Journal of Banking and Finance 75 (2017) 258–279

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method

Walid Mensi[a,b], Shawkat Hammoudeh[c,d,*], Syed Jawad Hussain Shahzad[d,e], Muhammad Shahbaz[d]

[a] Department of Finance and Accounting, University of Tunis El Manar, Tunis, Tunisia
[b] Department of Finance and Investment, College of Economics and Administrative Sciences, Al Imam Mohammad Ibn Saud Islamic University (IMSIU), P.O Box 5701 Riyadh, Saudi Arabia
[c] Lebow College of Business, Drexel University, Philadelphia, United States
[d] Energy and Sustainable Development (ESD), Montpellier Business School, Montpellier, France
[e] COMSATS Institute of Information Technology, Islamabad, Pakistan

ARTICLE INFO

Article history:
Received 13 September 2016
Accepted 20 November 2016
Available online 23 November 2016

JEL classification:
C58
F37
G11
G14

Keywords:
Oil prices
Stock markets
Risk spillovers
Copula
Variational mode decomposition
Delta CoVaR

ABSTRACT

This study combines the variational mode decomposition (VMD) method and static and time-varying symmetric and asymmetric copula functions to examine the dependence structure between crude oil prices and major regional developed stock markets (S&P500, stoxx600, DJPI and TSX indexes) during bear, normal and bull markets under different investment horizons. Furthermore, it analyzes the upside and downside short- and long-run risk spillovers between oil and stock markets by quantifying three market risk measures, namely the value at risk (VaR), conditional VaR (CoVaR) and the delta CoVaR (ΔCoVaR). The results show that there is a tail dependence between oil and all stock markets for the raw return series. By considering time horizons, we show that there is an average dependence between the considered markets for the short-run horizons. However, the tail dependence is also found for the long-run horizons between the oil and stock markets, with the exception of the S&P500 index which exhibits average dependence with the oil market. Moreover, we find strong evidence of up and down risk asymmetric spillovers from oil to stock markets and vice versa in the short-and long run horizons. Finally, the market risk spillovers are asymmetric over the time and investment horizons.

1. Introduction

Oil is a strategic and vital commodity for all the economies of the world. It underlies and interrelates to virtually every important sector of the economy. For at least the last two decades, oil prices have widely bounced up and down with varying passions over relatively short periods of time. The oil roller coaster rides affect businesses since oil serves as a fuel, as a feedstock and also influences consumers through its effects on final demand because this major energy source is used in transportation, home heating, services, etc. More recently, oil markets have been financialized as a result of increasing exposure to different sets of market participants including individual investors, money managers, hedge funds, banks, insurance companies among others. The oil financialization has been helped by several financial tools such as options, futures, index funds, exchange traded funds, bespoke products, etc. Investors use the oil asset to enhance returns, diversify portfolios and hedge against inflation since this fuel is considered as a resource stock and a store of value. These characteristics have brought oil markets closer to stock markets, and global forces also have increased their connectedness. Those markets have also come closer to each other in the short run through the activity of speculators and money managers.

That said, changes in oil prices play a significant role in the relationship between oil and stock markets and have become one of the important determinants of international stock markets' volatility. Thus, investors' decisions are based not only on the available fundamental information in the stock markets but also on the information prevailing in the oil markets. Therefore, examining the oil-stock market dependence is important for asset allo-

* Corresponding author at: Lebow College of Business, Drexel University, Philadelphia, United States. Fax: +1 2155714670.
E-mail addresses: walid.mensi@fsegt.rnu.tn (W. Mensi), shawkat.hammoudeh@gmail.com (S. Hammoudeh), jawad.kazmi5@gmail.com (S.J.H. Shahzad), shahbazmohd@live.com (M. Shahbaz).

http://dx.doi.org/10.1016/j.jbankfin.2016.11.017
0378-4266/

cation and portfolio risk management. Given the oil intensity in developed economies and the financialization of commodities in those economies, investors should be susceptible to the impact of oil price fluctuations on future equity returns. As expected discounted cash flows of any asset have the power to predict its price,[1] any factors altering these discounted cash flows can have a significant effect on these asset prices. Consequently, an increase in oil prices may lead to a decrease in equity returns; however; the status of the individual country being either an importer or an exporter is of utmost importance for the oil-stock relationship. An increase in oil prices exhibits a positive effect on the equity returns of oil-exporting countries (Jiménez-Rodríguez and Sanchez, 2005; Bjørnland, 2009), whereas other studies argue that such an increase in oil prices can result in a decrease in Dow Jones Stoxx600 equity returns of European countries (Arouri and Nguyen, 2010).[2] Moreover, the relationship between oil prices and stock market returns varies across bear and bull market conditions due to hedging and herding among other reasons. Further, the oil-stock market dependence varies across investment time horizons (i.e., at short- and long-run investment horizons). Specifically, modeling the evolving extreme dependence structure between these markets has important implications for financial risk management and hedging strategies.

Although there is a large body of the empirical literature that deals with the oil-stock market comovements, little is known about how oil prices and stock markets co-move both during different market conditions and at different investment horizons and what the upside and downside short- and long-run risk spillovers between them are. To discern the oil and stock co-movements at different investment horizons, we use an advanced multiresolution decomposition method, namely the variational mode decomposition (VMD), to decompose the original series into short- and long-run components and capture the dependence in the upper and lower tail distributions, using different specifications of copulas.[3] VMD can decompose the non-stationary signal into couple Intrinsic Mode Functions adaptively and non-recursively (Li et al., 2017). We use a range of time-invariant, time-varying, symmetric and asymmetric copula functions namely the Gaussian, Student-t, Gumbel, rotated Gumbel, Frank, Plackett, Clayton, rotated Clayton and SJC copulas to compute the upside and downside spillover risk effects from crude oil to stock markets and vice versa for four major and regional stock markets (i.e., the S&P500 index for the U.S., the TSX index for Canada, the Stoxx600 for Europe and the Dow Jones Pacific Stock Index excluding Japan for the Pacific basin) at different investment horizons. We are also interested in regional market risks using three different risk measures which are the Value at Risk (VaR), the Conditional Value at Risk (CoVaR) and the delta Conditional Value at Risk (ΔCoVaR) to measure the risk spillovers.

Our choice of those four major stock markets is motivated by their respective regional locations (the United States, Canada, Europe and Pacific basin) and their relative global importance for equity and commodity markets. The Stoxx Europe600 index represents European stock markets, which are capitalized at $9.3 trillion dollars in free-float market cap.[4] The TSX index, which is considered as the benchmark for Canadian equities, is selected because Canada is a developed country with a clear resource oil and gas-based economy and a stock market capitalization of about $2 trillion. The S&P500 index is a major benchmark of the U.S. equity markets which have a market capitalization of about $22 trillion. This index is also a major reference for international investors since it is considered as the most accurate gauge of the performance of large-caps. Finally, the Dow Jones Pacific Stock Index is a reference for the Pacific-Rim region.

To the best of the authors' knowledge, no paper to date has: (i) examined the dependence structure between oil and stock markets at different time investment horizons (short- and long-run) and under different market conditions (normal, bearish and bullish) by combining the VMD and copula methods; (ii) explored the upside and downside risk spillovers of oil markets to stock markets and vice versa at short- and long-run investment horizons, using different risk measures such as Value at VaR, CoVaR and delta CoVaR; (iii) tested if the up and down risk spillovers are asymmetric; and (iv) investigated whether the risk spillovers have asymmetric effects over the different time horizons for long and short positions.

The empirical results provide strong evidence of tail dependence between oil and the considered major regional developed stock markets for the raw return series. For the short-run investment horizons, we find an average positive dependence between oil and those four major developed stock markets. As for the long-run investment horizons, we find asymmetric upper and lower dependence between those major markets as provided by the TVP SJC copula, with the exception of the U.S. stock market which exhibits an average dependence with the oil market as detected by the TVP Gaussian copula. On the other hand, we find significant risk spillovers to the stock and to oil markets for the raw return series at both short- and long-run horizons.

More importantly, we find that the upside and downside risk spillovers (from oil to stock markets and vice versa) are stronger in the long-run than in the short-run for all cases. It also is worth noting that the risk spillovers to oil are higher than those to stock markets. More interestingly, there is supportive evidence of asymmetric upside and downside risk spillovers to stock and to oil markets for all cases in the short- and long-run investment horizons. The downside and upside CoVaRs and ΔCoVaRs are asymmetric in the short- and long-run for the oil and stock markets. Finally, the impact of the onset of the GFC on risk spillovers is evident for all cases, as we find significant abrupt variations during the 2008–2009 crisis period.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the empirical methods. Section 4 provides the data and some preliminary statistics. Section 5 reports and discusses the empirical results. Section 6 presents the portfolio risk implications. Section 7 draws policy implications and concludes the paper.

2. Review of literature

A large body of the empirical literature has attempted to examine the intriguing links between oil and stock markets, using different econometric methods. In this review, we focus mostly on the recent studies that are related to our methodology and markets located in different regions but don't provide a detailed review of the old literature which is available in earlier studies.

Kling (1985) uses the vector autoregressive (VAR) model to explore the effects of oil prices on the S&P500 index and five U.S.

[1] See Fisher (1930); Williams (1938).

[2] A negative relationship between oil price shocks and international equity returns also is suggested by Jones and Kaul (1996), Sadorsky (1999) and Ciner (2001) for different countries. Jones and Kaul (1996) document that oil prices are a risk factor for stock prices. However, studies by Chen et al. (1986) and Huang et al. (1996) do not support this negative association.

[3] VMD has at least three advantages over the wavelet (Discrete Wavelet Transform) approach. (1) DWT is not as adaptive as the VMD technique, (2). DWT requires a pre-determined wavelet function and a scale of decomposition, (3). The number of observations decreases with the level of decomposition, and this negatively affects the linear estimates.

[4] Source: STOXX Europe Total Market Index (TMI). https://www.stoxx.com/document/Research/Expert-speak-articles/article_european_equity_market_201502.pdf

industries. Chen et al., (1986) show that stock market returns are exposed to systematic economic news. More interestingly, the authors find no statistically significant relationship between oil price and stock returns. Jones and Kaul (1996) use the current and future changes in real cash flows and/or changes in expected returns to explain the reaction of international stock markets (Canada, Japan, UK and U.S.) to oil shocks. The authors demonstrate that the reaction of the U.S. and Canadian stock prices to oil shocks can be completely accounted for by the impact of these shocks on real cash flows alone. Huang et al., (1996) demonstrate that oil futures returns lead some individual oil company stock returns but oil future returns do not have much impact on broad-based market indices as the S&P 500 index. Sadorsky (1999) uses the vector autoregression to determine how oil price movements play a crucial role to explain a larger fraction of the forecast error variance in real stock returns than interest rates do. Latter, Sadorsky (2012) uses the multivariate GARCH model to analyze the correlations and volatility transmission between oil and the stock prices of clean energy and technology companies. Mohanty et al., (2010) explore the connection between oil prices and the stock returns of oil and gas firms in Central and Eastern European (CEE) countries. The authors find no significant linkages between oil prices and the stock returns over the 1998–2010 period. Using a subperiod analysis, the results show that oil price exposures of some oil and gas companies do vary across firms and over time. Vo (2011) investigates the stock volatility-oil futures market linkages using the multivariate stochastic volatility structure. The author finds that both markets are inter-related and that the dynamic behavior increases when the markets are more volatile. Balcilar and Ozdemir (2013) use the Markov switching vector autoregressive (MS-VAR) model to demonstrate that oil futures prices have strong regime prediction power for subgroups of the S&P 500 stock index during different subperiods in the sample. They find weak evidence for the regime prediction power of a sub-grouping of the S&P 500 stock indexes.

Using the copula method, Aloui et al., (2013) provide evidence of a contagion effect between oil and CEE transition economies (Bulgaria, Czech Republic, Hungary, Poland, Romania and Slovenia). In addition, the lower tail dependence is much stronger than that of the upper tail. In contrast, Cong et al., (2008) apply the multivariate vector auto-regression and show no significant relationship between oil price shocks and the real stock returns of most Chinese stock sector indices, except for the manufacturing index and some oil companies where important oil price shocks depress oil company stock prices.

Du and He (2015) address the issue of extreme risk spillovers between the S&P500 stock index and West Texas Intermediate (WTI) crude oil futures returns, using the method of Granger causality-in-risk, the Value at Risk (VaR) risk measure, and a class of kernel-based tests to detect negative and positive risk spillover effects. The results show strong evidence of significant risk spillovers between the considered markets. Also, the authors find that extreme movements in the oil market may have a significant predictive power for those in the stock market and vice versa. Using a Markov-Switching vector error-correction model, Balcilar et al., (2015) examine the relationship between the U.S. crude oil and stock market prices and find that the high-volatility regime exists more frequently prior to the 1929 Great Depression and after the 1973 oil price shock engineered by the Organization of Petroleum Exporting Countries (OPEC).

Kang et al. (2015) use a mixture innovation time-varying parameter VAR model to investigate the impact of structural oil price shocks on the U.S. stock market returns and find evidence of time variations in both the coefficients and the variance–covariance matrix. Sim and Zhou (2015) examine the dependence between oil prices and U.S. stock markets, using the quantile-on-quantile (QQ) approach. These authors find that large, negative oil price shocks (or low oil price shock quantiles) can affect the U.S. stock market positively when this market is performing well (i.e., at high return quantiles or during the bull stock markets). Moreover, they find that the dependence structure of oil prices on the U.S. stock market is asymmetric.

As for Ding et al. (2016), the authors examine the causal linkages between the WTI and Dubai crude oil returns and five other stock markets, including one in the U.S. and four in Asia (i.e., China, Hong Kong, Korea, and Japan), using the quantile causality approach. They find that the Nikkei and Hang Seng indices Granger-cause the WTI returns. Moreover, all stock index returns Granger-cause the Dubai crude oil returns over almost all quantile levels except the Shanghai returns. The authors also show an asymmetric causality running from the Dubai crude oil returns to the Shanghai returns and from the Korean KOSPI returns to the Dubai crude oil returns.

Yang et al. (2016) examine the cross-correlations between the WTI crude oil and the ten sector stock markets in China. The results show that the strength of the multi-fractality between the WTI crude oil and the Chinese energy and financial sector stock markets is the highest, indicating a close connection between energy and financial markets. Furthermore, the authors use the vector autoregression (VAR) method to analyze the interdependence among the multiple time series. The results reveal that the VAR model could not be used to describe the dynamics of the cross-correlations between the WTI crude oil and the ten Chinese stock sectors.

Lu et al. (2016) consider a time-varying coefficient vector autoregressions (VAR) model to investigate the relationships between the WTI crude oil and the U.S. S&P500 stock index. These authors find that the causal relations between oil and the U.S. stock market are time- varying and display complex characters.

Liu et al. (2016) examine the dynamic spillovers between WTI crude oil prices and two important stock markets (i.e., the S&P 500 index for the United States and the MICEX index for Russia). Applying a wavelet-based GARCH-BEKK method, the results show a presence of spillover effects between oil and the U.S. stock market and oil and the Russian stock market and that these effects vary across the wavelet scales in terms of strength and direction. The spillover relationship between oil and the U.S. stock market is shifting to the short-term, while the spillover relationship between oil and the Russian stock market is changing to all time scales (daily, weekly, bimonthly and monthly), indicating that the linkage between oil and the U.S. stock market is weakening in the long-term, while the linkage between oil and the Russian stock market is getting closer in all time scales.

Raza et al. (2016) examine the asymmetric impact of gold prices, oil prices and their associated volatilities on stock markets of emerging economies, using the nonlinear ARDL (NARDL) approach. The results show that gold prices have a positive impact on the stock market prices of emerging BRICS markets and a negative impact on the stock markets of Mexico, Malaysia, Thailand, Chile and Indonesia. Moreover, oil prices are found to have a negative impact on the stock markets of the emerging economies of China, India, Brazil, Russia, South Africa, Mexico, Malaysia, Thailand, Chile, and Indonesia. On the other hand, gold and oil volatilities have a negative impact on the stock markets of all emerging economies in both the short- and the long-run.

