous studies have investigated the contagion effect among financial and commodity markets. Over the recent years, the connectedness dynamics between crude oil and other major asset classes have received considerable attention from both academics and market participants. Researchers, in this regard, have utilized several empirical frameworks to evaluate this relationship. However, to the best of our knowledge, the examination of connectedness dynamics of crude oil with other asset classes using high-frequency data and vine copulas has not received any attention in the previous literature.

Existing literature utilizing the high-frequency crude oil data primarily focus on the utilization of various forecasting approaches (see, for example, Manickavasagam et al., 2020; Chen et al., 2020; Ma et al., 2019, among others) and spillover dynamics (see, for example, Luo and Ji, 2018; Zhu et al., 2020, among others). Furthermore, several studies examined the connectedness dynamics between crude oil and other asset classes using daily or weekly data by utilizing copulas (see, for example, Dai et al., 2020; Albulescu and Ajmi, 2021; Syuhada et al., 2021; Ding et al., 2021; Echaust and Just, 2021; Zhang and Zhao, 2021; Tiwari et al., 2021; Zhang and Hamori, 2021; Salisu et al., 2021; Jia et al., 2021; Ahmad et al., 2021; Shi, 2021; Cao and Cheng, 2021; Niu et al., 2021; Salisu et al., 2021, among others). To model relationship and interconnectedness structure, the recent literature on the crude oil employs various approaches (see notes Table 1). Table 1 provides a detailed review of the literature.

Table 1
Review of Literature.

Study	Assets and Data	Method	Key findings
Bouri et al. (2021)	Crude oil Daily (May-11–May-20)	TVP-VAR spillover	Spillover positively increased during COVID-19
Echaust and Just (2021)	OVX and Oil Daily (May-07–Mar-20)	Copula frameworks	Strong tail dependence behavior
Zhang and Hamori (2021)	Oil and stocks Daily (Jan-06–Aug-20)	Time-frequency spillover	Impact of COVID-19 exceeds that of GFC
Farid et al. (2021)	oil, gold, and FA 5-min (Jan-19–May-20)	MCS-GARCH DY	Significant effects of COVID-19 on volatility linkage
Naeem et al. (2021)	OVX and IVs Daily (Aug-08–Oct-19)	Time-frequency spillover	short- and log-term dynamic connectedness
Zhang and Broadstock (2020)	Oil and commodities Monthly (Jan-82–Jun-17)	DY GC	Increased connectedness during post-2008
Hung (2021)	Oil and agriculture Daily (Feb-14–Jan-19)	DY WC	Increased asymmetric connectedness
Huynh et al. (2021)	Oil and crypto Daily (Feb-14–Jan-19)	copula frameworks	Increased connectedness among assets
Luo and Ji (2018)	Crude oil and agriculture 5-min (Jan-06–Dec-15)	DY (2012) & HAR	asymmetric connectedness between oil and other commodities
Salisu et al. (2021)	Oil and gold Daily (Jan-06–Aug-20)	VARMA-GARCH model	Increased hedging effectiveness of gold against risk associated with oil
Avdulaj and Barunik (2015)	crude oil and stocks 5-min (Jan-03–Dec-12)	DCRG GAS	decreasing benefits from diversification over the past ten years.
Zhang and Hamori (2021)	Oil and stocks Daily (Jan-06–Aug-20)	DY spillover	Impact of COVID-19 exceeds that of the 2008 financial crisis
Gil-Alana and Monge (2020)	Oil and COVID Daily (May-10–May-20)	Fractional integration	Inefficiency in oil markets
Wang et al. (2021)	Energy futures Daily (Jan-11–Jul-20)	Optimization Techniques	Crude oil fails to diversify any portfolio
Karanasos et al. (2021)	Emerging economies Daily (Jan-00–Nov-20)	HEAVY APARCH	financial and health crisis events raises markets' turbulence
Akhtaruzzaman et al. (2021)	various assets Daily (Jan-00–Nov-20)	HEAVY APARCH	Increased connectedness between oil and other assets during COVID-19
Ji et al. (2021)	Oil futures 1-hour (Jan-18–Apr-20)	DY DCC	Asymmetric relationship between various futures

Notes. Time-varying parameter vector autoregression (TVP-VAR), Diebold and Yilmaz (2012) (DY (2012)), financial assets (FA), Granger Causality (GC), Wavelet coherence (WC), multiplicative component GARCH (MCS-GARCH), heteroscedastic autoregressive (HAR), Vector autoregression moving average (VARMA), Dynamic copula realized GARCH (DCRG), generalized autoregressive score (GAS), High-frequency-based-volatility (HEAVY), Asymmetric Power GARCH (PARCH), generalized autoregressive conditional heteroscedasticity model (GARCH)

In the strand of literature focusing on the connectedness dynamics between crude oil and other asset classes during the COVID-19 pandemic, Echaust and Just (2021) examined the tail dependence among WTI crude oil uncertainty index and WTI crude oil price movements using daily data by utilizing static and dynamic copula frameworks. Their findings indicate strong tail dependence behavior among the underlying series. Zhang and Hamori (2021) employs daily data in the time-frequency spillover framework to evaluate the impact of COVID-19 on oil and various stock markets. Their findings provide evidence of the uncertain impact of the COVID-19 pandemic on the financial markets over both the short- and long-run horizon. Bouri et al. (2021) examines the daily return dependence among several assets using the TVP-VAR connectedness approach. Their findings indicate that the connectedness spikes and alteration in the connectedness with the outbreak of COVID-19. Salisu et al. (2021) evaluate the safe haven potential of gold against the oil price risk by utilizing daily data in an asymmetric VARMA-GARCH model. Their findings indicate an increased hedging effectiveness of gold against the risk associated with oil. Jia et al. (2021) examines the effects and reactions of the COVID-19 pandemic on energy, the economy, and the environment in China. They report reduced oil prices and demand due to COVID-19. Ahmad et al. (2021) evaluates the relationship between US equity sectors, implied volatilities, and COVID-19 by utilizing time-frequency spillover analysis. Their findings indicate that the volatility index exhibits a strong dynamic effect on the various US sectors. Farid et al. (2021) examine the uncertainty transmission between energy, precious metals, and US stocks using high-frequency data spanning from January 2019 to May 2020. Furthermore, they apply a multiplicative component GARCH and utilized the conditional volatilities in a spillover framework by Diebold and Yilmaz (2012). Their findings indicate a Significant impact of COVID-19 on the volatility linkages.

To sum up, irrespective of theoretical foundations, the empirical results from the aforementioned literature offer diverse evidence regarding the best-suited approach to evaluate the connectedness dynamics among the crude oil and other asset classes under extreme market conditions. Furthermore, previous studies examining the interrelationship of crude oil with other asset classes primarily rely on daily data. However, it is well-documented in the literature that the utilization of high-frequency data can attain better performance in encapsulating the connectedness dynamics (see, for example, Degiannakis and Filis, 2017; Phan et al., 2016, among others). Therefore, the current study is an attempt to extend the existing literature by examining the connectedness dynamics between crude oil and various other major indices during extreme events by utilizing high-frequency data and vine-copulas.

3. Data and methodology

In this section, we begin with a summary of the unique data used in this paper and provide some motivational preliminary analysis that justifies the objectives and the methodology of the study. Then, we provide full technical details on vine copulas and on vine regression.

Table 2
Full sample characteristics of the one-minute returns.

Name	Mean	Median	SD	Upper quartile	Lower quartile	Skewness	ACF(1)	ACF(2)
CL1	0	0	0.00562	−0.00053	0.00054	12.81472	0.09075	0.01057
NG	0	0	0.00106	−0.00043	0.00044	−0.06485	−0.0304	−0.01299
VIX	−2e−05	0	0.00345	−0.0013	0.00125	2.69749	0.09155	0.00522
OVX	−4e−05	0	0.01002	−0.00075	6e−04	−1.09542	−0.26311	−0.03674
EX	0	0	0.00017	−8e−05	8e−05	0.35312	−0.03334	−0.004
SPX	0	0	0.00055	−0.00018	0.00018	0.60762	0.06247	−0.00586

3.1. Data and preliminary analysis

To investigate the effects of the COVID-19 outbreak and the Russian–Ukrainian conflict on financial and commodity markets, we utilize high-frequency data for a sample period from January 10, 2020 to June 24, 2022. This sample span is chosen, as the first few cases of COVID-19 were reported at the beginning of January 2020.[1] In addition, the initial stages of the current escalation in the Russian–Ukrainian conflict initiated due to the Russian invasion of Ukraine on February 24, 2022, are also covered in our sample. Consequently, the US and the EU countries have imposed sanctions on the import of crude oil and gas from Russia. This has significant implications for the behavior of crude oil prices as Russia is one of the major oil producers.[2]

The choice of sample span is motivated for the following reasons. Firstly, the primary objective of our study is to examine the impact of specific crisis periods on the underlying assets, which has occurred within the selected sample span. Therefore, the selected span was essential to capture the unique connectedness dynamics and characteristics over the crisis period under investigation. This facilitates us to provide a more focused analysis of the impact of the COVID-19 and Russian–Ukrainian conflict on the connectedness dynamics with other economic indicators. Secondly, by utilizing the selected sample period, we are reducing the under- or overfitting of the model, which may arise from the inclusion of data from non-crisis periods that is not relevant to the research questions of our underlying study. Furthermore, it is well established in the previous literature that the models fail to perform during periods of economic and financial turmoil. Therefore, by concentrating on the crisis periods, we provide a more comprehensive analysis of the impact of the crisis on the underlying assets.

