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ORIGINAL RESEARCH

Is oil price risk systemic to sectoral equity markets of an oil importing country? Evidence from a dependence-switching copula delta CoVaR approach

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Abstract
In this paper, a dependence-switching copula model is used for the first time to analyse the dependence structure between sectoral equity markets and crude oil prices for India, one of the largest oil importing countries. Specifically, we investigate the dependence and tail dependence for four distinctive states of the market, i.e. rising oil prices—rising equity markets, declining oil prices—declining equity markets, rising oil prices—declining equity markets, and declining oil prices—rising equity markets. Our results reveal that the tail dependence is symmetric (asymmetric) in positive (negative) correlation regimes. Based on the copula results, we estimate the systemic crude oil price risk to different sectors using CoVaR and delta CoVaR. A fleeting positive sectoral CoVaR and delta CoVaR across all sectors implies a time-varying oil price systemic risk. Yet, little difference between CoVaR and VaR across the sectors reveals that a bearish oil market does not add additional systemic risk to a bearish sectoral equity market. The carbon sector is found to be the safe haven investment when both the equity and the oil markets are in a downward phase.

Keywords Dependence-switching copula · Sectoral markets · Oil price · Dependence asymmetry · CoVaR · Delta CoVaR · India

JEL Classification C32 · G11 · Q41 · Q43

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1 Introduction

Because of globalization, financial markets have become more correlated than ever before. As a consequence, the benefits of international diversification across the financial markets have been reduced (Moghadam & Viñals, 2010). At the same time, sectoral equities are found showing an independent movement, thereby providing opportunities for diversification of risk through sectoral portfolio investments (Elyasianiet al., 2011). Mericet al. (2008) show that in a bull market more benefits are associated with international diversification, even if investments are made in the same sector in different countries, than with domestic diversification across sectors in the same country. Also in a bear market sectoral diversification opportunities across countries emerge, because the transition of the economies to a crisis is either non-synchronised, wherein few sectors are least affected (Alexakis & Pappas, 2018), or the responses of sectoral markets to an investment shock are heterogeneous (Kim & Sun, 2017). Generally, sectoral dynamics are endogenous to economic growth and, in a growing economy, diversification to new modern sectors first increases and later decreases. With such dynamics, the modern sectors should substitute and not complement the traditional sectors in the overall economic growth equilibrium (Zeira & Zoabi, 2015).

For an economy being oil importing or oil exporting, the extent that the sectoral equity market dynamics are affected by oil price changes depends on whether oil is an input or output for the particular sectors (Gogineni, 2010). The sectoral reactions to oil price changes are heterogeneous and they tend to become intensive in the case of extreme price movements. Degiannakis et al. (2013) and Mensi et al. (2017a) find time-varying and sector-specific impacts of the oil price on sectoral equity. This poses a problem for investors, portfolio managers, and policy makers. The unobserved variable behind the dynamics between the oil price and sectoral equity is the effect of economic growth on the demand side, as oil is a crucial commodity for economic development. In a high economic growth regime, it is possible for firms of the respective sectors to pass on hikes in the oil price to consumers, because of the pricing power they enjoy during such a growth regime. On the contrary, it is rather difficult to pass-through price increases in a low economic growth regime. Hence, the positive relationship between oil price changes and sectoral equity in a high economic growth regime may change to an insignificant or even negative relationship in a low economic growth regime.

Since the dependence between oil prices and sectoral indices depends on unobserved state variables, we, for the first time, apply the novel dependence-switching copula approach of Wang et al. (2013) to study this relationship. Their copula strongly replicates the actual markets by allowing the dependence structure to vary between positive and negative regimes. The conventional Pearson correlation is unsuitable for examining such dependence because it provides equal weight to both positive and negative returns, as well as large and small realisations. This therefore leads to the underestimation of risk from joint extreme events (Poon et al., 2004; Tastan, 2006). Several studies use multivariate-GARCH models (Ang & Chen, 2002; Dungey & Martin, 2007), the extreme value approach (Bae et al., 2003; Cumperayot et al., 2006), or regime-switching models (Ang & Chen, 2002) to overcome the concerns with the Pearson correlation. Since these studies consider symmetric multivariate normal distribution or Student's t-distribution, they do not examine the asymmetric tail dependence of the markets (Garcia & Tsafack, 2011; Patton, 2006).