Our study complements the related literature since it deals with up and down risk spillover effects and examines the dependence structure between oil and major regional stock markets during different downturn, tranquil and upturn periods under diverse time horizons (short- and long-run). The repercussions of the onset of the GFC on the risk spillovers are also considered in this analysis. We also go beyond this analysis by investigating the potential asymmetric risk spillovers for long and short positions as well as for short- and long-run.

3. Methodology

3.1. The marginal distribution model

To examine the dependence structure between oil and stock markets, we first estimate the marginal distributions of each financial time series using the ARFIMA-FIGARCH model which allows for a long range memory while keeping the residuals as standardized normal. The choice of this model is also supported by statistical tests (see Section 4). The mean equation of the return series (r_t) using an ARFIMA (m, d, n) model can be expressed as follows:

$$\Psi(L)(1-L)^d(y_t-\mu)=\Theta(L)\varepsilon_t, \tag{1}$$

$$\varepsilon_t=z_t\sqrt{h_t}\ ,\ \ z_t\sim N(0,\ 1) \tag{2}$$

where ε_t is the independently distributed error with variance h_t, d is the fractional difference parameter which measures the degree of long memory, L denotes the lag operator, and $\Psi(L)=1-\Psi_1L-\Psi_2L^2\ldots-\Psi_mL^m$ and $\Theta(L)=1+\Theta_1L+\Theta_2L^2\cdots+\ \Theta_nL^n$ are, respectively, the autoregressive (AR) and the moving-average (MA) polynomials.

To be more specific, the ARFIMA process is non-stationary when $d\geq 0.5$, and exhibits a LM for $0<d<0.5$. The process exhibits a short (intermediate) memory for $d\ =0$ ($d<0.5$). It exhibits a negative dependence between distant observations if $-0.5<d<0.5$ (anti-persistence).

We follow Baillie et al. (1996) by introducing the FIGARCH (p,ξ,q) process as follows,

$$\phi(L)(1-L)^{\xi}\varepsilon_t^2=\omega+[1-\beta(L)]V_t, \tag{3}$$

where $\phi(L)\equiv\phi_1L+\phi_2L^2+\cdots+\phi_qL^q$, $\beta(L)\equiv\beta_1L+\beta_2L^2+\cdots+\beta_pL^p$ and $V_t\equiv\varepsilon_t^2-h_t$. The $\{V_t\}$ process can be interpreted as the innovation for the conditional variance, which has a zero mean and is serially uncorrelated. All the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle. We have a stationary LM process when $0\leq\xi\leq 1$. If $\xi=1$, the process has a unit root, and thus a permanent shock effect.

In this paper, we consider the Student-t-distributions for the FIGARCH model. The Hansen (1994) skewed-t density distribution is defined as follows.

$$f(z_t,\upsilon,\eta)=\begin{cases} bc\left(1+\frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1-\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t<-a/b\\ bc\left(1+\frac{1}{\upsilon-2}\left(\frac{bz_t+a}{1+\eta}\right)^2\right)^{-(\upsilon+1)/2} & z_t\geq -a/b\end{cases} \tag{4}$$

where υ and η are the degree of freedom parameters ($2<\upsilon\leq\infty$) and the symmetric parameter ($-1<\eta<1$), respectively. The constants a, b and c are given by:

$$a=4\eta c\left(\frac{\upsilon-2}{\upsilon-1}\right),\ b^2=1\ +3\eta-a^2,\ \text{and}$$

$$c=\Gamma\left(\frac{\upsilon+1}{2}\right)/\sqrt{\pi(\upsilon-2)}\Gamma\left(\frac{\upsilon}{2}\right).$$

If $n=0$ and $\upsilon\to\infty$, then the skew-t converges to the standard Gaussian distribution, but if $\eta=0$ and υ is finite, then the skew-t converges to the symmetric Student-t distribution.

3.2. Copula approach

This study uses bivariate copulas to model the average and tail dependence between oil and stock markets. The cornerstone of the copula theory is the Sklar's theorem which states that a joint distribution $F_{XY}(x,y)$ of two continuous random variables X and Y can be expressed in terms of a copula function C(u,v) and the marginal distribution functions of the random variables, $F_X(x)$, $F_Y(y)$ as

$$F_{XY}(x,y)=C(u,v), \tag{5}$$

where $u=F_X(x)$ and $v=F_Y(y)$. Thus, a copula is a multivariate function with uniform marginals that represents the dependence structure between two random variables. It is uniquely determined on $\mathrm{Ran}F_X\times\mathrm{Ran}F_Y$ when the margins are continuous. In terms of construction, copulas can be used to connect marginals to a multivariate distribution function, which in turn can be decomposed into its univariate marginal distributions and a copula that captures the dependence structure.[5]

The joint probability density of the variables X and Y can be obtained from the copula density, $c(u,v)=\frac{\partial^2C(u,v)}{\partial u\partial v}$, as

$$f_{XY}(x,y)=c(u,v)f_Y(y)f_x(x), \tag{6}$$

where $f_Y(y)$ and $f_x(x)$ denote the marginal densities of the variables Y and X, respectively. Hence, to characterize the joint density of two random variables, we need information on the marginal densities and on the copula density.

An appealing feature of a copula is that it provides information on average dependence and on the probability that two variables jointly experience extreme upward or downward movements. The latter extreme dependence measure is called tail dependence. A measure of the upper (right) and lower (left) tail dependence is obtained from the copulas as:

$$\lambda_U=\lim_{u\to 1}\Pr\left[X\geq F_X^{-1}(u)|Y\geq F_Y^{-1}(u)\right]=\lim_{u\to 1}\frac{1-2u+C(u,u)}{1-u}, \tag{7}$$

$$\lambda_L=\lim_{u\to 0}\Pr\left[X\leq F_X^{-1}(u)|Y\leq F_Y^{-1}(u)\right]=\lim_{u\to 0}\frac{C(u,u)}{u}, \tag{8}$$

where $\lambda_U,\lambda_L\in[0,1]$. The lower (upper) tail dependence means that $\lambda_L>0$ ($\lambda_U>0$), which indicates a non-zero probability of observing an extremely small (large) value for one series together with an extremely small (large) value for another series.

Our study uses a diverse family of copula specifications with different dependence structures and time-invariant and time-varying parameters. Table 1 summarizes the copula specifications. The symmetric copulas include the bivariate Normal copula, the Frank copula and the Plackett copula with tail independence (or zero-tail dependence). They also include the Student-t copula with equal lower and upper tail dependence. The asymmetric copulas are the Gumbel copula with an upper tail dependence and lower tail independence, the rotated Gumbel copula with an upper tail independence and a lower tail dependence, the Clayton copula with an upper tail independence and a lower tail dependence, and the symmetrized Joe–Clayton copula (SJC) with a special case of the symmetric tail dependence.

For all the above copula functions, we model the time-varying dependence by allowing the copula dependence parameter to evolve according to an evolution equation. For the Gaussian and Student-t copulas, we specify the linear dependence parameter ρ_t which evolves according to an ARMA(1,q)-type process (see Patton, 2006):

$$\rho_t=\Lambda\left(\Psi_0+\Psi_1\rho_{t-1}+\Psi_2\frac{1}{q}\sum_{j=1}^{q}\Phi^{-1}\left(u_{t-j}\right).\Phi^{-1}\left(v_{t-j}\right)\right), \tag{9}$$

where $\Lambda(x)=(1-e^{-x})(1+e^{-x})^{-1}$ is the modified logistic transformation to keep the value of ρ_t in (−1,1). Hence, the dependence parameter is explained by a constant Ψ_0, by an autoregressive term Ψ_1, and by the average product over the last q observations of the

[5] For an introduction on copulas, see Joe (1997) and Nelsen (2006). For an overview of copula applications to finance, see Cherubini et al. (2004).

Table 1
Bivariate copula functions.

Copula Name	Formula	Parameter	Tail dependence
Normal (N)	$C_N(u, v, \rho) = \Phi(\Phi^{-1}(u), \Phi^{-1}(v))$	$\rho \in [-1\ 1]$	Zero tail dependence: $\lambda_L = \lambda_U = 0$
Student-t (t)	$C_{ST}(u, v, \rho, \upsilon) = T(t_\upsilon^{-1}(u), t_\upsilon^{-1}(v))$	$\rho \in [-1\ 1]$	Symmetric tail dependence: $\lambda_U = \lambda_L = 2t_{\upsilon+1}(-\sqrt{\upsilon+1}\sqrt{1-\rho}/\sqrt{1+\rho}) > 0$
Clayton (CL)	$C_{CL}(u, v; \delta) = \max\{(u^{-\delta} + v^{-\delta} - 1)^{-1/\delta}\ , 0\}$	$\alpha \in [-1,\ \infty)\backslash\{0\}$	Asymmetric tail dependence: $\lambda_L = 2^{-1/\delta},\ \lambda_U = 0$
Gumbel (Gu)	$C_G(u, v; \delta) = \exp(-((-\log u)^\delta + (-\log v)^\delta)^{1/\delta})$	$\delta \in [1,\ \infty)$	Asymmetric tail dependence $\lambda_L = 0,\ \lambda_U = 2 - 2^{1/\delta}$
Rotated Gumbel	$C_{RG}(u, v; \delta) = u + v - 1 + C_G(1-u, 1-v; \delta)$	$0 < \delta < \infty$	Upper tail independence and lower tail dependence
Frank (F)	$C_F(u, v; \delta) = \delta\log([(1-e^{-\delta}) - (1-e^{-\delta u})(1-e^{-\delta v})]/(1-e^{-\delta}))$	θ	Zero tail dependence: $\lambda_L = \lambda_U = 0$
Placket	$C_P(u, v; \theta) = \frac{1}{2(\theta-1)}(1 + (\theta-1)(u+v)) - \sqrt{(1+(\theta-1)(u+v))^2\ - 4\theta(\theta-1)uv}$	$\lambda_L \in (0, 1)$	Zero tail dependence: $\lambda_L = \lambda_U = 0$
SJC	$C_{SJC}(u, v; \lambda_U, \lambda_L) = 0.5(C_{JC}(u, v; \lambda_U, \lambda_L) + C_{JC}(1-u, 1-v; \lambda_U, \lambda_L) + u + v - 1)$	$\lambda_U \in (0, 1)$	$\lambda_U = \lambda_L$
Joe Clayton	$C_{JC}(u, v; \lambda_U, \lambda_L) = 1 - (1 - \{[1-(1-u)^k]^{-\gamma} + [1-(1-v)^k]^{-\gamma} - 1\}^{-1/\gamma})^{1/k}$	$\lambda_L \in (0, 1)$	$\lambda_t^U = \Delta(\omega_U + \beta_U\rho_{t-1} + \alpha_U\frac{1}{q}\sum_{j=1}^{q}\lvert u_{t-j} - v_{t-j}\rvert)$
		$\lambda_U \in (0, 1)$	$\lambda_t^L = \Delta(\omega_L + \beta_L\rho_{t-1} + \alpha_L\frac{1}{q}\sum_{j=1}^{q}\lvert u_{t-j} - v_{t-j}\rvert)$

Notes: λ_L and λ_U denote the lower and upper tail dependence, respectively. For the Normal copula, $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are the standard normal quantile functions and Φ is the bivariate standard normal cumulative distribution function with correlation ρ. For the Student-t copula, $t_\upsilon^{-1}(u)$ and $t_\upsilon^{-1}(v)$ are the quantile functions of the univariate Student-t distribution with υ as the degree-of-freedom parameter and T is the bivariate Student-t cumulative distribution function with υ as the degree-of-freedom parameter and ρ as the correlation. For the SJC copula, $\kappa = 1/\log_2(2-\lambda_U)$, $\gamma = -1/\log_2(\lambda_L)$.

transformed variables, Ψ_2. For the Student-t copula, the parameter dynamics are also given by Eq. (9) by substituting $\Phi^{-1}(x)$ by $t_\upsilon^{-1}(x)$. The dynamics of the Gumbel and the rotated Gumbel copulas are assumed to follow the ARMA(1,q) process that is specified as

$$\delta_t = \omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|. \tag{10}$$

Finally, for the SJC copula, the tail dependence parameters evolve according to:

$$\lambda_t^U = \Delta\left(\omega_U + \beta_U\rho_{t-1} + \alpha_U\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right), \tag{11}$$

$$\lambda_t^L = \Delta\left(\omega_L + \beta_L\rho_{t-1} + \alpha_L\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right), \tag{12}$$

where $\Delta(x) = (1 + e^{-x})^{-1}$ is the logistic transformation used to retain λ_t^U and λ_t^L in (0,1).

The main characteristics of the bivariate copula functions used in this study are summarized in Table 1.

3.3. Variational mode decomposition (VMD)

The fundamental concept of VMD decomposes a time series f into a discrete k number of sub-series (known as modes) u_k, and the bandwidth of each mode is limited in the spectral domain. Each decomposed variational mode k is assumed to be compressed around a center pulsation, ω_k, which is determined along with the decomposition. The determination of the algorithm of the bandwidth of a time series requires: (i) obtaining a unilateral frequency spectrum for each mode u_k by computing the associated analytic signal by means of the Hilbert transform; (ii) for each mode, shifting the mode's frequency spectrum to a baseband by mixing with an exponential tuned to the respective estimated center frequency; and (iii) estimating the bandwidth through the Gaussian smoothness of the demodulated signal (Dragomiretskiy and Zosso, 2014).

Thus, the resulting constrained variational problem can be given as:

$$min_{\{u_k\},\{\omega_k\}} = \left\{\sum_k\left\|\partial_t\left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\}$$
$$s.t \quad \sum_k u_k = f \tag{13}$$

where ∂_t denotes the partial derivatives, k indicates the set (number) of modes u of the original signal f while ω, $\delta(t)$ and $*$ represent the frequency, the Dirac distribution and the convolution, respectively. Thus, $\{u_k\} := \{u_1, \ldots . u_k\}$ and $\{\omega_k\} := \{\omega_1,\ \ldots . \omega_k\}$ are the sets of all variational modes and their central frequency, respectively. Eq. (13) decomposes the original signal into a set of modes (k) with a limited bandwidth in the Fourier domain. The solution to the original minimization problem is the saddle point of the following augmented Lagrange $(\mathcal{L})$ expression:

$$\mathcal{L}(u_k, \omega_k, \lambda) = \alpha\sum_k\left\|\partial_t\left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right]\right\|_2^2 + \left\|f - \sum u_k\right\|_2^2 + \left\langle\lambda, f - \sum u_k\right\rangle \tag{14}$$

where α denotes the balancing parameter of the data-fidelity constraint, λ is the Lagrange multiplier and $\|\cdot\|_p$ denotes the usual vector ℓ_p norm where $p = 2$. The solution to Eq. (14) is found in a sequence of k iterative sub-optimizations. Finally, the solutions for u and ω are found in the Fourier domain and are given by

$$u_k^{n+1} = \left(f - \sum_{i \neq k} u_i + \frac{\lambda}{2}\right) \frac{1}{1 + 2\alpha(\omega - \omega_k)^2} \tag{15}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |u_k(\omega)|^2 d_\omega}{\int_0^\infty |u_k(\omega)|^2 d_\omega} \tag{16}$$

and for λ it's updated as

$$\hat{\lambda}^{n+1} \leftarrow \hat{\lambda}^n + \tau\left(\hat{f} - \sum_k \hat{u}_k^{n+1}\right) \tag{17}$$

until convergence: $\sum_k \|\hat{u}_k^{n+1} - \hat{u}_k^n\|_2^2 / \|\hat{u}_k^n\|_2^2$, where k is the number of iterations. We set the number of modes k to ten. It is worth noting that the sum of VMD components equals to the original signal (see Dragomiretskiy and Zosso, 2014).

3.4. VaRs, CoVaRs and delta CoVaRs risk measures

We quantify both the downside and upside VaRs and CoVaRs for the oil and stock market returns using the copula results. The VaR risk measure quantifies the maximum loss that an investor may incur within a specific time horizon and with a confidence level by holding a long position (i.e., downside risk) or a short position (i.e., upside risk).