We address the issues discussed in the previous section empirically by focusing on the following series: VIX (1), NG1 (2), EURUSD (3), SPX (4), and CL1 (5). The VIX is the fear index of the US stock market. EURUSED and S&P500 (SPX) are two financials and crude oil (CL1) with natural gas (NG1) build the pair of commodities. Contrary to the usual setting in the literature, we use not daily data but prices at the one-minute frequency. We collect all observations falling into the interval 09:35:00-16:05:00 (EDT). From the one-minute level values, we compute log-returns that are used subsequently in the modeling. The basic statistics of the returns for the full sample are summarized in Table 2. We observe that the crude oil returns have the most skewed distribution as measured by the skewness. They are less volatile than the volatility indices but riskier than the financials. The autocorrelation is negligible for all but the volatility indices, which is also consistent with evidence for daily data. Note that we do not correct for overnight bias, since the below analysis focuses on the observations during trading hours only.

To gain insights into the intraday dependence and its dynamics we compute daily values of Kendall's τ between the crude oil return and the remaining covariates. We opt for the rank correlation coefficient of Kendall for several reasons. First, Kendall's τ is typically used as an intermediate step in more complex dependence models and thus it is consistent with the copula modeling below. Second, in contrast to the correlation coefficient of Pearson, it is not restricted to linear dependence and is capable to capture highly nonlinear monotone relationships. It is high if the ranks of paired observations tend to be similar (concordant pairs) and negative if the ranks are different (discordant pairs). Let $x_{t,i}$, $y_{t,i}$ denote the ith intraday observations on the day t with M being the number of intraday periods. Then

$$\tau_t(X,Y) = \frac{2}{M(M-1)} \sum_{i<j} sgn(x_{t,i} - x_{t,j}) sgn(y_{t,i} - y_{t,j}). \tag{1}$$

The daily values of the correlations are shown in Fig. 1. We observe a clear and robust pattern in the dynamics. First, in terms of dependence between crude oil and the volatility indexes, we observe an average negative connectedness of these assets with crude oil. Whereas, the dependence between crude oil and SPX, EURUSD, and NG1 is characterized by positive dependence. The dependence structure among these assets increased significantly during March with the declaration of COVID-19 as a pandemic by the WHO. Furthermore, the dependence structure among the assets remains relatively stable and even drops to almost zero from the middle (May-2020) to the conclusion (May-2020) of the first wave. In addition, the dependence structure among the assets significantly gradually with the beginning of the second wave of COVID-19 in September. In contrast with the first wave, the increase in dependence structure with the initiation of the second wave remains relatively high and stable from September 2020 to December 2020. Moreover, we observe a significant increase in dependence with the commencement of the third wave of COVID-19 between January 2021 to March 2021. However, with the commencement of vaccination programs around the globe, the dependence structure among the assets converges around zero for nearly all the assets between March 2021 to August 2021. Second, we observe a significant change in the connectedness structure among the assets during the last quarter of 2021 and the first quarter of 2022, which is attributed to the Russia–Ukraine conflict. Notably, this has led to increased uncertainty in the global crude oil market, affecting the connectedness of the underlying assets in our study. The interdependence among the assets gradually declines to zero with increased sanctions by the US and the EU on the Russian oil and gas import thereby disentangling the impact of crude oil on the prices of other underlying assets.

Note that Kendall's τ is a single measure of dependence for the whole range of the values. We can, however, suspect that very low values of a particular dependent variable might have a different impact on the crude oil return than very high values. To capture this effect, we additionally consider the cross-quantilogram as popularized in Han et al. (2016). Let $\psi_\tau(u) = I[u < 0] - \tau$ and $q_X(\tau) = inf\{v \;:\; F_X(v) \geq \tau\}$ is the quantile function of X. Then the cross-quantilogram on the day t at intraday-lag k is defined as

$$\rho_{t,\tau_1,\tau_2}(k) = \frac{E[\psi_{\tau_1}(X_{t,i-k} - q_X(\tau_1)) \cdot \psi_{\tau_2}(Y_{t,i} - q_Y(\tau_2))]}{\sqrt{E[\psi^2_{\tau_1}(X_{t,i-k} - q_X(\tau_1))]}\sqrt{E[\psi^2_{\tau_2}(Y_{t,i} - q_Y(\tau_2))]}}. \tag{2}$$

[1] We have considered the onset of the COVID-19 pandemic from the first week of January 2020 as four different countries (China (278 cases), Thailand (2 cases), Japan (1 case) and the Republic of Korea (1 case)) reported cases of COVID-19 by 15th of January 2020. Whereas the World Health Organization (WHO) declared COVID-19 as pandemic on 11th Mar 2020 (WHO, 2020).

[2] https://www.worldstopexports.com/worlds-top-oil-exports-country/

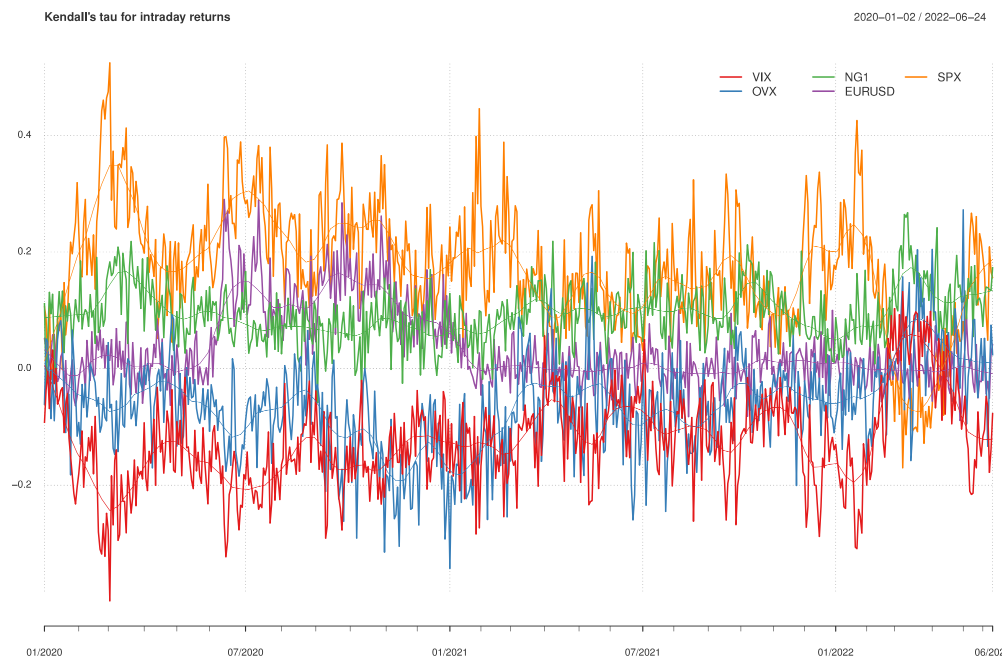

Fig. 1. Kendall' τ for intraday returns of the crude oil and covariates.

The corresponding sample counterpart is calculated as

$$\hat{\rho}_{t,\tau_1,\tau_2}(k) = \frac{\sum_{i=k+1}^{M}[\psi_{\tau_1}(x_{t,i-k} - \hat{q}_X(\tau_1)) \cdot \psi_{\tau_2}(Y_{t,i} - \hat{q}_Y(\tau_2))]}{\sqrt{\sum_{i=k+1}^{M}[\psi_{\tau_1}^2(X_{t,i-k} - \hat{q}_X(\tau_1))]}\sqrt{\sum_{i=k+1}^{M}[\psi_{\tau_2}^2(Y_{t,i} - \hat{q}_Y(\tau_2))]}}. \tag{3}$$

$\hat{\rho}_{\tau_1,\tau_2}(k)$ measures the dependency in terms of the direction of deviation from quantiles and thus measures the directional predictability from one series to another at different quantile levels. Fig. 2 visualizes the cross-quantilogram for the crude oil return with quantiles τ_1 and the quantiles of OVX, VIX and SPX at the quantile τ_2 on two different days (10.01.2020 and 03.03.2020). For simplicity, we set $k = 1$ and thus consider cross-quantilogram with a time lag of one minute. We observe that the patterns heavily depend on the day. Very small risk measured by OVX on 10.01.2020 tends to be followed by higher returns of crude oil, particularly at modest quantiles of 0.4 and 0.5. If the risk is high this impact diminishes. The situation is different on 03.03.2020, where we observe a very weak correlation at low levels of OVX that steadily increases with a higher quantile of the energy market volatility. Several factors contribute to the increased variation in the quantiles. First, the plunging demand for crude oil due to curtailed economic and transportation activities in China, the largest importer of crude oil, with the outbreak of COVID-19. Second, the positive increase in supply from OPEC+ countries together with negative demand shock lead to an increased uncertainty across various quantiles of the return distribution. These results stress the necessity for a nonlinear model that can reflect the specific connectedness between the considered variables.