Many studies have used copula models to understand movements across markets (e.g. Ning, 2010; Meng and Liang, 2013; Reboredo & Ugolini, 2015; Kleinow & Moreira, 2016; Lourme & Maurer, 2017; Pircalabu & Benth, 2017; Ji et al., 2018). A copula is a multivariate cumulative distribution function with uniform marginal distributions on the interval (0, 1). It allows estimation of the dependence structure between multivariate random variables. Some researchers argue that a time-invariant copula is not appropriate to capture actual relations, and therefore allow the parameters to change in the copula function (Busetti & Harvey, 2010; Lourme & Maurer, 2017) or allow the copula function itself to change over time (Okimoto, 2008). The latter technique is more suited to estimate dependence switching between different financial markets because allowing the parameters in the copula function to change with time, as in the former technique, does not necessarily suggest dependence switching between negative and positive correlation regimes.

In this paper, we argue that conditional correlations between oil and sectoral equity markets change between negative and positive regimes. As such, we employ a time-varying dependence-switching copula to examine dependence across these markets for a number of reasons. First, by combining the Clayton copula (which captures left side dependence) with the survival copula (which captures right side dependence), we allow for asymmetric tail dependence. Second, we allow the dependence structure across oil and sectoral equity markets to fluctuate between positive and negative correlation regimes which simulate the real world where dependence can vary. Finally, we measure the tail dependence structure across the various market conditions of rising oil prices—rising sectoral equity markets, falling oil prices—falling sectoral equity markets, rising oil prices—falling sectoral equity markets, and falling oil prices—rising sectoral equity markets.

Furthermore, as pointed out by Huang et al. (2005), the stock market is negatively affected by changes in the crude oil price only when it crosses a threshold level. Similarly, investors are more concerned about extreme price changes (Barber & Odean, 2008). The consideration of tail dependency helps achieve a better portfolio diversification than a portfolio based on the traditional mean–variance optimization (Trabelsi, 2017). Moreover, there is a risk premium attached to oil price changes, which is systematically priced into stock prices (Christoffersen & Pan, 2017; Demirer et al., 2015). Thus, using the results of the best fit copula, our study is the first to estimate the systemic oil price risk spillover to different sectors using the conditional value-at-risk (CoVaR) and delta CoVaR by following Adrian and Brunnermeier (2016).

With this backdrop, our study is also the first in the context of India, one of the fastest growing emerging economies and the third biggest oil consuming country. In its yearly report, the International Monetary Fund (IMF, 2018) pointed out that India will be a key player in global growth. Concurrently, the IMF articulated its concern, citing among other economic risk factors, that the oil price risk may be a headwind for the Indian economic growth. India ranks third, after the US and China, in the world oil consumption. 80% of its oil use is imported, making India the fourth largest oil importing country in the world (MCX India, 2017). In the near future, the demand for oil is expected to be further increased by energy-intensive economic growth. This growth is driven by the manufacturing sectors' expansion, stimulated through the Make-in-India campaign initiated by the Indian Government to make India a manufacturing hub.[1]

We consider daily closing prices for crude oil and 16 sectoral indices. Our results reveal that in a positive correlation regime, the dependence and tail-dependence between the sectoral indices and the oil price are asymmetric and symmetric, respectively. However, in a negative correlation regime, both dependence structures are asymmetric. The average sectoral CoVaR is positive across the sectors and greater than the corresponding VaR. The CoVaR fleets over

[1] The Indian government has launched the Make-in-India campaign in order to increase the share of the manufacturing sectors' contribution to the GDP by 25% by the year 2020.

time, implying that a bearish oil market does not add additional systemic risk to a bearish sectoral equity market. The carbon sector is found to be the safe haven investment when both the oil and equity markets are in a downward phase. As far as the oil price risk is concerned, our results will help achieving better sectoral portfolio diversification and improve the economic policymaking by initiating sectoral policy rather than a common policy for all sectors.

The remaining work is structured as follows. Section 2 discusses the literature and further highlights the importance of our study. Section 3 explains the methodology. While Sect. 4 provides an overview of the data, Sect. 5 presents the main results. Section 6 concludes.