The downside VaR at time t and for a confidence level $1 - \alpha$ is expressed by $Pr(r_t \leq VaR_{\alpha,t}) = \alpha$, which can be computed from the marginal models as $VaR_{\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t$, where μ_t and σ_t are the conditional mean and standard deviation of the return series, computed according to mean and variance equation of the ARFIMA-FIGARCH model (Eqs. (1)–(3)), and where $t_{\upsilon,\eta}^{-1}(\alpha)$ denotes the α quantile of the skewed Student-t distribution in Eq. (4). Similarly, the upside VaR is given by considering $Pr(r_t \geq VaR_{1-\alpha,t}) = \alpha$; thus the upside VaR is given by $VaR_{1-\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_t$.

Given the strong linkages between oil and stock markets, we consider the impact of financial distress in the oil market, as measured by its VaR, on the VaR of the stock market and vice versa. For a deeper analysis, we study CoVaR that is developed by Adrian and Brunnermeier (2011) and Girardi and Ergün (2013). As a definition, the CoVaR for the asset i is the VaR for asset i conditional on the fact that asset j exhibits an extreme movement.

Let r_t^s be the returns for stock and r_t^o be the returns for oil. The downside CoVaR for stock returns for an extreme downward oil movement and a confidence level $1 - \beta$ can be formally expressed as the β-quantile of the conditional distribution of r_t^s as:

$$Pr\left(r_t^s \leq CoVaR_{\beta,t}^s | r_t^o \leq VaR_{\alpha,t}^o\right) = \beta \tag{18}$$

where $VaR_{\alpha,t}^o$ is the α-quantile of the oil price return distribution and $\Pr(r_t^o \leq VaR_{\alpha,t}^o) = \alpha$ measures the maximum loss that oil price returns may experience for a confidence level $1 - \alpha$ and a specific time horizon.

Similarly, the upside CoVaR for an extreme upward movement in oil price returns:

$$Pr\left(r_t^s \geq CoVaR_{\beta,t}^s | r_t^o \geq VaR_{1-\alpha,t}^o\right) = \beta, \tag{19}$$

where $VaR_{1-\alpha,t}^o$ quantifies the maximum loss by considering a short position for a confidence level $1 - \alpha$ and for a specific time horizon.

Interestingly, we can measure the systemic impact of a stock on oil by considering the CoVaR for the oil market instead of the stock market as in Eqs. (18) and (19). The CoVaR in those equations can be represented in terms of copulas, since the conditional probabilities can be re-written, respectively, as:

$$C\left(F_{r_t^s}\left(CoVaR_{\beta,t}^s\right), F_{r_t^o}\left(VaR_{\alpha,t}^o\right)\right) = \alpha\beta \tag{20}$$

$$1 - F_{r_t^s}\left(CoVaR_{\beta,t}^s\right) - F_{r_t^o}\left(VaR_{1-\alpha,t}^o\right) + C\left(F_{r_t^s}\left(CoVaR_{\beta,t}^s\right), F_{r_t^o}\left(VaR_{1-\alpha,t}^o\right)\right) = \alpha\beta, \tag{21}$$

where $F_{r_t^s}$ and $F_{r_t^o}$ are the marginal distributions of the stock and oil returns, respectively. We follow Reboredo and Ugolini (2015) to compute the CoVaR by following a two-step procedure.

In step 1, we can solve Eq. (20) or (21) in order to obtain the value of $F_{r_t^s}(CoVaR_{\beta,t}^s)$, given the significance levels for the VaR and CoVaR and β respectively, and for specific forms of the copula function. In step 2, we use the distribution function for the oil and stock market returns as given by the marginal model in Eqs. (1)–(3) and compute the CoVaR for stock as $F_{r_t^s}^{-1}(F_{r_t^s}(CoVaR_{\beta,t}^s))$.

We follow Adrian and Brunnermeier (2011) and Girardi and Ergün (2013) to define the systemic risk contribution of a stock market s as the delta $CoVaR$ (Δ $CoVaR$), which is the difference between the VaR of the stock market as a whole conditional on the distressed state of market s ($R_t^s \leq VaR_{\alpha,t}^s$) and the VaR of the stock market as a whole conditional on the benchmark state of market s, considering it as the median of the return distribution of market s, or, alternatively, the VaR for $\alpha = 0.5$. The systemic risk contribution of market s is thus defined as:

$$\Delta CoVaR_t^{s/o} = \frac{\left(CoVaR_{\beta,t}^{s/o} - CoVaR_{\beta,t}^{s/o,\ \alpha=0.5}\right)}{CoVaR_{\beta,t}^{s/o,\alpha=0.5}} \tag{22}$$

$\Delta CoVaR$ is useful as it captures the marginal contribution of market s to the overall systemic risk.

We test for the significance of systemic risk using the KS bootstrapping test developed by Abadie (2002) to compare the CoVaR values. The KS test measures the difference between two cumulative quantile functions relying on the empirical distribution function but without considering any underlying distribution function. It is defined as:

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{t}} \sup_x |F_m(x) - G_n(x)|, \tag{23}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR and VaR distribution functions, respectively, and n and m are the sizes of the two samples. Thus, we test the hypothesis of no systemic impact between stock and oil markets as: $H_0 : CoVaR_{\beta,t}^s = VaR_{\beta,t}^s$.

4. Data and descriptive statistics

Our analysis is based on the daily closing spot prices for the WTI crude oil, which is a global benchmark for determining the prices of other light crudes in the United States, and four regional developed stock markets (i.e., S&P500, stoxx600, Dow Jones Pacific Stock Index and TSX-Toronto Stock Exchange 300 Composite Index).[6] The study spans the period from June 4, 1998 to May 6, 2016. The data for S&P500, Stoxx600 and TSX indexes are sourced from Datastream, while for the DJPS index it is obtained from Bloomberg. The data for the WTI oil price is obtained from the US Energy Information Administration. The sample period is marked by several extreme events and turbulences including the 1997–1998 Asian crisis, the 2001 dot-com bubble, the 2007–2009 global financial crisis and the 2009–2012 euro-zone debt crisis. This period is also characterized by higher volatility of the oil price.

Fig. 1 illustrates the trajectory of the daily level series over the sample period. This figure displays a spectacular rise in the

[6] The Dow Jones Pacific Stock Index is a capitalization-weighted index comprised of companies traded publicly in selected countries located in the Pacific-Rim region excluding Japan. It is calculated in US dollars.

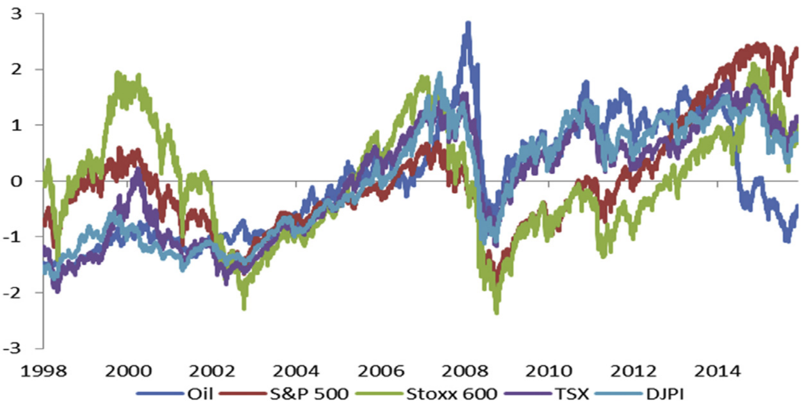


Fig. 1. Time-variations of daily WTI crude oil prices and the four major developed stock indexes.

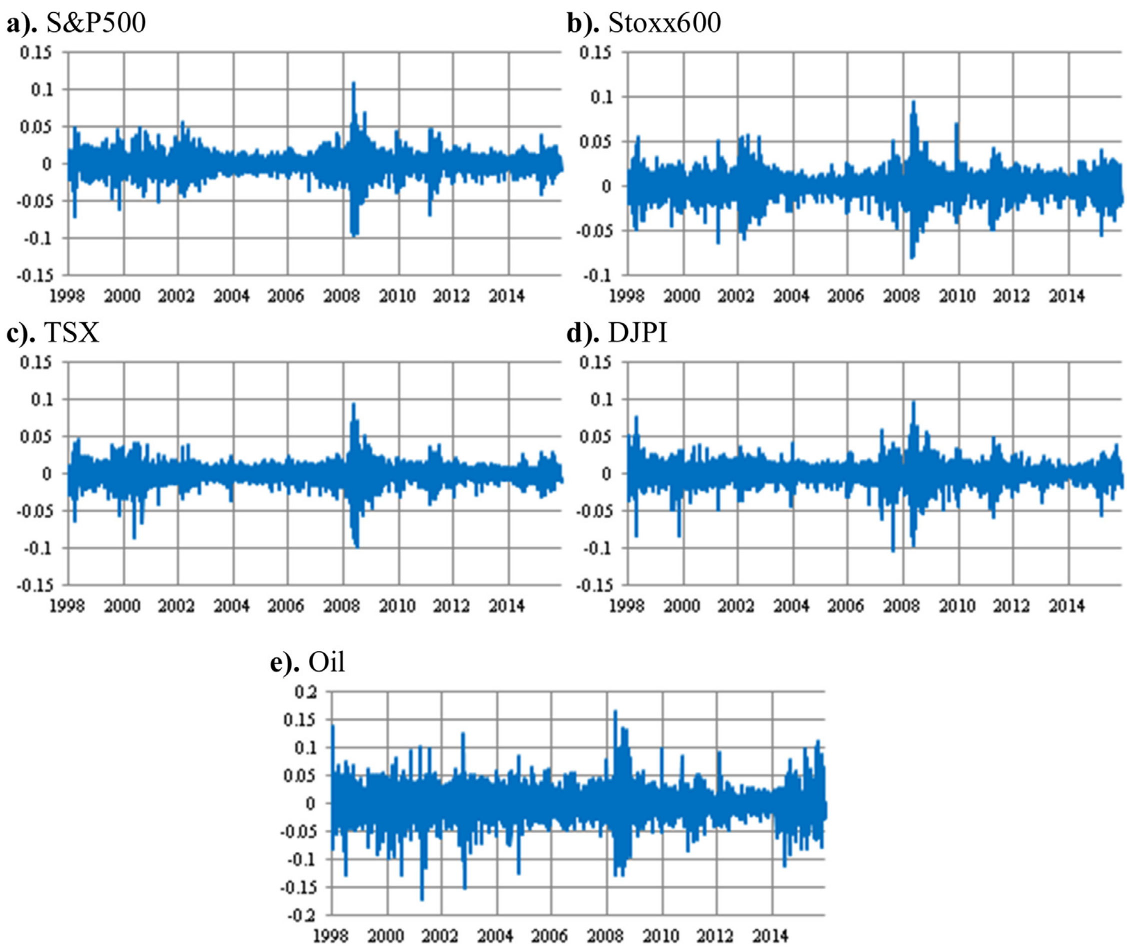


Fig. 2. The WTI crude oil price returns and major developed stock index returns dynamics.

oil price in 2008 where the price of a barrel of crude oil exceeds US$140/barrel in July 2008, while it shows a significant decline for most of the period dating back to 2015 during which the oil price remains under US $50 a barrel. The continuously compounded daily returns are computed by taking the difference in the logarithm of two consecutive prices. Fig. 2 depicts the evolution dynamics of the return series and illustrates the stylized facts (e.g., volatility clustering) for the oil and the four major stock index return series.

Table 2 presents the descriptive statistics of the oil price returns and the four regional developed index returns between May 1998 and May 2016. The average return series are positive for all the series. More precisely, oil and DJPI hold the highest average returns, while stoxx 600 index has the lowest average returns. The unconditional volatility is similar across the four stock markets. Oil is more volatile than those stock markets. The negative values for skewness are common for all the series, which also exhibit excess kurtosis. The Jarque–Bera test rejects the null of Gaussian distribution for all the series. DJPI has the highest Sharp ratio, indicating the most rewarding investment, while the stoxx600 index has the lowest ratio and thus is the least rewarding. As for the TSX and S&P500 indexes, they offer a similar expected return per unit of risk.

Table 2
Statistical properties of oil and stock return series.

	Oil	S&P500	Stoxx600	TSX	DJPI
Mean	0.00023	0.00014	0.00002	0.00013	0.00023
Maximum	0.16413	0.10957	0.09410	0.09370	0.09486
Minimum	−0.17091	−0.09469	−0.07929	−0.09788	−0.10219
Std. Dev.	0.02525	0.01265	0.01286	0.01150	0.01267
Skewness	−0.14472	−0.20146	−0.13524	−0.59903	−0.63073
Kurtosis	7.18190	10.44401	7.50069	11.55291	10.44125
Jarque-Bera	3294.03***	10,418.12***	3810.92***	13,982.0***	10,678.28***
Sharp ratio	0.00930	0.01106	0.00208	0.01156	0.01830
ADF	−68.70***	−51.75***	−30.30***	−49.83***	−61.92***
PP	−68.80***	−72.99***	−67.69***	−66.91***	−61.97***
KPSS	0.24	0.11	0.07	0.04	0.10
Q(20)	43.32***	98.63***	62.61***	68.21***	75.89***
Q^2 (20)	2024.59***	5904.93***	4568.92***	6240.48***	3946.48***
ARCH(20)	762.51***	1686.93***	1047.85***	1415.00***	1218.53***

Notes: Q(20) and Q^2(20) refer to the empirical statistics of the Ljung-Box test for autocorrelation of the returns and squared returns series, respectively. QADF, PP and KPSS are the empirical statistics of the Augmented Dickey and Fuller (1979), and the Phillips and Perron (1988) unit root tests, and the Kwiatkowski et al., (1992) stationarity test, respectively. The ARCH-LM(20) test of Engle (1982) checks the presence of the ARCH effect.
*** denotes the rejection of the null hypotheses of normality, no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at the 1% significance level.

Table 3
Unconditional correlations between oil and stock markets returns.

	Oil	S&P500	Stoxx600	TSX	DJPI
Oil	1.0000				
S&P500	0.1881***	1.0000			
	[12.847]				
Stoxx600	0.2051***	0.5707***	1.0000		
	[14.054]	[46.612]			
TSX	0.3002***	0.7275***	0.5571***	1.0000	
	[21.107]	[71.119]	[44.981]		
DJPI	0.1701***	0.2168***	0.4534***	0.3197***	1.0000
	[11.580]	[14.897]	[34.121]	[22.630]	

Notes: The values in [ ] are t-statistics.
*** indicates significance at the 1% level.

The unit root and stationary tests indicate that all the markets are stationary. The Ljung–Box statistics for autocorrelation and squared autocorrelation up to the 20th order indicate the presence of a temporal dependence in returns. The Lagrange multiplier test for conditional heteroscedasticity shows evidence of the ARCH effect in all the series. The unconditional correlation results, reported in Table 3, indicate that oil is significantly and positively correlated with the stock markets, meaning that commodity and stock markets are more integrated. The highest correlation is observed for the TSX-oil pair which is not surprising. This result is explained by the fact that Canada is a major oil-exporting country to the United States. The DJPI-oil pair exhibits the lowest correlation. The oil benchmark in the Pacific basin is the Brent and not the WTI price. It is worth noting that the four developed stock markets are correlated, indicating the existence a high level of integration between these developed markets.

5. Empirical results

5.1. Marginal model results

This analysis considers four competing GARCH models, namely the ARFIMA-GARCH, the ARFIMA-FIGARCH, the ARFIMA-FIEGARCH and the ARFIMA-FIAPARCH models, with all having skewed student-t distributions. To select the best marginal model for each region, we consider different combinations of the lag parameters p, q, r, and m for the values ranging from lag zero to a maximum lag of 2. The minimum value for the AIC is used to select the most adequate model.

Table 4 presents the estimation results of the marginal models. Note that the ARMA(2,2)-FIGARCH(1,ξ,1) model with skewed student-t innovations is the best model for Stoxx 600 and S&P 500 indexes, while the ARFIMA(2,d,2)-FIAPARCH(1 ξ,1) model with skewed student-t innovations is the best model for the remaining two stock indexes. As for the WTI oil market, the ARFIMA(2,d,2)-FIAPARCH(2,ξ,2) model with skewed student-t innovation is the adequate model. The lagged autoregressive (AR(1) and AR(2)) coefficients of the mean equation are statistically significant for almost all series at the 1% level, indicating that the past information set (past returns) is instantaneously and rapidly embodied in those current market returns. More interestingly, it can be seen that almost all the series exhibit significant ARCH components, meaning that one-period lagged squared shocks affect the current conditional volatility. The volatility is quite persistent for all series as shown by the significance GARCH components (Beta1). The fractional differencing (long memory) parameter is significant for all the markets. It is close to one for oil, indicating a high level of persistence. The evidence on the degrees of freedom of the Student-t distribution and the asymmetry shows that fat tails characterize the distribution of the oil and stock return series, and that there is a potential of dependence in the tails of the joint distribution. The diagnostic tests show that the estimated residuals exhibit no autocorrelation and no remaining ARCH effects.