3.2. Dependence via paired vine copulas

Vine copulas offer a very flexible approach to modeling both general and causal dependence. We begin with the vine copulas as a general dependence model. Let $X_1, \dots, X_d$ be a random vector with the joint cumulative distribution function (cdf) $F(x_1, \dots, x_d)$, the joint density $f(x_1, \dots, x_d)$ and the marginal cdf's $F_i(x_i)$ and densities $f_i(x_i)$ respectively. Following Sklar's theorem any continuous can be decomposed into a product of and the copula as the pure dependence measure, i.e.

$$f(x_1, \dots, x_d) = \prod_{i=1}^{d} f_i(x_i) \cdot c(u_1, \dots, u_d), \tag{4}$$

where $u_i = F_i(x_i)$. The idea of the vine copulas builds upon the factorization of the joint density into a product of conditional densities, i.e.

$$f(x_1, \dots, x_d) = \prod_{i=2}^{d} f(x_i \mid x_1, \dots, x_{i-1}) \cdot f_1(x_1). \tag{5}$$

For example, in a four-dimensional case with $d = 4$, we can obtain the following representation

$$\begin{aligned} f(x_1, \dots, x_4) = {} & f_1(x_1) \cdot f_2(x_2) \cdot f_3(x_3) \cdot f_4(x_4) \\ & \times c_{12}(u_1, u_2) \cdot c_{13}(u_1, u_3) \cdot c_{14}(u_1, u_4) \\ & \times c_{23;1}(F_{2|1}(u_2 \mid u_1), F_{3|1}(u_3 \mid u_1)) \\ & \times c_{24;1}(F_{2|1}(u_2 \mid u_1), F_{4|1}(u_4 \mid u_1)) \\ & \times c_{34;12}(F_{3|12}(u_3 \mid u_1, u_2), F_{4|12}(u_4 \mid u_1, u_2)) \end{aligned} \tag{6}$$

In general, any d-dimensional distribution can be decomposed into a product of $d(d-1)/2$ conditional and unconditional bivariate copulas. The problem is obviously, that there are numerous ways how exactly these copulas are selected. Two popular fixed structures offer C- and D-vines. Their basic representation for the case $d = 5$ is shown in Fig. 3. The C-vines structure assumes a central node with the strongest overall correlation with the remaining covariates. This leads to a star-like first graph. Every edge of this structure becomes a node in the second tree that has a similar star-type structure. Every edge of this tree is then characterized by a conditional bivariate copula. Further trees are built by a similar principle. The vine structure can be selected manually or estimated tree-wise by maximizing the sum of absolute values of some dependence measure (usually Kendall's τ) for each edge of a tree. Next, a copula family is selected for each edge by estimating the parameters of all possible families and choosing the one with the smallest AIC. This procedure is often executed in a step-wise manner starting from the first tree. The resulting parameter estimates are used as starting values for a subsequent full MLE with a fixed structure.

Of particular importance in modeling extreme events in multivariate data are the tail dependence, i.e. the probability that two variables take

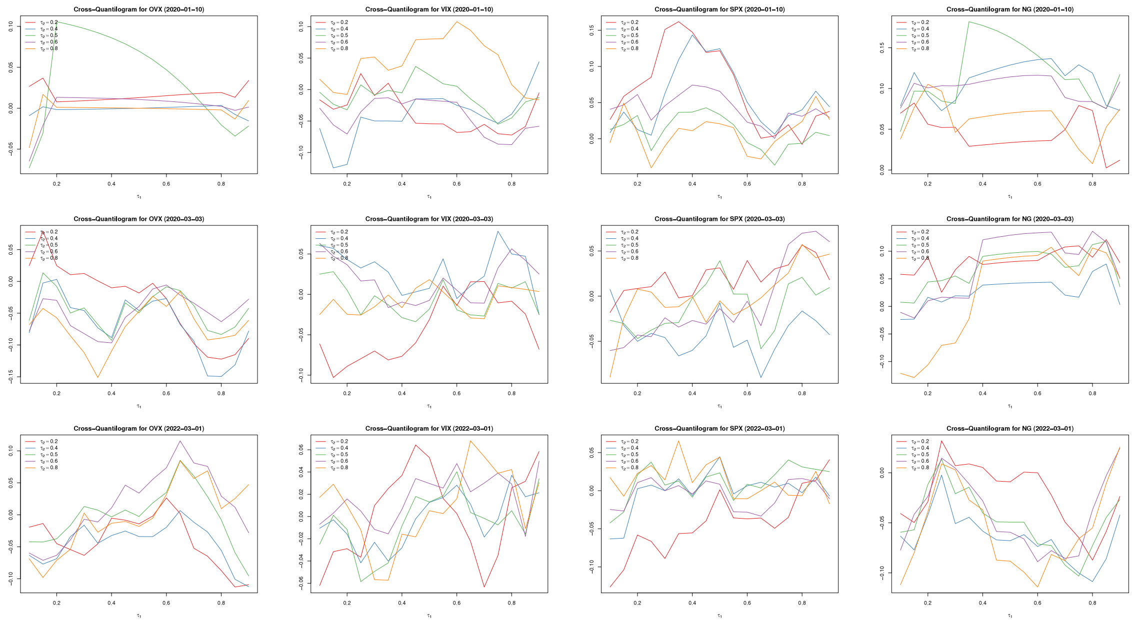

Fig. 2. Cross-quantilogram for crude oil returns at quantile τ_2 and the respective covariates at time lag $k = 1$ and quantile τ_1 on 10.01.2020, 03.03.2020, and 01.03.2022 (top to bottom).

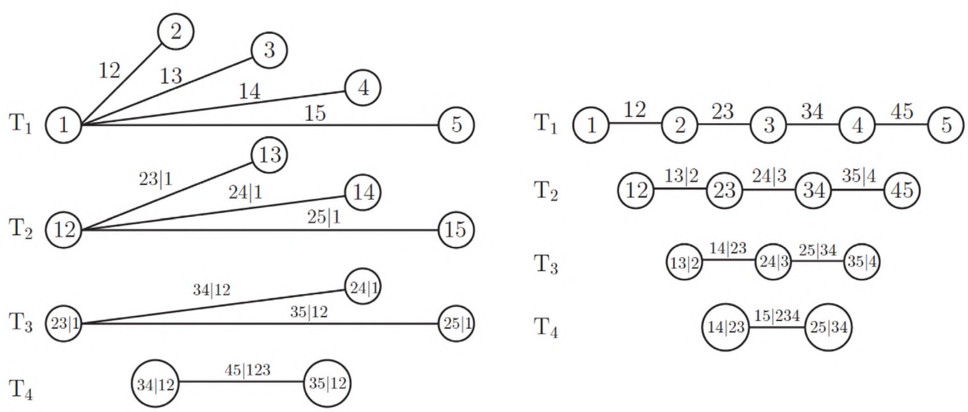

Fig. 3. The general structure of a C-vine (left) and D-vine (right) for a 5-dimensional data set.

extremely large or small values simultaneously. In the context of the copulas, we can specify the probability of an extreme event for one random variable, conditional on the fact the second or other variables take extreme values. These concepts are particularly important for the assessment of market conditions during crisis periods or during particularly flourishing phases. The lower and upper tail dependence for a bivariate copula $C(u, v)$ of (X_1, X_2) are defined as

$$\lambda_L = \lim_{v \to 0^+} P(X_1 < F_1^{-1}(v) \mid X_2 < F_2^{-1}(v)) = \lim_{v \to 0^+} \frac{C(v, v)}{v} \tag{7}$$

$$\lambda_U = \lim_{v \to 1^-} P(X_1 > F_1^{-1}(v) \mid X_2 > F_2^{-1}(v)) = \lim_{v \to 1^-} \frac{1 - 2v + C(v, v)}{1 - v} \tag{8}$$

If the limits are positive, this implies that the underlying variables have either upper or lower dependence. Note that if the copula is a Gaussian copula, then the variables are independent in the tails. This fact is, however, frequently criticized and rejected by empirical data. If we fix the copula family, then the tail dependence indices can be specified as functions of the copula parameters. Table 3 shows the indices for the most popular copula families. Having an estimate for the copula parameter one can compute and assess the tail dependence.

Table 3
Tail dependence coefficients for different copula families.

	Gauss	Student's t	Frank	Clayton	Joe	Gumbel
$\lambda^{(L)}$	0	$2t_{\nu+1}(-\frac{\sqrt{\nu+1}\sqrt{(1-\theta)}}{\sqrt{1+\theta}})$	0	$2^{-\frac{1}{\theta}}$	0	0
$\lambda^{(U)}$	0	$2t_{\nu+1}(-\frac{\sqrt{\nu+1}\sqrt{(1-\theta)}}{\sqrt{1+\theta}})$	0	0	0	$2-2^{1/\theta}$

3.3. Vine regression

In the next step, we concentrate on the causal relationship and aim to model the impact of the covariates on crude oil returns using vine regression. In contrary to the previous section, we focus here on D-vines, since they offer a more structured inference from the model. Several important features of the D-vine regression must be stressed. First, the first tree captures the impact of the covariates on the dependent variable not directly, but sequentially. Every link between the nodes reflects the unconditional correlation between the variables. In contrast, the central starting (root) node of the tree is the crude oil return and the order of the covariates is determined by our estimation procedure discussed below. In lower trees, we switch to conditional dependencies between the regressors and the pseudo-variable that arise from the edges of the previous tree. This is an extension to considering simple partial correlations. Secondly, the crucial difference is that the conditional density $f(x_d \mid x_1, \dots, x_{d-1})$ used for predictions is given for D-vine by an analytic expression. In the case of C-vine, it must be approximated numerically. If all bivariate copulas are Gaussian, then the D-vine parameters equal the simple correlations in the first tree and the partial correlations in the lower trees.