Regarding the diagnostic tests (Panel C), the values of the Ljung–Box tests for serial correlation in the standardized residuals and the squared standardized residuals as well as the Hosking (1980) and McLeod and Li (1983) autocorrelation test results do not reject the null of no serial correlation in all cases. We also find that there is no remaining ARCH effect in the model residuals. The Kolmogorov–Smirnov goodness-of-fit test for the marginal distribution models indicates no evidence of statistical misspecification.

5.2. Variational mode decomposition results

One of the main objectives of this study is to consider different investment time horizons in order to have a complete picture of the oil-stock dependence structure as well as the risk spillovers. In this case we account for the behaviors of speculators, money managers, arbitragers, institutional investors, etc. For this purpose, we apply the variational mode decomposition (VMD) on the residual

Table 4
Marginal model estimations (ARFIMA-FIGARCH with skewed t innovations).

	WTI	S&P500	Stoxx600	TSX	DJPI
Panel A: *Mean equation*					
Cst(M)	0.0003	0.0004***	0.0005***	0.0002	0.0001
	(0.0005)	(0.0001)	(0.0001)	(0.0002)	(0.0003)
d-Arfima	0.1313			0.1070**	0.1408***
	(0.0864)			(0.0522)	(0.0384)
AR(1)	0.9121***	1.0231	1.4739***	0.2124	−0.0154
	(0.1444)	(0.2423)	(0.1946)	(0.2414)	(0.1084)
AR(2)	−0.0989	−0.2215***	−0.6083***	0.3144*	0.6101***
	(0.0927)	(0.2050)	(0.1556)	(0.1878)	(0.0808)
MA(1)	−1.0756***	−1.0997	−1.4976***	−0.2946	−0.0241
	(0.1827)	(0.2401)	(0.1960)	(0.2118)	(0.0963)
MA(2)	0.19572*	0.2464**	0.6086***	−0.3767*	−0.6626***
	(0.1197)	(0.2154)	(0.1612)	(0.2013)	(0.0801)
Panel B: *Variance equation*					
Cst(V) x 10^4	0.1138	0.0210***	0.0176*	0.5846	0.5805
	(0.1057)	(0.0082)	(0.0096)	(0.3910)	(0.4435)
d-Figarch	0.9546***	0.6197	0.5507***	0.4635***	0.3728***
	(0.1185)	(0.0928)	(0.0583)	(0.0614)	(0.0575)
ARCH(Phi1)	0.6204***	0.0234***	0.0811**	0.2187***	0.2630***
	(0.1058)	(0.0386)	(0.0404)	(0.0394)	(0.0420)
GARCH(Beta1)	1.4902***	0.6362***	0.5813***	0.6321***	0.5741***
	(0.1855)	(0.0846)	(0.0609)	(0.0526)	(0.0591)
GARCH(Beta2)	−0.5086***				
	(0.1730)				
APARCH(Gamma1)	0.5485***			0.5679***	0.6797***
	(0.1898)			(0.1255)	(0.1528)
APARCH(Delta)	1.3892***			1.4017***	1.4491***
	(0.1594)			(0.0944)	(0.1040)
Asymmetry	−0.0799***	−0.1540***	−0.1390***	−0.1780***	−0.0901***
	(0.0213)	(0.0209)	(0.0231)	(0.0226)	(0.0200)
Tail	7.6377***	7.8455***	10.2998***	10.7184***	7.1543***
	(0.8422)	(0.9628)	(1.5293)	(1.5319)	(0.73159)
Panel C: *Diagnostic tests*					
LL	10,808.9	14,320.5	14,074.17	14,802.2	14,234.21
AIC	−4.798	−6.3611	−6.251	−6.573	−6.321
ARCH(20)	[0.4268]	[0.6130]	[0.5129]	[0.8779]	[0.9561]
Q(20)	[0.9958]	[0.1003]	[0.2544]	[0.6816]	[0.3899]
$Q^2(20)$	[0.3386]	[0.3732]	[0.5243]	[0.8569]	[0.9476]
McLeod-Li (20)	[0.9957]	[0.1827]	[0.3627]	[0.6813]	[0.3903]
Hosking (20)	[0.9814]	[0.2061]	[0.1514]	[0.5179]	[0.2566]
K-S Test	[0.3242]	[0.3966]	[0.3131]	[0.6936]	[0.8139]

Notes: This table reports the ML estimates and the standard deviations in parenthesis for the parameters of the marginal distribution model defined in Eqs. (1)–(3). The lags p, q, r and m are selected using the AIC for different combinations of values ranging from 0 to 2. $Q(20)$ and $Q^2(20)$ are the Ljung-Box statistics for serial correlation in the model residuals and squared residuals, respectively, computed with 20 lags. ARCH is the Engle LM test for the ARCH effect in the residuals up to the 20th order. K–S denotes the Kolmogorov–Smirnov test (for which the p-values are reported), representing the adequacy of the Student-t distribution model. Hosking (1980) and McLeod and Li (1983) are the autocorrelation tests until lag 20. The p-values [in the square brackets] below 0.05 indicate the rejection of the null hypothesis. The asterisks (***), (**) and (*) represent significance at the 1%, 5% and 10% levels, respectively.

of marginal models in order to decompose the series into short- and long-run components. The decomposition modes are arbitrarily set to ten. The mode-by-mode decomposition through the VMD enables us to distinguish between the short- (VMD 10) and long-run (VMD 1) dynamic dependence between the considered markets. Fig. 3[7] depicts the VMD for the residuals of marginal model for WTI oil return series for mode 1 (long-run) to 10 (short-run).[8] From modes 2 to 10, we observe a volatility clustering for the oil returns, while the evolution is smoother at mode 1.

Fig. 4 illustrates that the decomposed signal has a different variance over time from the lowest to the highest modes. A significant difference in the variation magnitudes is also observed. The variations in the VMD modes change over time and their values range between 0.22 and up to 0.185. VM 3 exhibits the highest variance, while VM 10 shows the lowest. These variabilities justify the consideration of this decomposition method.

5.3. Estimation results of copula functions

The estimated results of the raw, short- and long-run dependence structure using the static and dynamic copulas for each oil-stock return pair are summarized in Tables 5a and 5b. We use the AIC adjusted for the small-sample bias to select the best copula functions. By comparing the different copula specifications, the result in this table provides strong evidence that the time-varying parameter (TVP) copulas offer the best fit for all pairs. This result persists for the short- and long-run, suggesting that the dynamic copulas reveal temporal variations in the dependence structure of the considered markets. As shown in Table 5b, oil is the least tail

[7] We decompose the standardized residuals obtained from the marginal model fitting. These residuals show the variations in actual time series not explained by other factors (serial correlation and heterogeneity, etc.). Thus, when we decompose them (using any technique), they reflect the time series (depending on the short-, medium or long-run decomposed levels). They can also be regarded as fluctuations/variations in the original series, if not returns.

[8] The figures for the stock markets are available upon request.

Table 5a
Bivariate time-invariant copula estimates of oil with the developed stock markets.

Copula	S&P500			Stoxx600			TSX			DJPI		
	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run
Gaussian												
ρ	0.1530	0.0426	0.1481	0.1624	0.0628	0.1164	0.2900	0.0239	0.3271	0.1561	0.0163	0.3182
	(0.0146)	(0.0149)	(0.0146)	(0.0145)	(0.0149)	(0.0147)	(0.0137)	(0.0149)	(0.0133)	(0.0146)	(0.0149)	(0.0134)
AIC	−106.5813	−8.1591	−99.7840	−120.1812	−17.7825	−61.3922	−395.1310	−2.5656	−509.0425	−110.9659	−1.1873	−480.0636
Clayton's												
α	0.1997	0.0493	0.1728	0.2017	0.0519	0.1299	0.3845	0.0249	0.3524	0.1785	0.0105	0.3676
	(0.0200)	(0.0165)	(0.0195)	(0.0201)	(0.0171)	(0.0186)	(0.0225)	(0.0158)	(0.0218)	(0.0194)	(0.0156)	(0.0221)
AIC	−128.0012	−9.9345	−96.8311	−129.0005	−10.1841	−59.9501	−387.4006	−2.6234	−328.6203	−106.2396	−0.4611	−353.4411
Rotated Clayton												
α	0.1349	0.0485	0.1177	0.1541	0.0517	0.0946	0.2956	0.0246	0.3975	0.1425	0.0111	0.3546
	(0.0194)	(0.0165)	(0.0195)	(0.0195)	(0.0171)	(0.0177)	(0.0216)	(0.0155)	(0.0228)	(0.0191)	(0.0157)	(0.0219)
AIC	−57.7788	−9.6074	−41.6992	−75.8870	−10.0864	−33.7101	−231.9970	−2.6754	−397.3185	−67.2070	−0.5154	−332.0264
Plackett												
δ	1.6712	1.1562	1.5954	1.6866	1.2175	1.3804	2.5288	1.0683	2.7311	1.5800	1.0502	2.5789
	(0.0758)	(0.0537)	(0.0704)	(0.0767)	(0.0534)	(0.0604)	(0.1092)	(0.0488)	(0.1146)	(0.0704)	(0.0471)	(0.1073)
AIC	−124.1079	−9.7109	−109.4857	−128.0726	−19.7304	−53.9131	−418.4495	−2.1336	−512.3368	−102.9638	−1.2056	−466.4094
Frank												
δ	0.9978	0.2762	0.9434	1.0127	0.3990	0.6619	0.9756	0.1299	0.2815	0.9119	0.0979	0.5640
	(0.0916)	(0.0910)	(0.0901)	(0.0915)	(0.0892)	(0.0892)	(0.1542)	(0.0902)	(0.0009)	(0.0905)	(0.0897)	(0.0005)
AIC	−118.9912	−9.2541	−109.4453	−122.5958	−20.0211	−55.1189	−101.5357	−2.0931	−54.3263	−101.5995	−1.2053	−53.9137
Gumbel												
δ	1.1000	1.1000	1.1000	1.1000	1.1000	1.1000	1.1960	1.1000	1.2419	1.1000	1.1000	1.2192
	(0.0180)	(0.0185)	(0.0180)	(0.0179)	(0.0184)	(0.0181)	(0.0132)	(0.0187)	(0.0137)	(0.0179)	(0.0187)	(0.0134)
AIC	−79.5188	38.2142	−58.0387	−101.0073	47.1210	−22.0139	−304.8376	78.6684	−464.2839	−79.6531	103.7192	−381.6721
Rotated Gumbel												
δ	1.1104	1.1000	1.1000	1.1161	1.1000	1.1000	1.2228	1.1000	1.2247	1.1000	1.1000	1.2245
	(0.0113)	(0.0185)	(0.0178)	(0.0113)	(0.0184)	(0.0179)	(0.0133)	(0.0186)	(0.0135)	(0.0177)	(0.0187)	(0.0134)
AIC	−141.5395	36.4277	−98.8919	−153.8693	47.4748	−47.4973	−426.6067	76.4308	−377.8680	−111.0068	105.5718	−403.8561
Student's t												
ρ	0.1622	0.0440	0.1529	0.1690	0.0648	0.1162	0.2986	0.0233	0.3342	0.1573	0.0165	0.3253
	(0.0156)	(0.0160)	(0.1570)	(0.0155)	(0.1513)	(0.0128)	(0.0142)	(0.0147)	(0.5243)	(0.0133)	(0.1547)	(0.0000)
υ	9.4531	11.9534	10.7262	9.9887	10.7363	58.7616	12.1995	49.4238	10.7360	21.7819	0.1736	10.7361
	(1.5301)	(2.4877)	(7.0700)	(1.0010)	(1.6562)	(37.4969)	(2.4061)	(0.3894)	(13.5488)	(7.0783)	(7.0711)	(0.0000)
AIC	−155.8120	−33.7350	−99.9579	−162.5955	−16.0869	−62.8395	−425.0434	−4.1764	−509.0773	−121.0652	0.5601	−481.0630
SJC												
λ_U	0.0004	0.0000	0.0006	0.0064	0.0000	0.0015	0.0436	0.0000	0.1769	0.0075	0.0000	0.1129
	(0.0015)	(0.0002)	(0.0020)	(0.0072)	(0.0002)	(0.0028)	(0.0161)	(0.7637)	(0.0196)	(0.0081)	(1.8766)	(0.0386)
λ_L	0.0809	0.0000	0.0531	0.0755	0.0000	0.0210	0.1904	0.0000	0.0882	0.0483	0.0000	0.1386
	(0.0183)	(0.0002)	(0.0171)	(0.0178)	(0.0002)	(0.0113)	(0.0184)	(0.6505)	(0.0210)	(0.0164)	(0.4624)	(0.0355)
AIC	−136.5058	−13.5998	−97.6967	−149.3013	−13.6274	−68.2991	−419.2186	−2.8810	−456.3159	−119.3791	3.7673	−427.2411

Notes: The table reports the ML estimates for the different dynamic bivariate copulas. The standard error values (given in parenthesis) and the AIC values adjusted for the small-sample bias are provided for these different models. For the TVP Gaussian and Student-t copulas, q in Eq. (7) is set to 10. The asterisk (*) indicates significance at the 5% level. The bold values indicate the best copula.

Table 5b
Bivariate time-varying copula estimates of oil with the developed stock markets.