To illustrate the estimation procedure for an arbitrary R-vine, let I denote an index set $I = \{i_1, \dots, i_n\}$ and C_I with c_I are the copula function and the copula density of the variables $\boldsymbol{X}_I = (X_{i_1}, \dots, X_{i_n})$. Additionally, let $C_{I;D}$ associated with the conditional distribution of $\boldsymbol{X}_I$ given $\boldsymbol{X}_D = \boldsymbol{x}_D$ for an arbitrary index set D. In the special case that I consists of two indices only, for example, i and j, we obtain $C_{I;D} = C_{ij;D}$ as the copula associated with the bivariate distribution of (X_i, X_j) given $\boldsymbol{X}_D = \boldsymbol{x}_D$. Using a similar notation we can formalize the conditional univariate distributions. Let $j \in D$ and $D_{-j} = D\backslash\{j\}$. Then

$$F_{i|D}(x_i \mid \boldsymbol{x}_D) = h_{i|j,D_{-j}}(F_{i|D_{-j}}(x_i \mid \boldsymbol{x}_{D_{-j}}) \mid F_{j|D_{-j}}(x_j \mid \boldsymbol{x}_{D_{-j}})) \tag{9}$$

where $h(\cdot)$ denotes the derivative of the underlying conditional copula, i.e.

$$h_{i|j,D_{-j}}(u \mid v) = \frac{\partial C_{ij;D_{-j}}(u, v)}{\partial v}. \tag{10}$$

This structure allows us to determine the bivariate copulas at all nodes recursively. For example, let the bivariate copulas in the first tree of a C-vine be denoted by $C_{i,1}(u_i, u_1)$. Then

$$h_{i|1}(u_i \mid u_1) = \frac{\partial C_{i1}(u_i, u_1)}{\partial u_1} \quad \text{for} \quad i = 2, 3, 4, 5. \tag{11}$$

Then the copulas $C_{23;1}$, $C_{23;1}$, $C_{25;1}$ of the 2nd tree are determined using the pseudo observations

$$\begin{aligned} &(h_{2|1}(u_2 \mid u_1), h_{3|1}(u_3 \mid u_1)),\\ &(h_{2|1}(u_2 \mid u_1), h_{4|1}(u_4 \mid u_1)),\\ \text{and}\ \ &(h_{2|1}(u_2 \mid u_1), h_{5|1}(u_5 \mid u_1)). \end{aligned} \tag{12}$$

At the next level of the hierarchy, we have the copulas $C_{34;12}$ and $C_{35;12}$. The first is determined using the pseudo observations

$$h_{3|1,2}(h_{3|1}(u_3 \mid u_1) \mid h_{2|1}(u_2 \mid u_1)),\ h_{4|1,2}(h_{4|1}(u_4 \mid u_1) \mid h_{2|1}(u_2 \mid u_1)) \tag{13}$$

and similarly for the second one.

If the structure of the vine copula is fixed, then it is straightforward to estimate the copulas and the corresponding parameters. The recursive procedure induces, however, inefficient estimates. To overcome this problem one uses the recursive parameters as starting values for full maximum likelihood estimation. In practice, the structure of the copula or the order of the variables is unknown and must be determined from the data. In lower dimensions, it is can be done via enumeration of all possible structures, but this approach infeasible if the dimension increases. For this reason, we rely on a maximum spanning tree as suggested in Dißmann et al. (2013). At each level, we select the spanning tree that maximizes the sum of absolute empirical Kendall's taus.

The key objective of the modeling is to explain the intraday crude oil return. In the classical regression-type tools we typically obtain point predictions for the expected price conditionally on the values of the control variables. The vine-based regression offers, however, a forecast of the complete conditional distribution $\hat{F}_{X_d|X_1,\dots,X_{d-1}}(x_d \mid x_1, \dots, x_{d-1})$. Knowing this conditional distribution allows us to make predictions for different quantiles of the target variables as follows

$$\hat{F}^{-1}_{X_d|X_1,\dots,X_{d-1}}(\alpha \mid x_1, \dots, x_{d-1}) = \hat{F}^{-1}_{X_d}(\hat{C}_{d|1,\dots,d-1}(\alpha \mid \hat{u}_1, \dots, \hat{u}_{d-1})). \tag{14}$$

In the case of D-vine, this prediction can be established analytically, whereas one relies on numerical approximation in the case of C-vines. To obtain $\hat{u}_i$ one needs to estimate the marginal distribution for every variable. This can be performed either parametrically, by choosing from the set of standard univariate distributions, or non-parametrically by using a kernel density estimator to obtain

$$\hat{F}(x) = \frac{1}{M} \sum_{i=1}^{M} K\left(\frac{x - x_i}{h}\right). \tag{15}$$

Here x_i is a generic observation and K is the kernel function. Then $\hat{u}_i = \hat{F}(x_i)$.

Predicting conditional quantiles give much deeper insights into the relationship between the variables compared to classical linear regression. The idea is similar to that of the quantile regression, but again extends its framework to nonlinear dependencies.

4. Empirical study

In this section, we apply the above methodology of dependence modeling to the crude oil return and natural gas as commodities, S&P 500 and EUR/USD exchange rate as financials, and VIX as a fear index of the US stock market. Our particular setting extends the current literature in two ways. Firstly, we analyze the intraday data directly and thus are able to estimate momentum dependence on a particular day. Secondly, we use vines to model the nonlinear dependence and to build a nonlinear causal model for crude oil returns.

4.1. Intraday dependence

To model the intraday dependence, we fit a C-Vine copula to intraday returns for every trading day of the considered period. We select the optimal vine copula using the methodology discussed in the previous section. Preliminary analysis shows that the correlation in the lower trees is low and in many cases the collapse to independent copulas. This allows us to reduce the computational burden by simplifying the structure by assuming independent copulas at lower-level trees. Thus, we concentrate here on the first tree only. It appears that only two structures arise throughout the whole sample period. One has the VIX index as the root node and the second one is dominated by the S&P 500 returns. This implies that these variables have the highest total correlation with other covariates as measured by Kendall's τ. The temporal dynamics of these structures are shown in Fig. 4. We observe that the second structure has a strong dominance at the peak of the pandemic in March 2020. This is primarily attributed to the declaration of COVID-19 as a pandemic by the WHO on March 11 (WHO, 2020). This triggered various counteractive measures from several economies around the globe to mitigate the impact of a pandemic. Similarly, we observe significant fluctuations in Kendall's τ over the last quarter of 2021 and the first quarter of 2022, attributing to the heightened geopolitical uncertainty due to the Russia–Ukraine conflict. In addition, it is reasonable to assume that the expectations regarding future price fluctuations in the underlying assets may influence the dynamics of other assets across other markets owing to the predominance of underlying assets in the global portfolio of assets. Therefore, expectations concerning future prices may significantly alter the asset pricing and risk management decisions for various market participants and thereby further triggering the shocks in global financial and commodity markets. In addition, the fear of the second wave of COVID together with the heightened tension between Russia and Ukraine have added further uncertainty to the underlying assets, thereby altering the temporal dynamics of these structures. Else the two structures switch very frequently implying that both the S&P500 and the VIX index have a similar dependence on the remaining covariates. Additionally, we plot the time series of BIC and log-likelihood to assess the fit of the model from the time perspective. We observe a better model fit during the spikes of the pandemic, indicating that flexible distributional modeling is advantageous in uncertain periods. This is crucial as flexible distribution models are better able to capture the dependence across various quantiles of the

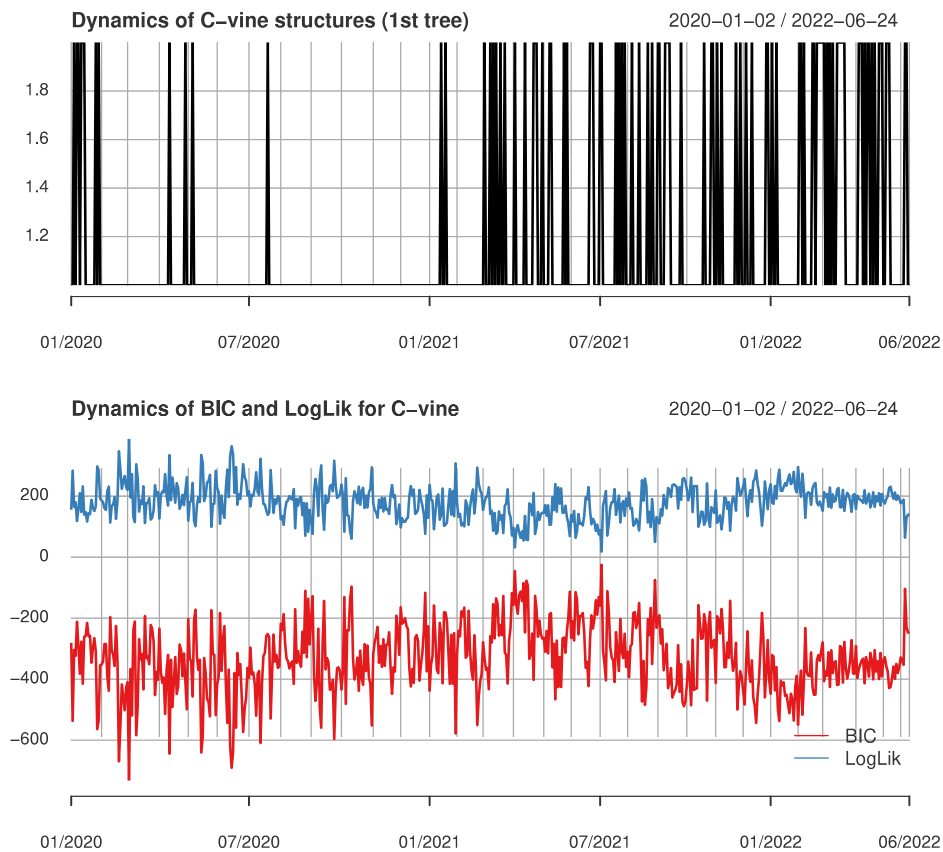

Fig. 4. Upper panel: the dynamics of the two realized intraday C vine structures. VIX is the most dominant in the first structure, whereas S&P 500 is the second one. Bottom panel: the dynamics of the BIC and log-likelihood for the intraday C vine fit.

distribution. Furthermore, the literature is increasingly favoring the utilization of flexible distributional modeling in capturing the dynamics in the underlying series (Patton, 2004; Oh and Patton, 2017; Patton, 2009; Okimoto, 2008).

The tail dependence is a key parameter that reflects the chances of extreme values observed simultaneously for two covariates. The largest upper and lower tail indices for all pairs of variables can be directly derived from the vine copula. The time series of these indices are shown in Fig. 5. It reveals several important facts. First, there is a much stronger tail dependence in the lower tail, e.g. there is a higher probability of two extreme negative returns than of two extreme positive returns. Moreover, the upper tail index is zero on the majority of trading dates, implying independence in the upper tail. These findings are in line with the (Reboredo and Ugolini, 2018; Elie et al., 2019; Dai et al., 2020), as they report asymmetric connectedness among the assets. In addition, several studies highlight the more prominent impact of negative shocks on assets than a positive shock of equal magnitude (Nelson, 1991; Glosten et al., 1993), thereby providing further support to the obtained results. The dynamics of the lower tail index well fit the peaks of the pandemic and the Russia–Ukraine conflict. Thus during high uncertainty caused by COVID and geopolitical uncertainty, the probability of simultaneous extreme negative returns of the covariates increases. This indicates that the covariates that pushed price co-movements among the assets became increasingly connected due to the COVID-19 shock and the Russia–Ukraine conflict. One argument could be related to the beliefs of the short-term investors that are hard to contemplate and extremely heterogeneous resulting in the strengthening of the internal relationship among the underlying covariates under high uncertainty.

Next, we run the D-vine copula regression to estimate the conditional distribution of the crude oil return given the other explanatory variables lagged in time for one minute. This is in line with the setting used for the cross-quantilogram in Section 2. As mentioned above we concentrate on the first three only. This implies that the order of the variables in the first tree corresponds to their importance in explaining the oil returns. Fig. 6 shows the first three variables in the tree for every day of the considered period. Contrary to the pure dependence modeling, here we observe a slightly different pattern. The most dominant predictive variable is the returns of the S&P500 index. The second most influential variable during the peak becomes the natural gas price. These findings are in line with earlier studies documenting strong connectedness between crude oil and the S&P500 and natural gas. Specifically, the relationship between crude oil and S&P500 is well-documented in the previous literature. Both of these assets reflect the health of the global commodity and financial markets (Nazlioglu and Soytas, 2011; Avdulaj and Barunik, 2015; Chen et al., 2019; Baruník et al., 2015; Awartani et al., 2016). Our findings on the dynamic connectedness between crude oil and natural gas are in line with (Batten et al., 2017; Brigida, 2014; Bunn et al., 2017), indicating strong uni- and bi-directional explanatory power flowing between crude oil and natural gas. We additionally observed that the fit of the model drops during the beginning of the pandemic, indicating the covariates have lower explanatory power for the crude oil returns during a turmoil period.

To get more insights into dependence in the tails, we plot the quantile predictions on three different days (15.01.2020, 06.03.2020, 01.03.2022 - from top to bottom, respectively) in Fig. 7. The figures show the nonlinear impact of the explanatory variables on the 10%, 50%, and 90% quantiles of the crude oil return. We observe a clear difference between calm and turmoil periods. Specifically, the connectedness between the assets is close to zero across different quantiles of the return distribution during the pre-COVID period (top). However, close to the date of the announcement of COVID-19 (Middle) as a pandemic, we observe a significant increase in the connectedness between crude oil and other assets in our sample. This is primarily

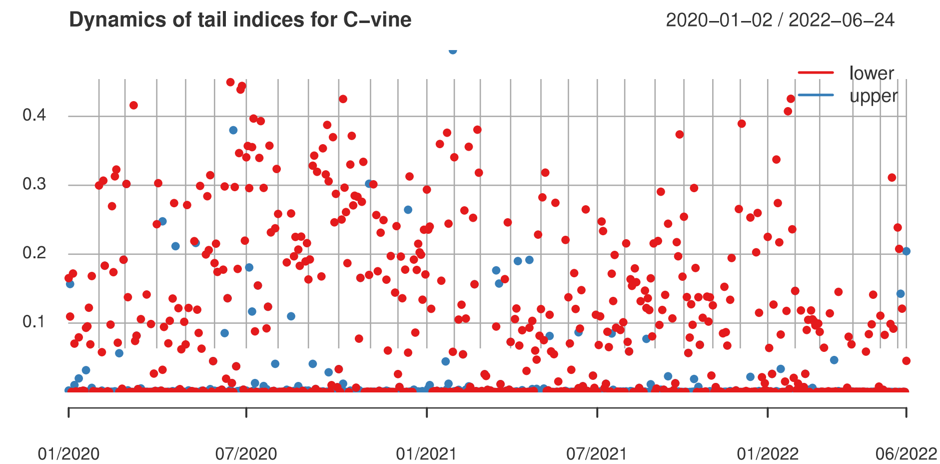

Fig. 5. Maximal lower and upper tail indices of bivariate copulas building the estimated C vine.

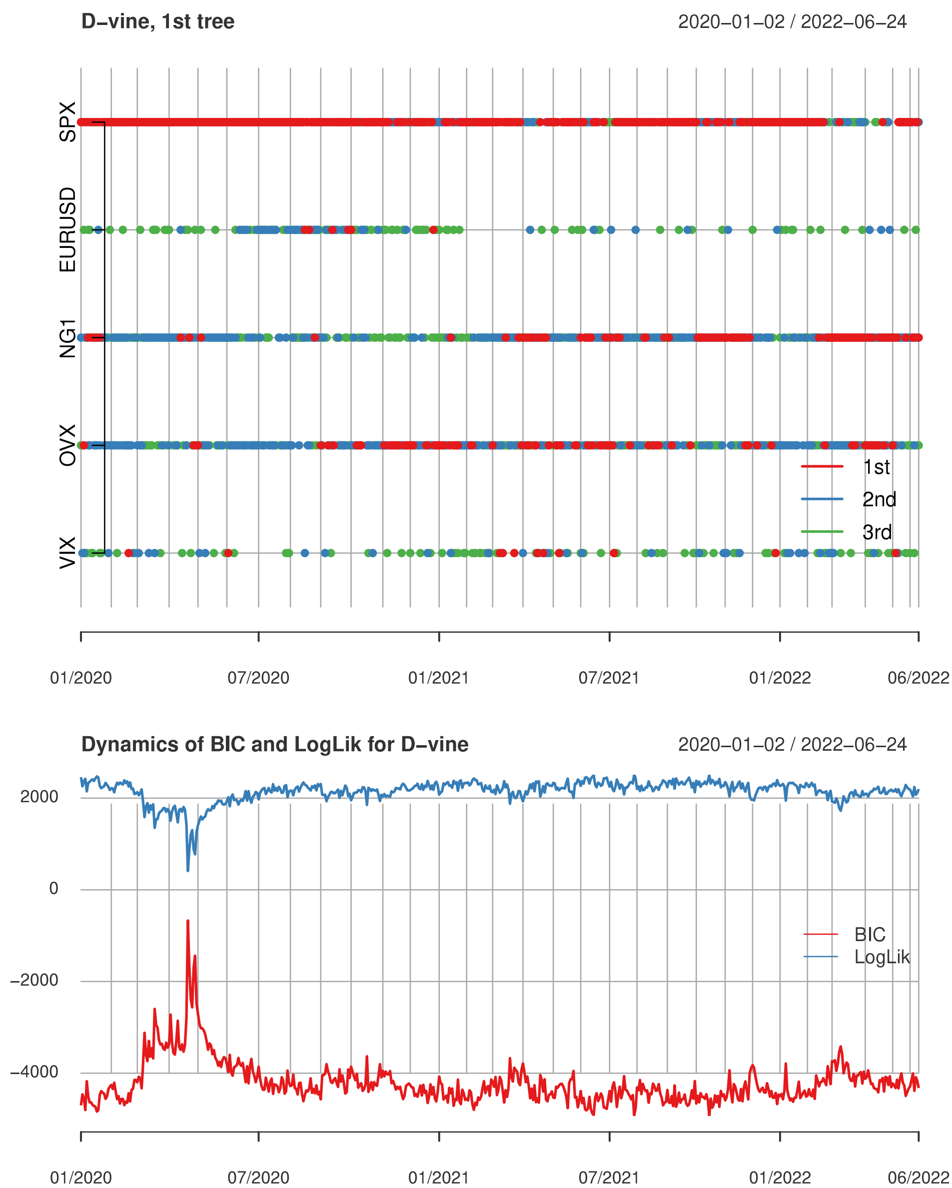

Fig. 6. Upper panel: the dynamics of the rank for the covariates in the D vine regression of the intraday crude oil return on the explanatory variables. Bottom panel: the dynamics of the BIC and log-likelihood for the intraday D vine fit.