Copula	S&P500			Stoxx600			TSX			DJPI		
	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run
TVP-Gaussian												
Ψ_0	0.0047	0.1551	0.0884	0.0095	0.1823	−0.0107	0.0033	0.0199	0.2501	0.3620	−0.0105	0.2802
	(0.0028)	(0.0346)	(0.0365)	(0.0052)	(0.0557)	(0.0324)	(0.0068)	(0.0069)	(0.0422)	(0.1575)	(0.0362)	(0.0610)
Ψ_1	0.0927	0.8917	0.7652	0.1032	0.8843	0.4097	0.0888	−0.8456	0.4691	0.3422	0.8936	0.5972
	(0.0158)	(0.0486)	(0.0612)	(0.0247)	(0.0603)	(0.0347)	(0.0188)	(0.0308)	(0.0491)	(0.1575)	(0.0663)	(0.0728)
Ψ_2	1.9371	−2.0292	0.0917	1.8906	−2.0185	0.3091	1.9869	1.6800	0.6795	−0.6287	−2.0227	0.0385
	(0.0239)	(0.0119)	(0.2256)	(0.0487)	(0.0166)	(0.2150)	(0.0386)	(0.0369)	(0.2174)	(1.0831)	(0.0100)	(0.3392)
AIC	−284.3461	**−248.722**	**−1174.086**	−243.1930	**−202.692**	−753.235	−507.5723	**−791.909**	−1235.523	−122.2840	**−163.820**	−1171.879
TVP-Clayton												
ω	0.7310	1.3485	0.9158	−0.6969	1.2701	1.0617	−1.3174	0.3982	1.0185	0.4453	1.2054	1.0365
	(0.0486)	(0.0671)	(0.0310)	(0.0632)	(0.0244)	(0.0614)	(0.0830)	(0.0886)	(0.0212)	(0.0792)	(0.0940)	(0.0312)
α	0.4426	−0.7216	0.2781	−0.4562	−0.8787	0.1115	0.7642	−0.3827	0.2572	0.7097	−1.0085	0.2479
	(0.0227)	(0.0634)	(0.0163)	(0.0351)	(0.0502)	(0.0530)	(0.0203)	(0.0713)	(0.0063)	(0.0864)	(0.0267)	(0.0129)
β	−1.3199	−2.2349	−1.5066	1.1920	−2.1225	−1.5968	1.5077	−1.5943	−1.8609	−0.5156	−2.1378	−1.8810
	(0.0486)	(0.0671)	(0.0310)	(0.0632)	(0.0244)	(0.0614)	(0.0830)	(0.0886)	(0.0212)	(0.0792)	(0.0940)	(0.0312)
AIC	−253.8755	−155.611	−925.4033	−216.9540	−114.861	−694.669	−415.0390	−97.5763	−1307.206	−128.9203	−74.9868	−1373.804
TVP-Rotated Clayton												
ω_U	−0.9535	1.2442	0.9795	−0.7811	1.2620	1.0005	0.6156	0.3993	1.2930	0.4366	1.0935	1.0418
	(0.0807)	(0.0707)	(0.0252)	(0.0959)	(0.0646)	(0.0506)	(0.0454)	(0.0780)	(0.0666)	(0.0880)	(0.0010)	(0.0506)
α_U	−0.3570	−0.5959	0.2649	−0.4242	−0.9335	0.1654	0.4959	−0.4020	0.0843	0.7418	−0.9179	0.1907
	(0.0340)	(0.1022)	(0.0099)	(0.0517)	(0.0670)	(0.0422)	(0.0286)	(0.0648)	(0.0389)	(0.1013)	(0.0025)	(0.0339)
β_U	2.2812	−2.0758	−1.6690	1.6035	−2.0813	−1.5624	−0.8419	−1.5777	−2.1150	−0.5641	−2.0262	−1.7654
	(0.0807)	(0.0707)	(0.0252)	(0.0959)	(0.0646)	(0.0506)	(0.0454)	(0.0780)	(0.0666)	(0.0880)	(0.0010)	(0.0506)
AIC	−184.5043	−147.163	−999.699	−159.7553	−111.538	−613.087	−309.9344	−95.8524	−1417.634	−82.1578	−67.1563	−1093.525
TVP-Gumbel												
ω	0.3129	−2.5676	0.4460	0.0672	−2.0798	0.5247	−0.0694	0.8741	0.7294	−0.5923	−1.8024	0.5440
	(0.1150)	(0.0021)	(0.0327)	(0.1094)	(0.1210)	(0.0717)	(0.0757)	(0.0534)	(0.0737)	(0.1691)	(0.0025)	(0.0505)
α	0.4462	1.6185	0.3341	0.5429	1.1280	0.2592	0.5908	−0.4892	0.2164	0.9402	0.9741	0.2877
	(0.0484)	(0.0014)	(0.0124)	(0.0504)	(0.1232)	(0.0393)	(0.0358)	(0.0650)	(0.0332)	(0.1099)	(0.0492)	(0.0228)
β	−1.7954	1.5632	−1.3311	−1.2351	1.6054	−1.2489	−0.7511	−1.4173	−1.6027	−0.4663	1.6278	−1.4565
	(0.1150)	(0.0021)	(0.0327)	(0.1094)	(0.1210)	(0.0717)	(0.0757)	(0.0534)	(0.0737)	(0.1691)	(0.0025)	(0.0505)
AIC	−237.2136	−158.318	−1125.945	−201.2303	−121.154	−761.073	−401.8006	−115.839	−1645.509	−100.9370	−74.1833	−1374.789
TVP-rotated Gumbel												
ω_L	0.1084	−2.1798	0.4094	−0.0069	−2.1004	0.5715	−0.0584	0.8598	0.5420	−0.6128	−1.7823	0.5456
	(0.0082)	(0.0317)	(0.0337)	(0.0903)	(0.1042)	(0.0845)	(0.0639)	(0.0485)	(0.0292)	(0.1533)	(0.0034)	(0.0393)
α_L	0.5250	1.1500	0.3431	0.5712	1.1373	0.2328	0.5803	−0.4705	0.3066	0.9479	0.9683	0.3020
	(0.0003)	(0.0123)	(0.0132)	(0.0415)	(0.1134)	(0.0469)	(0.0303)	(0.0647)	(0.0100)	(0.1013)	(0.0143)	(0.0152)
β_L	−1.2675	1.7845	−1.2575	−1.0178	1.6179	−1.2552	−0.6851	−1.4419	−1.5231	−0.3977	1.6107	−1.5446
	(0.0082)	(0.0317)	(0.0337)	(0.0903)	(0.1042)	(0.0845)	(0.0639)	(0.0485)	(0.0292)	(0.1533)	(0.0034)	(0.0393)
AIC	**−285.5113**	−180.887	−1065.654	**−252.3739**	−123.718	−812.443	**−529.7577**	−118.933	−1556.690	−132.2819	−76.5868	−1564.226

(*continued on next page*)

Table 5b (*continued*)

Copula	S&P500			Stoxx600			TSX			DJPI		
	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run	Raw	Short-run	Long-run
TVP-SJC												
ω_U	−10.5023	3.1367	−4.5122	2.1693	−11.4166	4.4039	0.4185	−13.1698	2.0321	0.2188	−13.1698	0.6680
	(14.6021)	(0.731)6	(0.2309)	(1.1632)	(6.8674)	(0.2959)	(0.8736)	(4.2868)	(0.0241)	(2.5806)	(0.5268)	(0.0192)
β_U	−3.3151	−25.0000	−5.1077	−23.3676	−1.9290	−23.1527	−14.1571	16.0608	−12.7105	−17.9898	−28.2605	−15.0965
	(18.2555)	(4.1261)	(1.7815)	(5.6757)	(11.0923)	(1.2559)	(3.8432)	(0.0678)	(0.0752)	(11.0246)	(3.0374)	(0.2838)
α_U	−0.0036	−3.5477	−1.4723	0.8304	−0.0012	−5.2568	1.1438	−3.4824	−1.5272	3.4812	−6.7292	−0.0352
	(1.0004)	(0.7066)	(0.9787)	(1.3294)	(1.0000)	(0.1068)	(1.5383)	(8.8316)	(0.0211)	(9.8316)	(1.0855)	(0.0607)
ω_L	3.8455	4.5796	2.9825	1.8250	−11.4298	4.7374	−0.7229	−10.0896	3.3980	−1.3402	7.7199	2.3103
	(0.8537)	(0.6748)	(0.0194)	(0.8503)	(7.2656)	(0.3474)	(0.6126)	(6.1794)	(0.0197)	(1.0862)	(0.3668)	(0.0251)
β_L	−22.2041	−25.0000	−18.4916	−15.5661	−2.0611	−24.3436	−4.6402	4.4429	−24.8597	−6.5039	−42.8352	−17.3447
	(3.2051)	(2.7865)	(0.4170)	(2.9038)	(11.7504)	(2.0030)	(1.7410)	(8.0859)	(0.1572)	(3.6645)	(2.4199)	(0.4780)
α_L	−2.2157	−4.4092	−0.9492	−1.1772	−0.0010	−4.3218	2.5368	−4.8308	−0.9929	4.8298	−5.2710	−0.2356
	(1.1180)	(0.2172)	(0.0194)	(1.2889)	(1.0000)	(0.2079)	(0.9233)	(−1.9751)	(0.0075)	(2.9751)	(0.2273)	(0.0164)
AIC	−236.8107	−199.360	−1093.577	−231.3705	−10.9459	**−865.073**	−503.5430	8.2372	**−1812.261**	**−133.5855**	20.6345	**−1653.291**
TVP-Student-t												
Ψ_0	0.0058	0.1402	0.0725	0.0056	0.1867	0.0350	−0.0015	0.0115	0.1457	0.4928	−0.0127	0.1971
	(0.0035)	(0.0511)	(0.0232)	(0.0035)	(0.0609)	(0.0152)	(0.0003)	(0.0031)	(0.0274)	(0.0819)	(0.0658)	(0.0367)
Ψ_1	0.0569	0.4178	0.3234	0.0442	0.4204	0.1604	0.0379	−0.3372	0.2413	0.1664	0.4704	0.2997
	(0.0124)	(0.0757)	(0.0612)	(0.0130)	(0.0845)	(0.0331)	(0.0157)	(0.0490)	(0.0576)	(0.0678)	(0.0901)	(0.0519)
Ψ_2	1.9284	−2.0169	0.8347	1.9397	−2.0083	1.1579	2.0275	1.9161	1.1247	−1.6824	−2.0152	0.5597
	(0.0271)	(0.0204)	(0.1726)	(0.0298)	(0.0166)	(0.1133)	(0.0180)	(0.0254)	(0.2211)	(0.4471)	(0.0152)	(0.2127)
υ	7.5267	5.7566	5.9547	4.7252	5.6519	5.7804	5.7363	5.7821	6.1757	5.6353	5.6671	5.9931
	(0.0394)	(0.0766)	(1.1401)	(0.0429)	(0.5486)	(1.2166)	(0.0337)	(0.5915)	(1.7652)	(0.5149)	(0.6252)	(2.3567)
AIC	−256.0016	−136.553	−840.3397	−220.7487	28.8205	−431.098	−467.3701	−462.731	−983.9642	−48.3068	26.1257	−912.3326

Notes: See the notes of Table 5a. The minimum AIC values (in bold) indicate the best fitted copula fit.

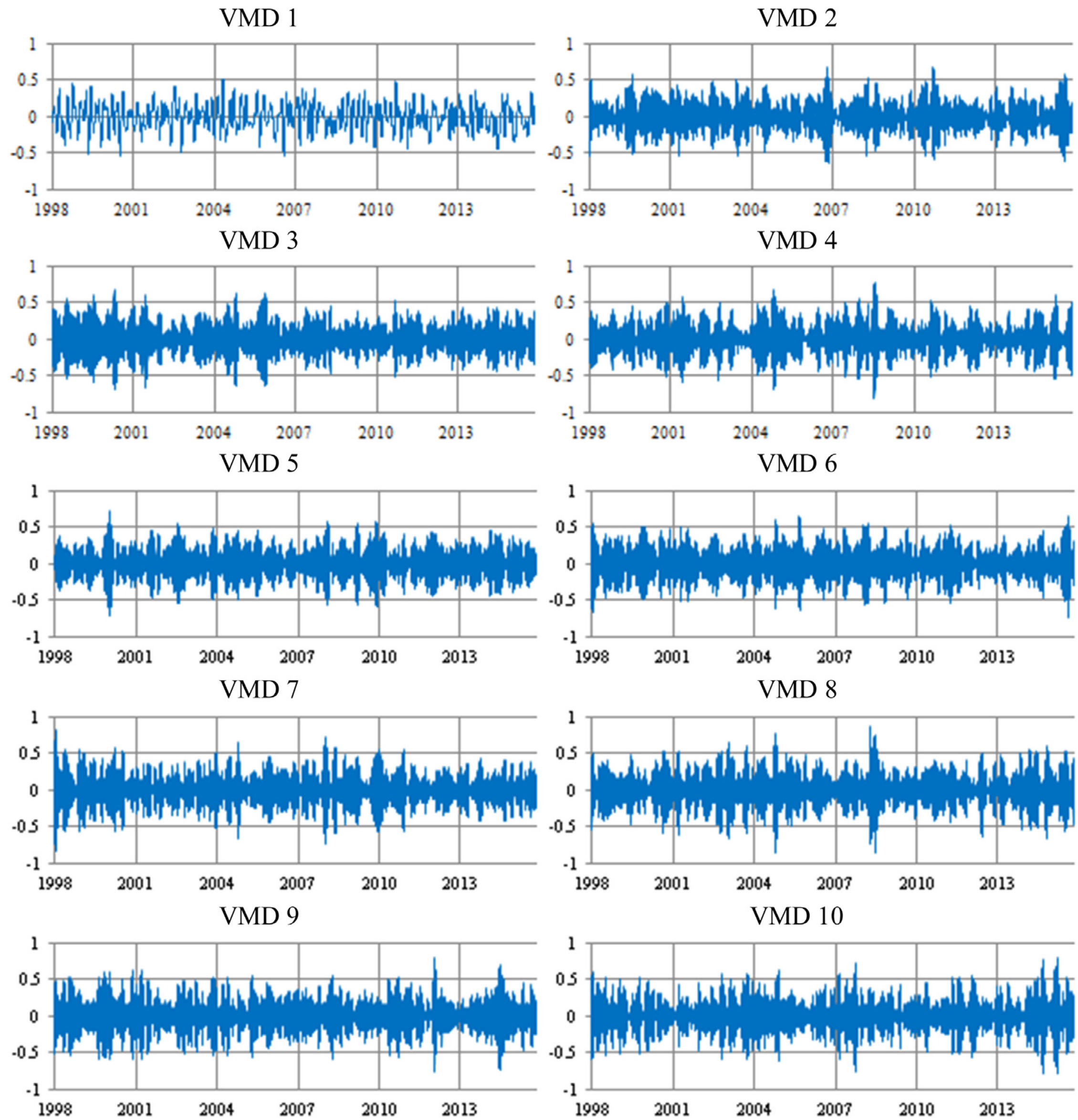


Fig. 3. Variational mode decompostion for the WTI return series. Note: We have set the maximum variational modes = 10, and the above figures shows mode 1 (long-run) to 10 (short-run).VM denotes variational mode.

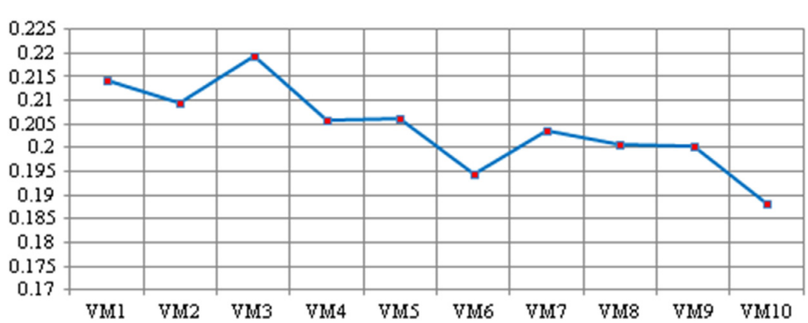


Fig. 4. The VMD variances. Note: see the note of Fig. 3.

dependent with the stoxx600 and TSX indexes as shown by the TVP rotated Gumbel for the raw return series.

The finding for the S&P500 index shows that this index is upper tail dependent with the oil market, reflecting a decline in aggregate demand. This result also indicates that both markets co-move in the same direction, that is, when the oil price plunges it leads to a low U.S. stock market performance. Oil is independent with the S&P500, stoxx600 and TSX indexes during bull markets. Looking at the Dow Jones Pacific Stock Index (DJPI), we find an asymmetric tail dependence with oil as shown by the SJC copula. More specifically, the time-varying dependence is negative in the downturn periods and positive in the upturn periods, suggesting the preponderance of strong aggregate demand shocks.

Motivated by the fact that the investor expectations are not identical and the strategies of the investors and policy makers are based on time investment horizons, we re-examine the dependence structure between the oil and stock markets in the short- and long-run horizons. In the short-run, the results suggest that the TVP rotated Gumbel copula is the best fit for all stock indexes. On the other hand, there are a lower tail dependence and an upper tail independence between the oil price returns and the four regional stock indexes. During the bear markets, the dependence is positive for three-out of the four indexes, with the exception of the DJPI index. The latter is negatively lower tail dependent with oil. This result is important in terms of portfolio risk management because of the negative dependence for this index. In the long-run horizons, the TVP SJC copula fits all the indexes except the S&P500 index for which the TVP rotated Gumbel is the best model. In fact, for the TSX, stoxx600 and DJPI indexes, we find an asymmetric and positive tail dependence with oil, meaning that the oil-stock dependence differs during the upturn and downturn periods. It is worth noting that the oil-stock dependence is stronger in the long-run than in the short-run. To sum up, the above results have significant implications for risk spillovers between oil and stocks, which will be addressed in the next section.

Panels A–C of Fig. 5 display the time evolution of the dependence parameters for each of the oil-stock index return pairs for the raw series in the short- and long-run horizons, respectively. These panels offer graphical insights into the nature of the time-varying dependence between the oil and the stock indexes during major events. Among the four stock indexes, we observe a strong dependence between oil and the S&P500 index. The impact of the GFC of 2008–2009 is evident in all the stock markets as the dependence between oil and stock markets increases significantly during this period, supporting the re-coupling hypothesis. Looking at the TSX-oil pair dependence, we find that the dependence for this pair varies over time. Note that petroleum production in Canada is a major industry in its economy. As a country with the third largest oil reserves in the world, Canada is sensitive to oil price volatility. Thus, the downside and upside oil prices affect the Canadian stock market which is confirmed in Fig. 5. On the other hand, the dependence trajectory for all pairs differs in terms of the time horizons (in the short run and long run). The long run dependence is higher than the short run dependence. In fact, the short-run dependence is detected using the normal copula, while the dependence in the long run is determined via the dynamic SJC copula for three out of the four cases. If we consider for example the S&P500-oil pair, we note that the time variation in the long run is smooth, compared to those in the short run. The U.S. stock market is very sensitive to the oil price shocks. Extreme long-run dependence is a key ingredient for portfolio risk management, pricing and hedging.

6. Portfolio risk implications

6.1. Risk spillovers analysis

To study the implications of our copula results in terms of the risk spillovers between the oil-stock pairs, we quantify the VaR, CoVaR and ΔCoVaR risk measures for the oil and stock markets. Panels A and B of Fig. 6 illustrate the trajectory of the upside and the downside VaRs and CoVaRs for the stock and oil market returns, respectively. The graphical plots show that the downside and upside VaRs for the oil markets (Panel B) are systematically higher than those for the stock markets (Panel A), implying that the oil market is more risky than those of major regional stock markets in both the bearish and bullish market conditions.[9] This graphical evidence is in line with the descriptive statistics reported in Table 6. Indeed, the average and the standard deviations of the VaR values for the oil market are higher than their counterparts for the stock markets. Those results are important for controlling and monitoring market risk.

On the other hand, we observe that the upside and downside VaR and CoVaR trajectories display a similar trend for all the cases with slight differences in magnitude across the markets. More interestingly, the impact of the onset of the GFC on the oil and stock markets is clearly evident as we find significant abrupt changes during the 2008–2009 period. Concerning the risk spillovers from oil to the stock markets (Panel A), we note that the S&P500 index is the most affected by the oil market and the GFC among all the stock markets, while the DJPI index is the least influenced by the oil market. We find that both risk measures differ where the downside CoVaR abruptly falls or the upside CoVaR picks up much more than the downside and upside VaRs for all the markets during this period, implying that each market has a systemic impact on the other market. Again, the graphical analysis is confirmed by the average and standard deviations of the VaR and Co-VaR for the oil and stock markets. On the whole, this result suggests significant bidirectional risk spillovers between the oil and stock markets. Our results are in line with those of Du and He (2015) who find a significant risk spillover from WTI crude oil to the S&P500 index and vice versa. Detecting the origin of oil shocks is an important determinant of the risk spillovers between the oil and stock markets.

6.2. Short- and long-run upside and downside risk spillovers

To analyze in depth the risk spillovers to the oil and to stock markets in terms of investment horizons, we consider a VMD multiresolution approach to re-examine this issue in the short- and long-run horizons. Panels A and B of Fig. 7 plot the temporal evolution of both the short- and long-run upside and downside CoVaRs from oil to stock markets and from stock markets to oil, respectively. By looking at the risk spillovers from oil to stock markets (Panel A), we see that the upside and downside CoVaRs display the same trajectory in the short- and long-run, but with a slight difference in magnitude. The spillovers from oil to stock markets during the GFC for both the short- and long-run is evident for the four stock markets. By analyzing the downside risk, we find that the CoVaRs in the long run are below the CoVaR in the short run, implying that oil has a greater systemic impact on the stock markets in the long run and that increasing the VaR of oil would increase the conditional VaR of the stock markets. This result is important for doing asset allocation and constructing hedging strategies. Regarding the upside risk, the graphical inspection demonstrates that in the long run the CoVaRs are above the CoVaRs in the short run, underlying the key distinctive role of the oil market in determining the risk spillovers in the stock markets for different investment horizons. The descriptive statistics reported in Table 6 confirm the graphical evidence.

Regarding the risk spillovers from stocks to oil (Panel B), we find evidence of risk spillovers from all stock markets to oil, suggesting that the stock markets have a systemic risk for the oil mar-

[9] Note that a bull market is a rise in value of the market by at least 20%. A bear market is the opposite of a bull market in the sense that. If a market falls by more than 20%, then we enter a bear market. A bull market refers to a market that is on the rise and it is characterized by a sustained increase in share prices. Investors believe the increase will continue in the long run. In this case, we observe a strong demand and a weak supply for securities. In contrast, a bear market is one that is in decline where share prices are continuously dropping, resulting in a downward trend that investors believe will continue in the long run. In this case, we see a strong supply of securities and a weak demand. The key determinant of whether the market is a bull or a bear is the long-term trend.

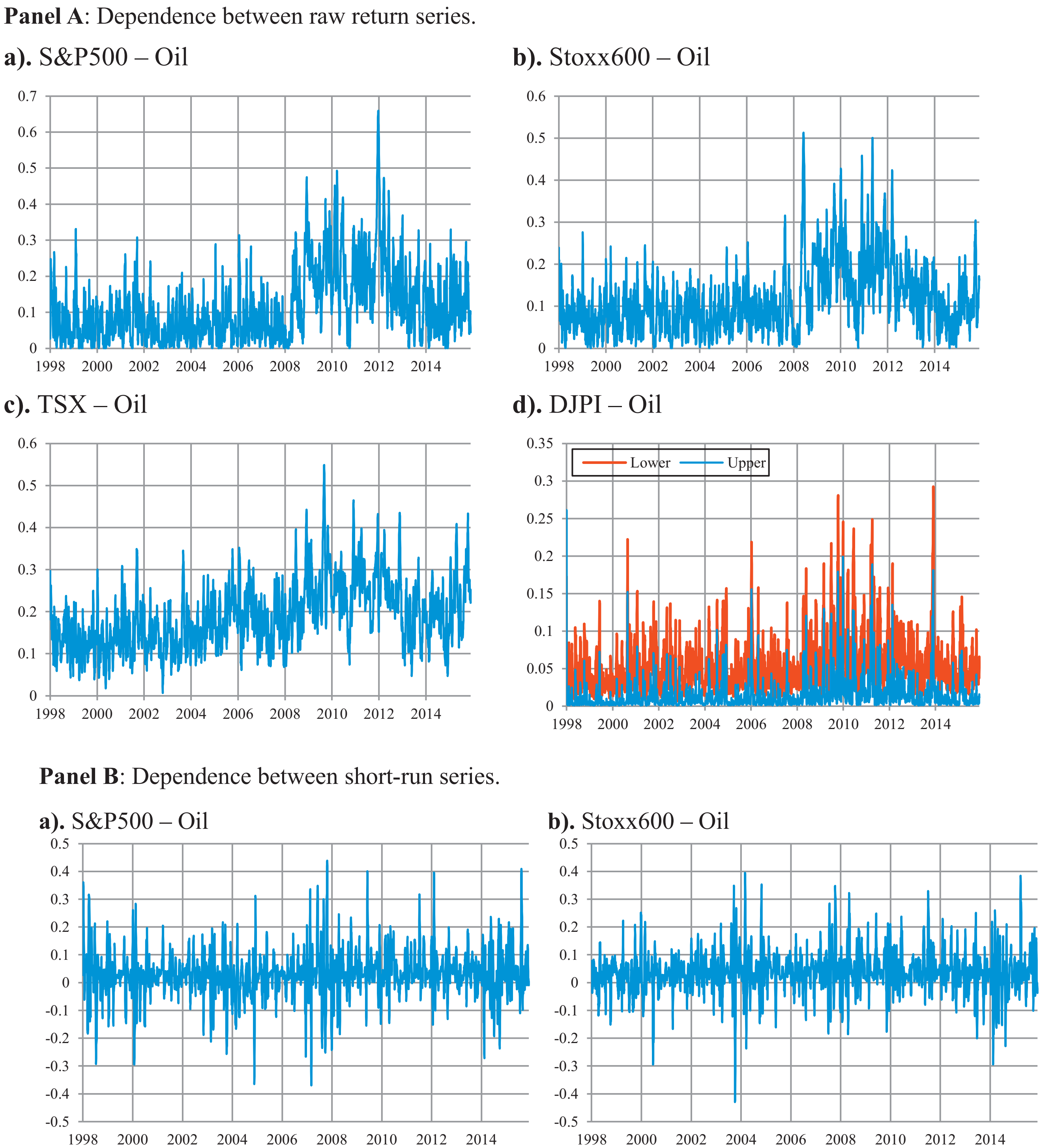
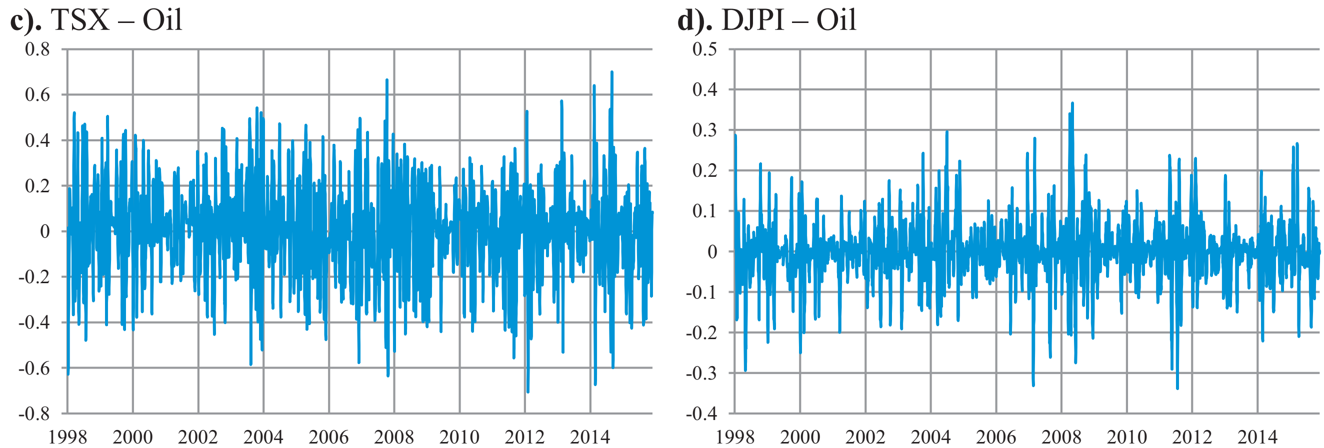


Fig. 5. Time variations of bivariate stock-oil markets copula dependence. Note: The time-varying dependence structure is based on the best fitted copulas (see Tables 5a and 5b). For comparative analysis, we report the Kendall's tau derived from the dependence parameters except for the SJC copulas where lower and upper tail dependence is shown to reflect the asymmetry.

ket in all cases. Panels A and B of Fig. 7 also show that the upside CoVaR in the long horizon is greater than the upside CoVaR in the short horizon, while the downside CoVaR in the long horizon is below the down CoVaR in the short horizon. We can conclude that the long-run risk spillovers are more important than the short-run risk spillovers. This result indicates that these regional developed stock markets are an important factor in driving up international crude oil prices, particularly in the long run. To sum up, we conclude that portfolio managers and investors should consider the investment horizons as an important factor in order to effectively manage their portfolios.

For robustness, we use the Kolmogorov–Smirnov (K-S) test to confirm the above graphical evidence and to test for the significance of the systemic risk. More precisely, we first test the presence of a significant difference between VaRs and CoVaRs. Second, we investigate whether the short-run downside (upside) CoVaRs is



Panel C: Dependence between long-run series.

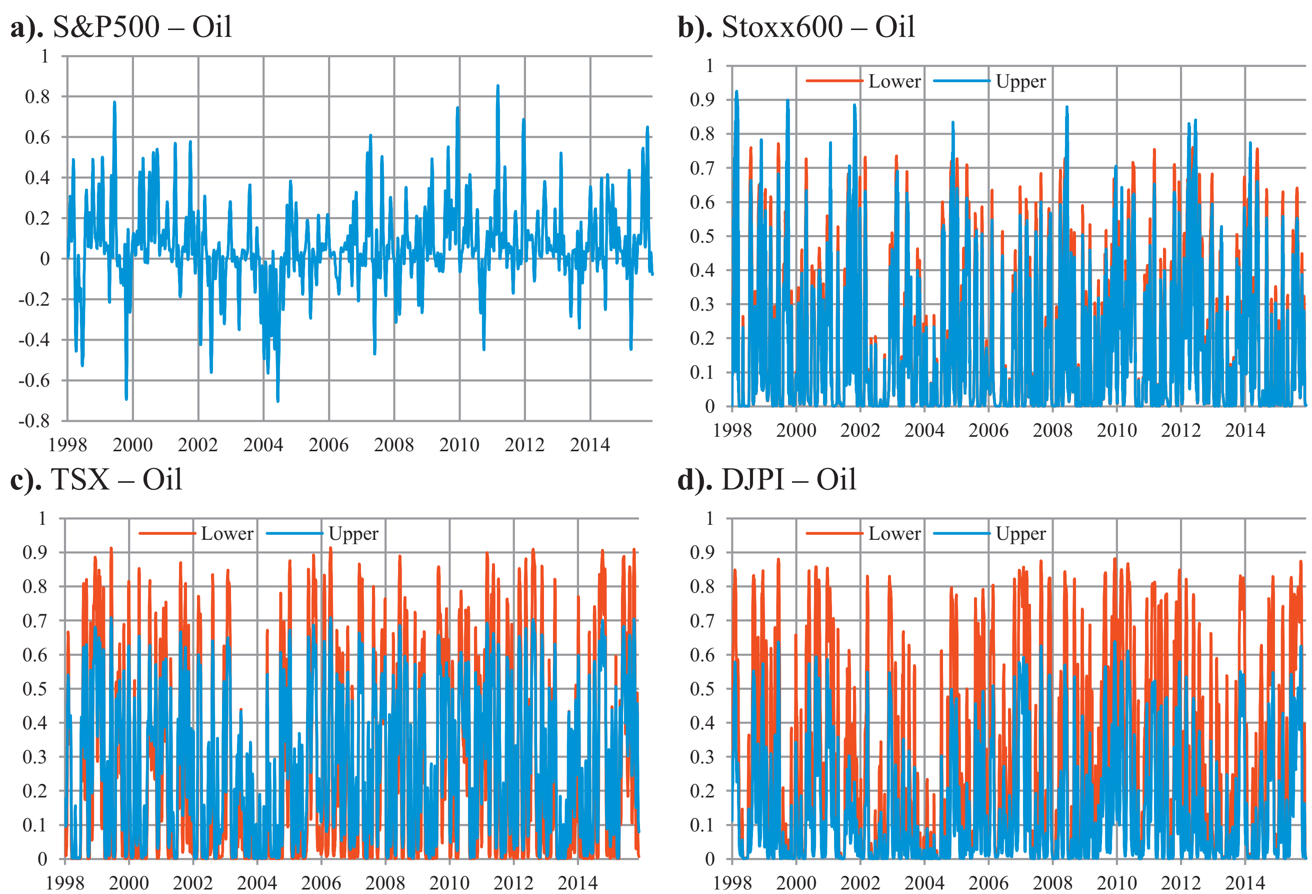


Fig. 5. Continued

statistically different from the long-run downside (upside) CoVaRs. The estimation results of the K-S test are presented in Table 7 and show significant differences between the VaRs and CoVaRs for the raw series (for both risk spillovers from stock to oil market and from oil to stock markets) for all cases, confirming the importance of the risk spillovers. We also provide evidence of a significant difference between the short-run downside CoVaRs and long-run downside CoVaRs from oil to stock and vice versa for all cases. A similar result is also obtained for the upside CoVaR case. On the whole, the downside (upside) CoVaRs are not equal in the short-run and long-run. Thus, the time-horizon is crucial for investors to assess the holding short position and long position.