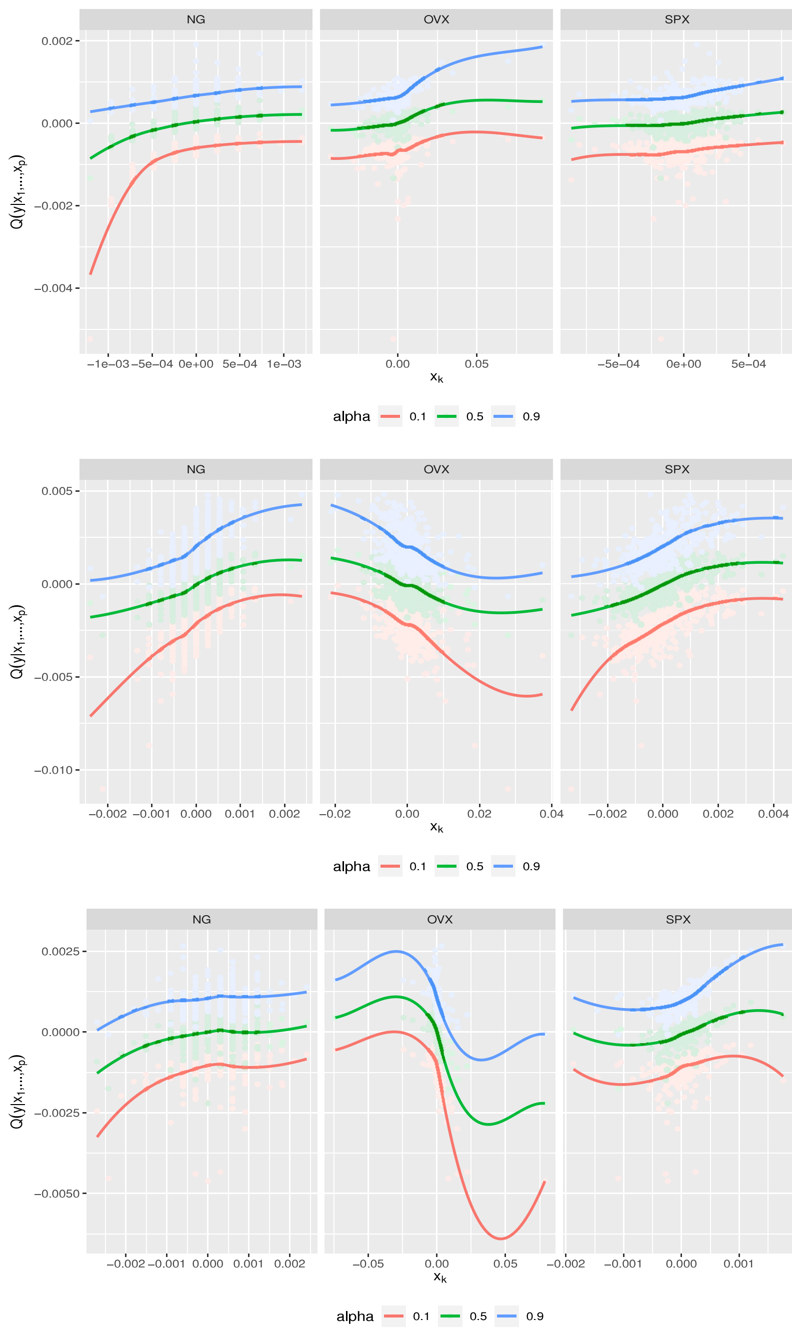

Fig. 7. Conditional quantiles of the crude oil return derived from the D vine regression on 15.01.2020, 06.03.2020, 01.03.2022 - from top to bottom, respectively.

attributed to the negative shock due to COVID-19 in the global financial and commodity markets, leading to an increased disruption in the connectedness equilibrium among these assets. Similarly, the bottom figure emphasizes the connectedness dynamics arising from the Russian–Ukrainian conflict, showcasing a remarkable increase in heterogeneous and asymmetric quantile connectedness. The Russian invasion of Ukraine intensified geopolitical tensions and magnified the uncertainty in global markets, which, in turn, amplified the interconnectedness among the underlying assets. Furthermore, the heightened supply–demand shock in crude oil prices, primarily attributed to sanctions imposed due to the conflict, introduced additional uncertainty into the dynamics of these assets, thereby reinforcing the connectedness among the underlying assets. These findings add to the findings of Dai et al. (2020), Bouri (2015), Wei and Guo (2017), Sun et al. (2021), Yang et al. (2021) and Liu et al. (2021), indicating an increased connectedness among the assets during periods of turmoil.

4.2. Risk management

The objective of the next part of the analysis is a practical evaluation of hedging opportunities of risk exposure in crude oil. We go beyond the classical variance-based approaches to calculating hedge ratios and focus on non-linear dependence between the variables as documented above. We restrict the discussion to a bivariate setting, i.e. to going long in one crude oil asset and going h units short in one of the alternative investment opportunities. The return on the portfolio is then given by

$$r_p(h) = r_{CL1} - hr_a,$$

where a stands for one of the alternatives: VIX, OVX, NG1, EURUSD, and SPX. Let $\rho(r)$ be the risk measure we use for risk quantification. Then the optimal hedge ratio solves the minimization problem

$$h^* = \underset{h}{\operatorname{argmin}} \ \rho(r_p(h)).$$

The Value-at-Risk and Expected Shortfall are the two most popular risk measures and are used in this study. Note, that both measures depend explicitly on the distribution function of the portfolio return. For example,

$$VaR_{\alpha}^{h} = F_{r_p(h)}^{-1}(1-\alpha),$$

where $F_{r_p(h)}(x)$ is a cdf of a linear combination of two random variables and is calculated using the convolution of their joint bivariate cdf. To reflect the nonlinear dependence documented above, we model the joint distribution of the crude oil return and the alternative investments using a bivariate copula. Contrary to the previous studies on hedging, we use intraday data and estimate the optimal copula for every trading day. We select the best copula in terms of the AIC criterion among independence copula, Gaussian, Student t, Clayton, Gumbel, Frank, and Joe copula, whereas the margins are estimated non-parametrically. In the next step, we solve the optimization problem in 4.2 numerically both for VaR and ES.

The resulting estimates of the optimal hedging ratio are shown in Fig. 8. Our findings indicate that the hedge ratios among crude oil and other asset classes increase significantly with the declaration of COVID-19 as a pandemic in March 2020. The increased values of hedge ratios indicate that hedging the long position with these assets became more expensive. This may be attributed to the increased tendency of these series tending to exhibit joint extreme movements as that of crude oil. In addition, our findings indicate a significant increase in hedge ratios between crude oil and EURUSD from August 2020 to November 2020, which may be attributed to the lockdown measures to control the spread of COVID-19. Notably, the hedge ratios between crude oil and EURUSD decline significantly and remain relatively low during the first three quarters of 2021. However, the ratios increase sharply during October 2021, which may be attributed to the heightened geopolitical tensions surrounding the Russian–Ukrainian war, adding uncertainty in the crude oil prices. Similarly, the hedge ratios between crude oil and SPX increases sharply between July 2021 and October 2021 attributing to heightened uncertainty surrounding Russian actions before the initiation of the invasion of Ukraine. However, the ratios decline gradually from January 2022 to the end of our sample period, which may be attributed to the increased decoupling of crude oil prices and SPX influenced by the Russia–Ukraine conflict. These findings are in line with (Wang et al., 2021; Hung, 2021; Ji et al., 2021; Gil-Alana and Monge, 2020) as they report an increased inefficiency of crude oil futures in attaining diversification and risk management potential. Similarly, our findings indicate that the turmoil and geopolitical uncertainties significantly alter the hedging effectiveness and the overall cost of hedging.

5. Conclusion

In light of the outbreak of COVID-19 and the recent Russia–Ukraine conflict, this paper investigates the asymmetric and nonlinear interconnectedness between the financial and commodity markets by utilizing high-frequency intraday data. Specifically, we investigate the heterogeneous and asymmetrical connectedness among various underlying assets by utilizing the cross-quantilograms (CQ), paired vine-based copulas, and copulas vine-based regression analysis. The rationale behind the utilization of CQ is to evaluate the intraday connectedness dynamics among the assets. This is of particular significance when we are evaluating the impact of underlying assets on any specific dates and therefore provides a strong basis to examine the dynamics of connectedness between two or multiple dates across different quantiles of the return distribution. Furthermore, we have utilized paired vine copulas, which offer a very flexible approach to modeling the generic connectedness among the underlying assets. In addition, we utilize the vine-based regression analysis to evaluate the causal relationship between the underlying assets on crude oil returns. The vine regression is of particular interest while modeling the impact of various covariates on the explained variable not directly, but sequentially. Secondly, and most crucially, the conditional density used for the predictions is given by an analytical expression. Utilization of such information is important as the returns of different underlying assets from various asset classes behave rather heterogeneously. Therefore, to accurately capture the conditional density for various covariates, the employment of D-vine is of high significance. Lastly, we provide a practical evaluation of hedging opportunities for risk exposure in the crude oil market by considering the non-linear dependence between the underlying variable.

Our study has several interesting findings. First, based on the cross-quantilograms, we observe that the patterns heavily depend on the day with a time lag of one minute. Specifically, our findings indicate that the connectedness between the assets is close to zero across different quantiles of the intraday return distribution during the pre-COVID period. However, close to the announcement of the COVID-19 pandemic, the connectedness structure sharply increased. Second, the quantile connectedness increases significantly as the Russia–Ukraine conflict introduces additional sources of uncertainty in the crude oil market, contributing positively to the connectedness structure and tail dependence between crude oil and other assets in our sample. Third, from the C-vine copula framework, we observe that the structure has a strong dominance at the peak of the pandemic in March 2020 and with the Russian invasion of Ukraine in February 2022. Fourth, our findings show a much stronger tail dependence in the lower tail than the higher tails indicating asymmetric connectedness among the assets. For example, there is a higher probability of two extreme negative returns than of two extreme positive returns. Moreover, the upper tail index is around zero on the majority of trading dates, implying independence in the upper tails of the return distributions. Fifth, based on the findings from vine regression, the dynamics of the lower tail index well-fit the peaks of the pandemic and the Russian–Ukrainian conflict. Thus, during high uncertainty caused by COVID and geopolitical tensions, the probability of simultaneous extreme negative returns of the covariates increases. This indicates that the covariates that pushed price co-movements among the assets became increasingly connected due to the COVID-19 shock and the Russian–Ukrainian conflict. Finally, our findings indicate that the S&P500 and natural gas have a predictive influence on the crude oil market. These results stress the necessity for a nonlinear model that can reflect the heterogeneous and asymmetric connectedness dynamics between the considered variables under extreme market conditions.