6.3. Asymmetric risk spillovers

Further, we test whether the upside and downside systemic risks between the oil and stock markets are asymmetric for the raw, short- and long-run series. However, this stylized fact (asymmetry) has direct implications for portfolio risk management and hedging as investor behaviors differ during downturn and upturn markets. Based on these arguments, we first test the presence of

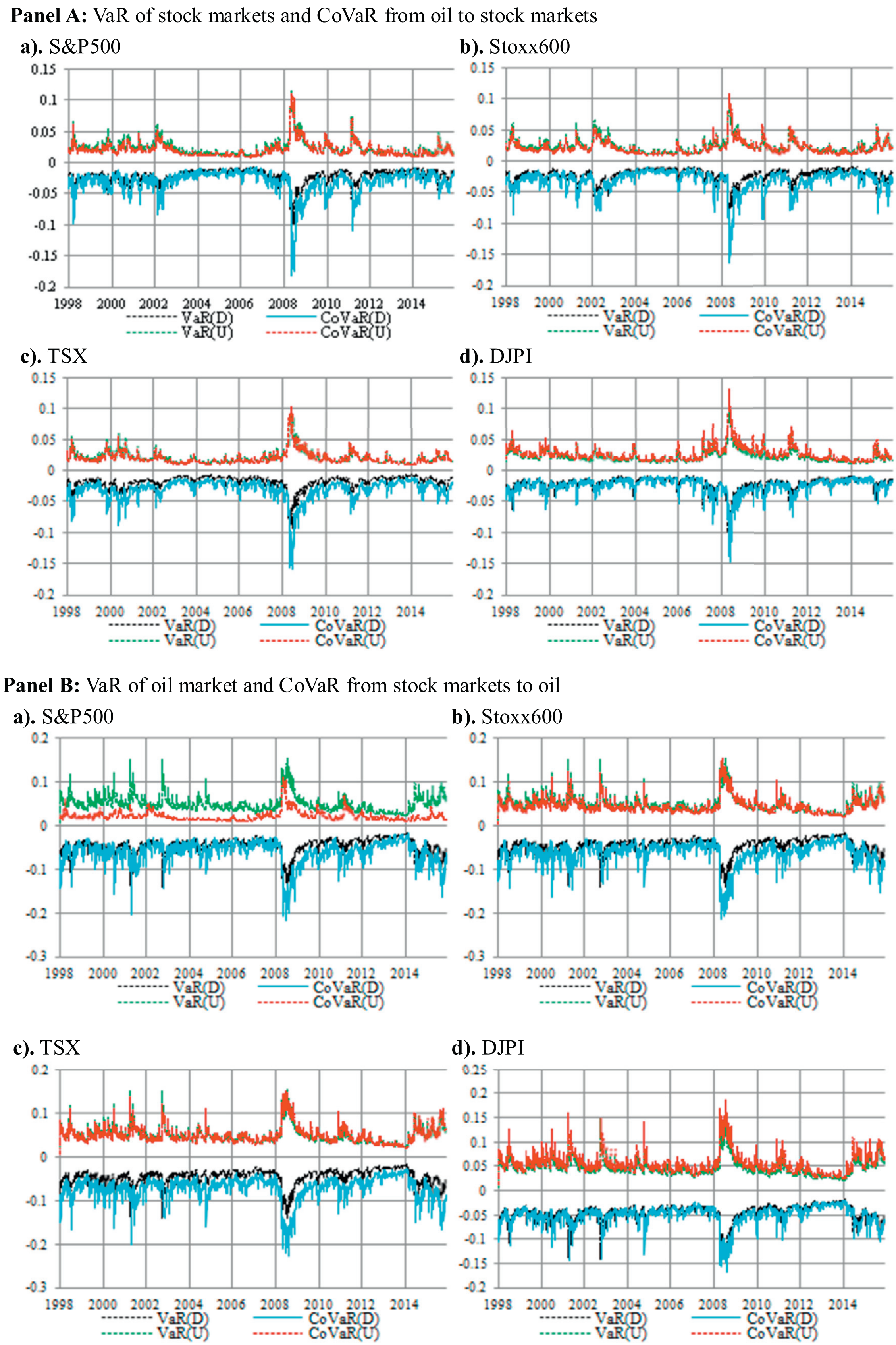


Fig. 6. Upside and downside value-at-risk (VaR) and conditional value-at-risk (CoVaR) between oil and stock markets. Note: Downside and upside value-at-risk (VaRs) are calculated using Eqs. (18) and (19), respectively. The conditional value-at-risk (CoVaR) is calculated using Eq. (20).

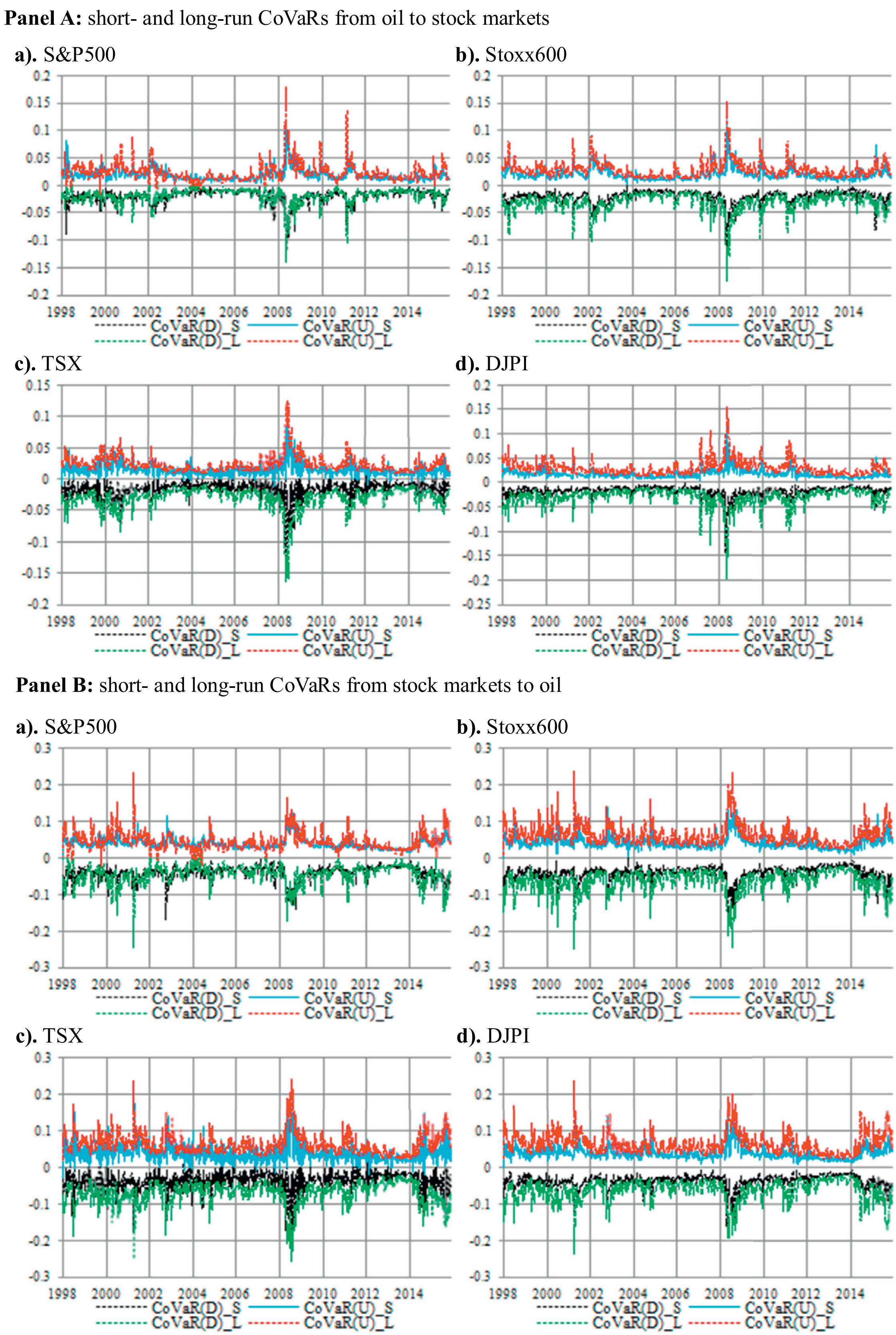


Fig. 7. Upside and downside short- and long-run conditional value-at-risk (CoVaR) between oil and stock market returns. Note: The conditional value-at-risk (CoVaR) is calculated using Eq. (21).

Table 6
Descriptive statistics of value-at-risk (VaR) and conditional value-at-risk (CoVaR).

	Down				Up			
	VaR	CoVaR (Raw)	CoVaR (Short)	CoVaR (Long)	VaR	CoVaR (Raw)	CoVaR (Short)	CoVaR (Long)
Panel A: *VaR of stock markets and CoVaR from oil to stock markets*								
S&P500	−0.0217	−0.0306	−0.0204	−0.0185	0.0228	0.0204	0.0188	0.0228
	(0.0115)	(0.0190)	(0.0125)	(0.0130)	(0.0119)	(0.0115)	(0.0110)	(0.0165)
Stoxx600	−0.0224	−0.0313	−0.0213	−0.0310	0.0235	0.0213	0.0200	0.0276
	(0.0106)	(0.0167)	(0.0117)	(0.0164)	(0.0110)	(0.0111)	(0.0106)	(0.0143)
TSX	−0.0195	−0.0312	−0.0169	−0.0303	0.0199	0.0190	0.0150	0.0232
	(0.0103)	(0.0169)	(0.0126)	(0.0171)	(0.0101)	(0.0101)	(0.0100)	(0.0131)
DJPI	−0.0219	−0.0246	−0.0186	−0.0304	0.0223	0.0258	0.0177	0.0293
	(0.0108)	(0.0128)	(0.0108)	(0.0175)	(0.0098)	(0.0119)	(0.0088)	(0.0152)
Panel B: *VaR of oil returns and CoVaR from stock markets to oil*								
S&P500	−0.0456	−0.0612	−0.0414	−0.0439	0.0463	0.0204	0.0366	0.0413
	(0.0170)	(0.0262)	(0.0181)	(0.0254)	(0.0169)	(0.0115)	(0.0133)	(0.0225)
Stoxx600	−0.0456	−0.0627	−0.0422	−0.0629	0.0463	0.0427	0.0399	0.0581
	(0.0170)	(0.0259)	(0.0182)	(0.0280)	(0.0169)	(0.0168)	(0.0165)	(0.0253)
TSX	−0.0456	−0.0719	−0.0384	−0.0701	0.0463	0.0468	0.0365	0.0594
	(0.0170)	(0.0271)	(0.0239)	(0.0293)	(0.0169)	(0.0175)	(0.0213)	(0.0259)
DJPI	−0.0456	−0.0507	−0.0386	−0.0621	0.0463	0.0535	0.0369	0.0607
	(0.0170)	(0.0192)	(0.0172)	(0.0268)	(0.0169)	(0.0197)	(0.0156)	(0.0251)

Note: This table presents the average and the standard deviation (in parenthesis) of the VaR and CoVaR of the oil and stock markets. The downside and upside value-at-risk (VaRs) are calculated using Eqs. (18) and (19), respectively.

Table 7
Tests of equalities of VaR and CoVaR and difference of CoVaR for short- and long-run series.

	$H_0 : CoVaR(D) = VaR(D)$ $H_1 : CoVaR(D) < VaR(D)$	$H_0 : CoVaR(SD) = CoVaR(LD)$ $H_1 : CoVaR(SD) \neq CoVaR(LD)$	$H_0 : CoVaR(U) = VaR(U)$ $H_1 : CoVaR(U) > VaR(U)$	$H_0 : CoVaR(SU) = CoVaR(LU)$ $H_1 : CoVaR(SU) \neq CoVaR(LU)$
Panel A: *From oil to stock markets*				
S&P500	0.2902	0.2804	0.0020	0.4283
	[0.0000]	[0.0000]	[0.9821]	[0.0000]
Stoxx600	0.3018	0.7614	0.0044	0.7456
	[0.0000]	[0.0000]	[0.9145]	[0.0000]
TSX	0.4616	0.6756	0.0022	0.6598
	[0.0000]	[0.0000]	[0.9779]	[0.0000]
DJPI	0.1205	0.8808	0.1677	0.8712
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Panel B: *From stock markets to oil*				
S&P500	0.3331	0.1892	0.0002	0.6444
	[0.0000]	[0.0000]	[0.9998]	[0.0000]
Stoxx600	0.3949	0.7658	0.0029	0.7569
	[0.0000]	[0.0000]	[0.9629]	[0.0000]
TSX	0.5797	0.6773	0.0169	0.6696
	[0.0000]	[0.0000]	[0.2750]	[0.0000]
DJPI	0.1505	0.8817	0.2126	0.8790
	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Notes: This table summarizes the results of the Kolmogorov–Smirnov (KS) test. The KS tests the hypothesis of no systemic impact between the oil and stock markets. The p-values for the KS statistic are in squared brackets. The upside and downside conditional value-at-risk (CoVaRs) are calculated using Eq. (21). SD and LD denote the short-run downside and long-run downside, respectively. SU and LU denote the short-run upside and long-run upside, respectively.

asymmetry in risk spillovers in the raw series. Also, we compare the downside CoVaR in the short-run horizon against the downside CoVaR in the long-run horizon as well as the upside CoVaR in the short-run horizon versus the upside CoVaR in the long-run horizon for the oil and stock markets, using the K-S test, searching for a significant difference. The estimates (see Table 7) reject the null of symmetric risk spillovers at different time horizons for all the markets. More precisely, we find asymmetric downside short- and long-run –upside risk spillover effects from the oil to stock markets and vice versa, suggesting that the short- and long-run down and upside spillovers are different and that investors should change their strategies accordingly. This result also confirms the importance of considering time horizons for risk management. Second, we investigate the asymmetric downside/upside risk spillover effects in the raw series as well as in both the short- and long-run horizons by testing for significant differences between the downside CoVaR normalized by the downside VaR and the upside CoVaR normalized by the upside VaR, by considering the K-S statistic to test for significant differences between the downside and upside spillovers. The results summarized in Table 8 show evidence of asymmetric behavior of the upside and downside risk spillovers to oil and to stock markets, with the exception of the DJPI index for the raw series and the S&P500 index when analyzing the oil risk spillovers to stock markets.

6.4. ΔCoVaR analysis

This study provides further analysis on risk spillovers by considering the ΔCoVaR risk measure. Fig. 8 depicts the time-varying ΔCoVaR estimates of the spillover from the oil to stock markets and shows that downside ΔCoVaR is greater than the upside ΔCoVaR for the stock markets of S&P500, stoxx600 and TSX indexes, with the exception of the DJPI index. Table 9 presents the descriptive statistics of ΔCoVaR and shows that the average and standard deviations for the downside ΔCoVaR are higher than their upside counterpart.

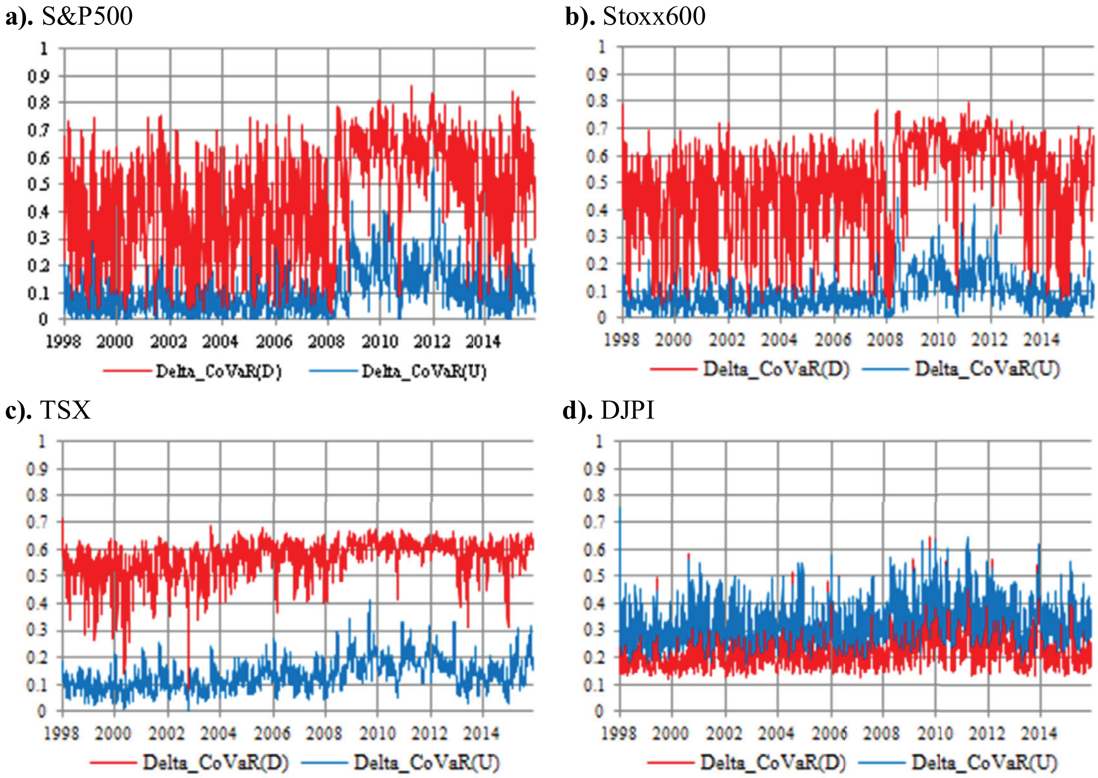


Fig. 8. Upside and downside delta conditional value-at-risk (ΔCoVaR) from oil to stock markets. Note: The delta conditional value-at-risk (ΔCoVaR) is calculated using Eq. (22).