Our study presents several interesting findings that contribute to and extend the prior literature on the connectedness dynamics of financial and commodity markets. Particularly, our results reveal that the connectedness among assets, which was initially negligible across different quantiles of the intraday return distribution, increased sharply with the outbreak of the COVID-19 pandemic and further intensified with the Russia–Ukraine conflict. Additionally, we find a stronger tail dependence in the lower tail, indicating asymmetric connectedness among the assets. These findings are aligned with the findings in previous studies, such as the increased spillover effects during COVID-19 (Bouri et al., 2021), heightened volatility linkages (Farid et al., 2021), and greater connectedness between oil and other assets during the pandemic (Akhtaruzzaman et al., 2021). Our research emphasizes the need for a non-linear framework that can capture the heterogeneous and asymmetric connectedness dynamics between variables under extreme market conditions, providing valuable insights to complement and advance the existing literature.

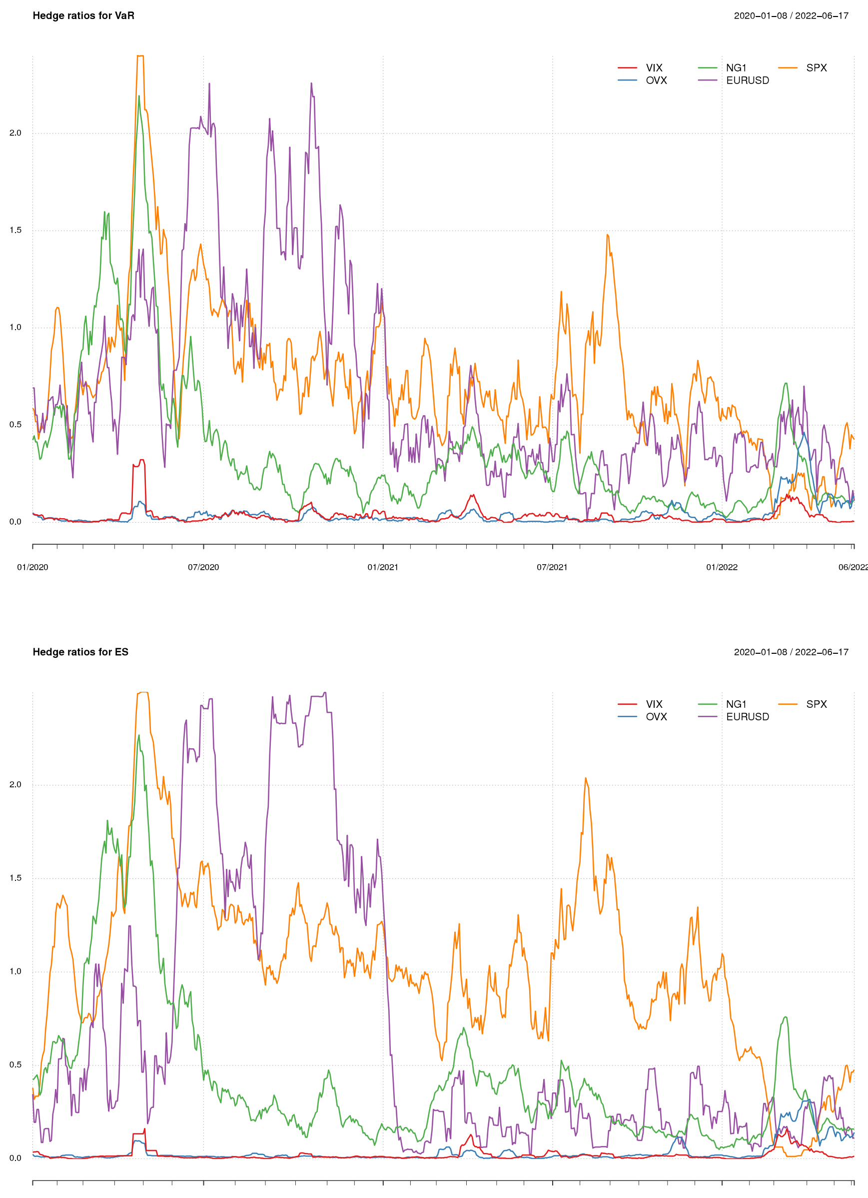

Fig. 8. Optimal hedging ratios based on the VaR (top) and ES (bottom) risk measures and optimal bivariate copulas for the joint distribution of the crude oil return and the alternative assets.

Our findings of increased asymmetric connectedness patterns across crude oil and various financial and commodity markets have important implications for governmental agencies, policymakers, investors, and portfolio managers. The unprecedented decline in prices of financial and commodity markets resulted in increased uncertainty across the market participants about the pricing of these assets. Governmental agencies and policymakers should prioritize understanding the underlying factors driving the asymmetric connectedness between the underlying assets and devise a roadmap to disentangle such behavior in the financial and commodity markets. This includes research and analysis in identifying the key drivers, such as geopolitical measures, macroeconomic variables, and global supply–demand imbalances. Portfolio managers and investors should accommodate the potential heterogeneous and asymmetric connectedness dynamics in their frameworks to devise relevant and appropriate investment allocation and management decisions.

Future research may employ intraday vine copula modeling and D-vine copulas to enhance price dependence forecasting and dynamic portfolio weight selection among various assets. Developing a dynamic portfolio strategy based on vine copulas presents methodological and computational challenges, representing a promising avenue for future exploration and investigation.

CRediT authorship contribution statement

Yarema Okhrin: Conceptualization, Methodology, Formal analysis, Software, Writing – original draft, Writing – review & editing. **Gazi Salah Uddin:** Conceptualization, Investigation, Resources, Writing – original draft, Writing – review & editing. **Muhammad Yahya:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

Acknowledgments

The authors are thankful to the Department of Statistics, Faculty of Business and Economics, University of Augsburg, Germany, for the academic facilities provided to Gazi Salah Uddin during his stay at the University of Augsburg, where important parts of this research work were completed. Gazi Salah Uddin is also thankful for the IEI research visit grant by Linköping University, Sweden. An earlier version of the paper was presented at Linköping University, Sweden and MAF2022 conference at Salerno University, Italy.

References

Ahmad, W., Hernandez, J.A., Saini, S., Mishra, R.K., 2021. The US equity sectors, implied volatilities, and COVID-19: What does the spillover analysis reveal? Resour. Policy 72, 102102.

Akhtaruzzaman, M., Boubaker, S., Lucey, B.M., Sensoy, A., 2021. Is gold a hedge or a safe-haven asset in the COVID–19 crisis? Econ. Model. 102, 105588.

Albulescu, C.T., Ajmi, A.N., 2021. Oil price and US dollar exchange rate: Change detection of bi-directional causal impact. Energy Econ. 105385.

Aloui, R., Aïssa, M.S.B., Nguyen, D.K., 2011. Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? J. Bank. Financ. 35 (1), 130–141.

Avdulaj, K., Barunik, J., 2015. Are benefits from oil–stocks diversification gone? New evidence from a dynamic copula and high frequency data. Energy Econ. 51, 31–44.

Awartani, B., Aktham, M., Cherif, G., 2016. The connectedness between crude oil and financial markets: Evidence from implied volatility indices. J. Commod. Mark. 4 (1), 56–69.

Barthel, N., Czado, C., Okhrin, Y., 2019. A partial correlation vine based approach for modeling and forecasting multivariate volatility time-series. Comput. Statist. Data Anal. 142, 106810.

Baruník, J., Kocenda, E., Vácha, L., 2015. Volatility spillovers across petroleum markets. Energy J. 36 (3).

Batten, J.A., Ciner, C., Lucey, B.M., 2017. The dynamic linkages between crude oil and natural gas markets. Energy Econ. 62, 155–170.

Berger, T., Uddin, G.S., 2016. On the dynamic dependence between equity markets, commodity futures and economic uncertainty indexes. Energy Econ. 56, 374–383.

Bouri, E., 2015. Return and volatility linkages between oil prices and the lebanese stock market in crisis periods. Energy 89, 365–371.

Bouri, E., Cepni, O., Gabauer, D., Gupta, R., 2021. Return connectedness across asset classes around the COVID-19 outbreak. Int. Rev. Financial Anal. 73, 101646.

Bouri, E., Kachacha, I., Roubaud, D., 2020. Oil market conditions and sovereign risk in MENA oil exporters and importers. Energy Policy 137, 111073.

Brigida, M., 2014. The switching relationship between natural gas and crude oil prices. Energy Econ. 43, 48–55.

Bunn, D., Chevallier, J., Le Pen, Y., Sevi, B., 2017. Fundamental and financial influences on the co-movement of oil and gas prices. Energy J. 38 (2).

Cao, Y., Cheng, S., 2021. Impact of COVID-19 outbreak on multi-scale asymmetric spillovers between food and oil prices. Resour. Policy 102364.