Table 8
Tests of asymmetric raw, short- and long-run risk spillover effects.

	Raw	Short-run $H_0: \frac{CoVaR}{VaR}(D) = \frac{CoVaR}{VaR}(U)$ $H_1: \frac{CoVaR}{VaR}(D) < \frac{CoVaR}{VaR}(U)$	Long-run
Panel A: *From oil to stock markets*			
S&P500	0.7667	0.4325	0.0031
	[0.0000]	[0.0000]	[0.9571]
Stoxx600	0.8679	0.4147	0.4321
	[0.0000]	[0.0000]	[0.0000]
TSX	0.9920	0.2113	0.6885
	[0.0000]	[0.0000]	[0.0000]
DJPI	0.0096	0.2317	0.2451
	[0.6615]	[0.0000]	[0.0000]
Panel B: *From stock markets to oil*			
S&P500	0.9582	0.7861	0.9611
	[0.0000]	[0.0000]	[0.0000]
Stoxx600	0.8234	0.2633	1.0000
	[0.0000]	[0.0000]	[0.0000]
TSX	0.9684	0.0965	1.0000
	[0.0000]	[0.0000]	[0.0000]
DJPI	0.0064	0.2217	1.0000
	[0.8286]	[0.0000]	[0.0000]

Notes: See the notes of Table 7.

Table 9
Descriptive statistics of the ΔCoVaR from oil to stock markets.

	Down			Up		
	Raw	Short	Long	Raw	Short	Long
S&P500	0.4410	0.0414	0.0510	0.0929	0.0375	0.0411
	(0.2099)	(0.1374)	(0.3823)	(0.0838)	(0.1157)	(0.3837)
Stoxx600	0.4852	0.0550	0.4408	0.0858	0.0444	0.3605
	(0.1708)	(0.1255)	(0.2313)	(0.0637)	(0.0970)	(0.1933)
TSX	0.5645	−0.0458	0.5056	0.1352	−0.0354	0.3330
	(0.0677)	(0.3653)	(0.1667)	(0.0575)	(0.2904)	(0.1729)
DJPI	0.2294	−0.0029	0.4214	0.3376	−0.0019	0.4416
	(0.0773)	(0.1226)	(0.2116)	(0.0773)	(0.1080)	(0.2061)

Notes: Numbers in parentheses are the standard errors. The delta conditional value-at-risk (ΔCoVaR) is calculated using Eq. (21).

By considering the time horizons, we show that the long-run down ΔCoVaR is higher than the short-run down ΔCoVaR for the S&P500, TSX and DJIP indexes. Similar results are also found for the upside ΔCoVaR. This result is consistent with those obtained when quantifying the CoVaR spillover from oil to stock markets. We investigate the short- and long-run ΔCoVaR asymmetry for the stock markets and the results are reported in Table 10. However, we find a significant difference between the downside ΔCoVaR in the short- and long-run horizons and the upside ΔCoVaR in the short and long horizons. This result indicates an asymmetric behavior of risk spillovers in time horizons. Table 11 reports the results of the down and upside ΔCoVaR asymmetry (oil spillovers to stock markets) and exhibits asymmetric downside and upside ΔCoVaRs for the raw series as well as for the short- and long horizons.

In the oil-to-stock direction, market participants are more vulnerable to the downside risk than the upside risk and more in the long run than in the short run. The result documents that the information set (extreme movements) of the oil market has a substantial predictive power for the stock markets. The reaction of stock market to crude oil shocks could be justified by changes in real cash flows and expected returns. Other plausible causes for the risk spillovers are not only the market fundamentals but also the contagion, investor reaction to news and investor sentiments. More interestingly, we note that the ΔCoVaR results (Tables 9–11) are in line with those of the conditional VaR to stock markets (Tables 6–8).

Table 10
Results of short- and long-run ΔCoVaR asymmetry from oil to stock markets.

	$H_0 : \Delta CoVaR_{Short} = \Delta CoVaR_{Long}$ $H_1 : \Delta CoVaR_{Short} \neq \Delta CoVaR_{Long}$	
	Down	Up
S&P500	0.1879	0.1870
	[0.0000]	[0.0000]
Stoxx600	0.8094	0.8048
	[0.0000]	[0.0000]
TSX	0.7154	0.7002
	[0.0000]	[0.0000]
DJPI	0.8939	0.8957
	[0.0000]	[0.0000]

Note: The values in brackets [ ] are the p-values of the K–S test. The delta conditional value-at-risk (ΔCoVaR) is calculated using Eq. (22).

Table 11
Results of the down and upside ΔCoVaR asymmetry from oil to stock markets.

		$H_0 : \Delta CoVaR_{Down} = \Delta CoVaR_{Up}$ $H_1 : \Delta CoVaR_{Down} \neq \Delta CoVaR_{Up}$	
	Raw	Short	Long
S&P500	0.7314	0.0507	0.0402
	[0.0000]	[0.0000]	[0.0013]
Stoxx600	0.8608	0.0892	0.3378
	[0.0000]	[0.0000]	[0.0000]
TSX	0.9889	0.0554	0.5637
	[0.0000]	[0.0000]	[0.0000]
DJPI	0.6100	0.0322	0.1187
	[0.0000]	[0.0182]	[0.0000]

Note: See the notes of Table 10.

7. Conclusion and policy implications

The dependence structure between oil and stock markets attracts a great deal of attention from researchers and practitioners, particularly in the wake of the dramatic oil price surge in summer 2008 (when it reached about $US 145 /barrel). However, oil prices have important effects on the stock markets and vice versa but these effects differ during bear and bull markets and under different investment time horizons, having different upside and downside risk spillovers, especially during and after the 2008–2009 GFC. Therefore, understanding these multifaceted effects is important for portfolio allocation and risk management.

This study examines the average and extreme dependence between oil and four major regional developed stock markets (the United States, Canada, Europe and the Pacific without Japan). We also quantify the upside and downside systemic risk spillovers from the oil to the stock markets and vice versa in the short- and long-run investment horizons. For this purpose, we combine a battery of copula functions with the variational mode decomposition (VMD) multiresolution method in order to decompose the marginal model's residuals into their short and long components. To assess the risk spillovers, we calculate the short- and long-run downside and upside VaRs, CoVaRs and ΔCoVaRs risk measures in order to have a new deeper look at the portfolio risk management.

The results provide strong evidence of dynamic tail dependence between the oil and those major regional stock markets. For the short-time investment horizon, the results show an average dependence between the oil and the stock markets, while for the long-run horizons we find tail dependence for all the stock markets with oil returns.

Based on the graphical analysis of the downside and upside VaRs, we observe that the oil market is more risky than the stock markets in both bearish and bullish market conditions. Comparing the upside and downside VaRs and CoVaRs systemic risk measures for the oil and stock raw return series, we observe the presence of a similar pattern of both systemic risks for all markets, with low differences in magnitude across the markets. On the other hand, the impact of the GFC on the VaRs and CoVaRs risk measures for the oil and stock markets is evident as we find significant abrupt variations during the 2008–2009 crisis period. The GFC has increased significantly the VaR and CoVaR for the oil market as well as for the major regional stock markets, particular for the U.S. stock market. In addition, the oil and stock markets show significant bidirectional risk spillovers in all the cases, particularly during the onset of the GFC.

In addition, the graphical analysis shows that the upside and downside CoVaRs display the same trajectory in the short and long run, but with a low difference in magnitude. Again, the effect of the GFC on the short- and long-run risk spillovers for the short and long positions is evident for all the markets. By analyzing the downside and upside risk, we find that oil has a greater systemic impact on the stock markets in the short-run and in the long-run than otherwise, indicating that increasing the VaR of oil would increase the conditional VaR of the stock markets. More interestingly, both risk spillovers (to oil and to stock markets) are more important in the long run than in the short-run. Similar results are also found for the upside risk spillovers. By using the Kolmogorov–Smirnov (K-S) test, we show significant differences between the downside and upside VaRs and CoVaRs for the raw series as well as for the short- and long-run horizons, underlying the presence of asymmetric downside short- and long-run –upside risk spillover effects from the oil to stock markets and vice versa, suggesting that the short- and long-run down and upside spillovers are different. Additionally, we find strong evidence of asymmetric behavior of the upside and downside risk spillovers to the oil and to stock markets, with the exception of the DJPI index for the raw series and the S&P500 index when analyzing the oil risk spillovers to stock markets.

Finally, using the ΔCoVaR risk measure we observe that the downside the ΔCoVaR is greater than the upside ΔCoVaR for the stock markets (S&P500, stoxx600 and TSX indexes), with the exception of the DJPI index. By considering the time horizons, we show that the long run down ΔCoVaR is higher than the short run down ΔCoVaR for the S&P500, TSX and DJIP indexes. Moreover, we find asymmetric downside and upside ΔCoVaRs at the short- and long-run horizons. The results also reveal asymmetric downside and upside ΔCoVaRs for the raw series as well as for the short- and long horizons.

These findings have several important implication for investors, portfolio managers and traders. All market participants should be cognizant of the bidirectional risk spillovers between the oil and stock markets for both the short and long positions. They also should consider the time horizons when they manage their portfolios. The portfolio managers should hedge and adjust their positions in consideration of investment horizons. As for policymakers, they should remain vigilant of the effects of oil price extreme movements on the stock markets and intervene, whenever is required, to keep the operation of the stock markets stable and less risky, having the broader objective of systemic financial stability in mind.

References

Abadie, A., 2002. Bootstrap tests for distributional treatment effects in instrumental variables models. J. Am. Stat. Assoc. 97, 284–292.
Adrian, T., Brunnermeier, M.K., 2011. CoVaR. Working paper, Federal Reserve Bank of New York.
Arouri, M.E.H., Nguyen, D.K., 2010. Oil prices, stock markets and portfolio investment: evidence from sector analysis in europe over the last decade. Energy Policy 38, 4528–4539.

Aloui, R., Hammoudeh, S., Nguyen, D.K., 2013. A time-varying copula approach to oil and stock market dependence: the case of transition economies. Energy Econ. 39, 208–221.

Baillie, R.T., Bollerslev, T., Mikkelsen, H.O., 1996. Fractionally integrated generalized auto-regressive conditional heteroskedasticity. J. Econ. 74, 3–30.

Balcilar, M., Gupta, R., Miller, S-M., 2015. Regime switching model of US crude oil and stock market prices: 1859 to 2013. Energy Econ. 49, 317–327.

Balcilar, M., Ozdemir, Z.A., 2013. The causal nexus between oil prices and equity market in the U.S.: a regime switching model. Energy Econ. 39, 271–282.

Bjørnland, H.C., 2009. Oil price shocks and stock market booms in an oil exporting country. Scott. J. Polit. Econ. 56, 232–254.

Cherubini, U., Luciano, E., Vecchiato, W., 2004. Copula methods in finance. Chichester, UK, John Willey & Sons.

Chen, N.F., Roll, R., Ross, S., 1986. Economic forces and the stock market. J. Bus. 59, 383–403.

Ciner, C., 2001. Energy shocks and financial markets: nonlinear linkages. Stud. Nonlinear Dyn. Econ. 5, 1–11.

Cong, R.G., Wei, Y.M., Jiao, J.-L., Fan, Y., 2008. Relationships between oil price shocks and stock market: an empirical analysis from china. Energy Policy 36 (9), 3544–3553.

Dickey, D., Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74, 427–431.

Ding, H., Kimb, H-G., Park, S-Y., 2016. Crude oil and stock markets: causal relationships in tails? Energy Econ. 59, 58–69.

Dragomiretskiy, K., Zosso, D., 2014. Variational mode decomposition. IEEE Trans. Signal Process 62, 531–544.

Du, L., He, Y., 2015. Extreme risk spillovers between crude oil and stock markets. Energy Econ. 51, 455–465.

Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50, 987–1007.

Fisher, I., 1930. The Theory of Interest. New York, p. 43.

Girardi, G., Ergün, A.T., 2013. Systemic risk measurement: multivariate GARCH estimation of covar. J. Bank. Financ. 37, 3169–3180.

Hansen, B.E., 1994. Autoregressive conditional density estimation. Int. Econ. Rev. 35, 705–730.

Hosking, J.R.M., 1980. The multivariate portmanteau statistic. J. Am. Stat. Assoc. 75, 602–608.

Huang, D.R., Masulis, R.W., Stoll, H., 1996. Energy shocks and financial markets. J. Futures Mark. 16, 1–27.

Jiménez-Rodríguez, R., Sánchez, M., 2005. Oil price shocks and real GDP growth: empirical evidence for some OECD countries. Appl. Econ. 37, 201–228.

Joe, H., 1997. Multivariate models and dependence concepts. Monographs in Statistics and Probability 73. London, Chapman and Hall.

Jones, C.M., Kaul, G., 1996. Oil and the stock markets. J. Financ. 51, 463–491.

Kang, W., Ratti, R.A., Yoon, K.Y., 2015. Time-varying effect of oil market shocks on the stock market. J. Bank Financ. 61, S150–S163.

Kling, J., 1985. Oil price shocks and stock-market behavior. J. Portfolio Manag. 12, 34–39.

Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shim, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series are non-stationary? J. Econ. 54, 159–178.

Li, Z., Chen, J., Zi, Y., Pan, J., 2017. Independence-oriented VMD to identify fault feature for wheel set bearing fault diagnosis of high speed locomotive. Mech. Syst. Signal Process. 85, 512–529.

Liu, X., An, H., Huang, S., Wen, S., 2016. The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH-BEKK model. Physica A: Stat. Mech. Appl. 65, 374–383.

Lu, F., Qiao, H., Wang, S., Lai, K.K., Li, Z., 2016. Time-varying coefficient vector autoregressions model based on dynamic correlation with an application to crude oil and stock markets. Environ. Res. forthcoming, http://dx.doi.org/10.1016/j.envres.2016.07.015.

McLeod, A.I., Li, W.K., 1983. Diagnostic checking ARMA time series models using squared residual autocorrelations. J. Time Ser. Anal. 4, 269–273.

Mohanty, S., Nandha, M., Bota, G., 2010. Oil shocks and stock returns: the case of the central and Eastern European (CEE) oil and gas sectors. Emerg. Markets Review 11, 358–372.

Nelsen, R.B., 2006. An Introduction to Copulas. New York, Springer-Verlag.

Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. Int. Econ. Rev. 47, 527–556.

Philips, P.C.B., Perron, P., 1988. Testing for unit roots in time series regression. Biometrika 75, 335–346.

Raza, N., Shahzad, S.H., Tiwari, A.K., Shahbaz, M., 2016. Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. Resour. Policy 49, 290–301.

Reboredo, J.C., Ugolini, A., 2015. Systemic risk in European sovereign debt markets: A CoVaR-copula approach. J. Int. Money Fin. 51, 214–244.

Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Econ. 21, 449–469.

Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Econ. 34, 248–255.

Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. J. Bank Financ. 55, 1–8.

Vo, M., 2011. Oil and stock market volatility: a multivariate stochastic volatility perspective. Energy Econ. 33, 956–965.

Williams, J.B., 1938. The Theory of Investment Value. Harvard University Press, Cambridge, Mass..

Yang, L., Zhu, Y., Wang, Y., Wan, Y., 2016. Multifractal detrended cross-correlations between crude oil market and Chinese ten sector stock markets. Physica A: Stat. Mech. Appl. 462, 255–265.