Charfeddine, L., Benlagha, N., 2016. A time-varying copula approach for modelling dependency: New evidence from commodity and stock markets. J. Multinat. Financial Manag. 37, 168–189.

Chen, W., Ma, F., Wei, Y., Liu, J., 2020. Forecasting oil price volatility using high-frequency data: New evidence. Int. Rev. Econ. Finance 66, 1–12.

Chen, Y., Ma, F., Zhang, Y., 2019. Good, bad cojumps and volatility forecasting: New evidence from crude oil and the US stock markets. Energy Econ. 81, 52–62.

Chuliá, H., Furió, D., Uribe, J.M., 2019. Volatility spillovers in energy markets. Energy J. 40 (3).

Czado, C., Ivanov, E., Okhrin, Y., 2019. Modelling temporal dependence of realized variances with vines. Econometr. Stat. 12, 198–216.

Czado, C., Nagler, T., 2022. Vine copula based modeling. Annu. Rev. Stat. Appl. 9 (1).

Dai, X., Wang, Q., Zha, D., Zhou, D., 2020. Multi-scale dependence structure and risk contagion between oil, gold, and US exchange rate: A wavelet-based vine-copula approach. Energy Econ. 88, 104774.

Degiannakis, S., Filis, G., 2017. Forecasting oil price realized volatility using information channels from other asset classes. J. Int. Money Finance 76, 28–49.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.

Ding, Q., Huang, J., Chen, J., 2021. Dynamic and frequency-domain risk spillovers among oil, gold, and foreign exchange markets: Evidence from implied volatility. Energy Econ. 102, 105514.

Dißmann, J., Brechmann, E., Czado, C., Kurowicka, D., 2013. Selecting and estimating regular vine copulae and application to financial returns. Comput. Statist. Data Anal. 59, 52–69.

Du, X., McPhail, L.L., 2012. Inside the black box: the price linkage and transmission between energy and agricultural markets. Energy J. 33 (2).

Dutta, A., 2018. Impacts of oil volatility shocks on metal markets: A research note. Resour. Policy 55, 9–19.

Echaust, K., Just, M., 2021. Tail dependence between crude oil volatility index and WTI oil price movements during the COVID-19 pandemic. Energies 14 (14), 4147.

Elie, B., Naji, J., Dutta, A., Uddin, G.S., 2019. Gold and crude oil as safe-haven assets for clean energy stock indices: Blended copulas approach. Energy 178, 544–553.

Farid, S., Kayani, G.M., Naeem, M.A., Shahzad, S.J.H., 2021. Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. Resour. Policy 72, 102101.

Gil-Alana, L.A., Monge, M., 2020. Crude oil prices and COVID-19: Persistence of the shock. Energy Res. Lett. 1 (1), 13200.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. J. Finance 48 (5), 1779–1801.

Han, H., Linton, O., Oka, T., Whang, Y.-J., 2016. The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series. J. Econometrics 193 (1), 251–270.

Hung, N.T., 2021. Oil prices and agricultural commodity markets: evidence from pre and during COVID-19 outbreak. Resour. Policy 73, 102236.

Huynh, T.L.D., Ahmed, R., Nasir, M.A., Shahbaz, M., Huynh, N.Q.A., 2021. The nexus between black and digital gold: evidence from US markets. Ann. Oper. Res. 1–26.

Ji, Q., Fan, Y., 2012. How does oil price volatility affect non-energy commodity markets? Appl. Energy 89 (1), 273–280.

Ji, Q., Zhang, D., Zhao, Y., 2021. Intra-day co-movements of crude oil futures: China and the international benchmarks. Ann. Oper. Res. 1–27.

Jia, Z., Wen, S., Lin, B., 2021. The effects and reacts of COVID-19 pandemic and international oil price on energy, economy, and environment in China. Appl. Energy 302, 117612.

Karanasos, M., Yfanti, S., Hunter, J., 2021. Emerging stock market volatility and economic fundamentals: the importance of US uncertainty spillovers, financial and health crises. Ann. Oper. Res. 1–40.

Kielmann, J., Manner, H., Min, A., 2021. Stock market returns and oil price shocks: A CoVaR analysis based on dynamic vine copula models. Empir. Econ..

Kraus, D., Czado, C., 2017. D-vine copula based quantile regression. Comput. Statist. Data Anal. 110, 1–18.

Kyritsis, E., Serletis, A., 2019. Oil prices and the renewable energy sector. Energy J. 40 (The New Era of Energy Transition).

Liu, X., An, H., Huang, S., Wen, S., 2017. The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH–BEKK model. Physica A 465, 374–383.

Liu, Z., Shi, X., Zhai, P., Wu, S., Ding, Z., Zhou, Y., 2021. Tail risk connectedness in the oil-stock nexus: Evidence from a novel quantile spillover approach. Resour. Policy 74, 102381.

Luo, J., Ji, Q., 2018. High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. Energy Econ. 76, 424–438.

Ma, F., Liao, Y., Zhang, Y., Cao, Y., 2019. Harnessing jump component for crude oil volatility forecasting in the presence of extreme shocks. J. Empir. Financ. 52, 40–55.

Manera, M., Nicolini, M., Vignati, I., 2013. Financial speculation in energy and agriculture futures markets: A multivariate GARCH approach. Energy J. 34 (3).

Manickavasagam, J., Visalakshmi, S., Apergis, N., 2020. A novel hybrid approach to forecast crude oil futures using intraday data. Technol. Forecast. Soc. Change 158, 120126.

Naeem, M.A., Qureshi, F., Farid, S., Tiwari, A.K., Elheddad, M., 2021. Time-frequency information transmission among financial markets: evidence from implied volatility. Ann. Oper. Res. 1–29.

Nakajima, T., Hamori, S., 2013. Testing causal relationships between wholesale electricity prices and primary energy prices. Energy Policy 62, 869–877.

Nazlioglu, S., 2011. World oil and agricultural commodity prices: Evidence from nonlinear causality. Energy Policy 39 (5), 2935–2943.

Nazlioglu, S., Soytas, U., 2011. World oil prices and agricultural commodity prices: evidence from an emerging market. Energy Econ. 33 (3), 488–496.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 347–370.

Niu, Z., Liu, Y., Gao, W., Zhang, H., 2021. The role of coronavirus news in the volatility forecasting of crude oil futures markets: Evidence from China. Resour. Policy 73, 102173.

Oh, D.H., Patton, A.J., 2017. Modeling dependence in high dimensions with factor copulas. J. Bus. Econom. Statist. 35 (1), 139–154.

Okimoto, T., 2008. New evidence of asymmetric dependence structures in international equity markets. J. Financial Quant. Anal. 43 (3), 787–815.

Patton, A.J., 2004. On the out-of-sample importance of skewness and asymmetric dependence for asset allocation. J. Financ. Econom. 2 (1), 130–168.

Patton, A.J., 2009. Copula–based models for financial time series. In: Handbook of Financial Time Series. Springer, pp. 767–785.

Phan, D.H.B., Sharma, S.S., Narayan, P.K., 2016. Intraday volatility interaction between the crude oil and equity markets. J. Int. Financial Mark. Inst. Money 40, 1–13.

Reboredo, J.C., Ugolini, A., 2018. The impact of energy prices on clean energy stock prices. A multivariate quantile dependence approach. Energy Econ. 76, 136–152.

Salisu, A.A., Vo, X.V., Lawal, A., 2021. Hedging oil price risk with gold during COVID-19 pandemic. Resour. Policy 70, 101897.

Shi, K., 2021. Spillovers of stock markets among the BRICS: New evidence in time and frequency domains before the outbreak of COVID-19 pandemic. J. Risk Financial Manag. 14 (3), 112.

Sun, J., Zhao, X., Xu, C., 2021. Crude oil market autocorrelation: Evidence from multiscale quantile regression analysis. Energy Econ. 98, 105239.

Syuhada, K., Suprijanto, D., Hakim, A., 2021. Comparing gold's and Bitcoin's safe-haven roles against energy commodities during the COVID-19 outbreak: A vine copula approach. Finance Res. Lett. 102471.

Tiwari, A.K., Boachie, M.K., Suleman, M.T., Gupta, R., 2021. Structure dependence between oil and agricultural commodities returns: The role of geopolitical risks. Energy 219, 119584.

Wang, L., Ahmad, F., Luo, G.-l., Umar, M., Kirikkaleli, D., 2021. Portfolio optimization of financial commodities with energy futures. Ann. Oper. Res. 1–39.

Wei, Y., Guo, X., 2017. Oil price shocks and China's stock market. Energy 140, 185–197.

WHO, W.H.O., 2020. Archived: WHO Timeline - COVID-19. World Health Organization: WHO, URL: https://www.who.int/news/item/27-04-2020-who-timeline---covid-19.

Yang, D.-X., Wu, B.-B., Tong, J.-Y., 2021. Dynamics and causality of oil price shocks on commodities: Quantile-on-quantile and causality-in-quantiles methods. Resour. Policy 74, 102246.

Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. Int. Rev. Financ. Anal. 68, 101239.

Zhang, W., Hamori, S., 2021. Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany. Int. Rev. Financ. Anal. 74, 101702.

Zhang, K.-S., Zhao, Y.-Y., 2021. Modeling dynamic dependence between crude oil and natural gas return rates: A time-varying geometric copula approach. J. Comput. Appl. Math. 386, 113243.

Zhu, B., Huang, L., Yuan, L., Ye, S., Wang, P., 2020. Exploring the risk spillover effects between carbon market and electricity market: A bidimensional empirical mode decomposition based conditional value at risk approach. Int. Rev. Econ. Finance 67, 163–175.