2 Literature review

A large number of studies in the extant literature has analysed the economic impact of oil price changes. These studies find that the impact is economy-specific, because the degree of oil dependence is distinct (Nandha & Brooks, 2009; Ramos & Veiga, 2011). In a broader market context, not only a positive impact of oil price changes (Arouri & Rault, 2012; Li et al., 2012), but also a negative (Miller & Ratti, 2009; Sadorsky, 1999) and no impact (Apergis & Miller, 2009; Huang et al., 1996) are found in the literature.

Few studies examine the influence of the oil price on equity markets by classifying the countries as oil importing and exporting nations. For oil importing economies, negative effects of the oil price on equity markets are reported by Sadorsky (1999) and Arouri and Nguyen (2010). Aloui et al. (2012), who analyse 25 emerging net oil importing countries including India, find no impact of the oil price on the stock market. However, stock markets of oil exporting countries tend to be significantly positively influenced by oil price increases (Aloui et al., 2012; Nandha & Faff, 2008). In another set of literature, the impact of the oil price on the stock market is studied by differentiating between supply- and demand-driven oil price shocks (Filis et al., 2011; Jammazi, 2012b). While the impact of demand shocks is positive, supply-driven shocks are reported to have mixed impacts on the equity market. Moreover, Filis et al. (2011) and Jammazi (2012a) report a dynamic effect of the oil price on the equity market. Similarly, Martín-Barragán et al. (2015) find that the correlation between the oil and stock market is dynamic. While the correlation is insignificant during normal times, it becomes significant due to a shock from either the oil market or stock market or both.

At the sectoral level, researchers have differentiated between sectors where oil is a major input and those where it is predominantly an output. For sectors where oil is an input (output), such as the automobile, transport, and airline industry (oil and gas industry), the effect tends to be harmful (affirmative). However, the strength of the association with oil price changes is heteroskedastic across industries (Boyer & Filion, 2007; Ramos & Veiga, 2011). The industry-specific influences of the oil price and the simultaneous time-varying correlations provide sectoral portfolio investment and diversification opportunities across sectors and over different investment horizons (Degiannakis et al., 2013; Nandha & Faff, 2008).

Kirkulak-Uludag and Safarzadeh (2018) examine the volatility spillover between six Chinese sectoral indexes and the OPEC oil price using the VAR-GARCH model. They find unidirectional volatility spillover from the oil to the sectoral markets. Thereby, they assume that the results hold in extreme market conditions of both the oil and sectoral indexes. Using the VAR model in the context of G-7 countries, Lee et al. (2012) find no impact of the oil price at the composite index level, while oil price changes have a negative causal effect on sectoral market returns. However, they consider only the average effect of the oil price, which is assumed to hold in all types of market conditions. Emphasizing the non-linear oil-stock relationship, Badeeb and Lean (2018) explore the asymmetric effect of oil on the Islamic equity market using the NARDL co-integration framework. The oil price linkage is weak at the aggregate market level, but the sectoral level reactions to oil price shocks are significantly different from each other and non-linear in the long run. Although their study captures the long and short run asymmetry, it does not consider the nature of asymmetry associated with extreme market conditions.

As far as the Indian context is concerned, only few studies have investigated the link between oil prices and equity markets, looking at both the aggregate and the sector-specific equity markets. For example, Ghosh and Kanjilal (2016) report a unidirectional causality from oil prices to the aggregate equity market without having any correlation between them. Singhal and Ghosh (2016) examine the effect of Brent oil on the Bombay Stock Exchange (BSE) Sensex at the aggregate level and on seven sectoral indices. They find no volatility spillover at the aggregate level, but oil price spillover are found in three out of seven sectors, namely in the automotive, power, and financial sector. However, the co-movement between the oil price and the seven indices is time-varying and persistent. Ali and Masih (2014) examine the impact of the oil price on 15 sectors using the DCC–GARCH and CWT methodology. They find that the correlations among oil prices and all the sectoral indices are time-varying and positive after the financial crisis. In terms of the data used, Tiwari et al. (2018) is the closest to our study. They analyse the impact of the oil price on 13 sectors, applying the QRA and frequency domain methodology. Their results show that in all market conditions, nine of the sectors are not affected by the oil price. However, Tiwari et al. (2018) capture the oil price impact in the extreme condition of the sectoral market only, whereas the oil market extreme conditions are ignored.

In terms of methodology, the work of Trabelsi (2017) is the closest to our analysis. Yet, his study focuses on the major oil exporting country Saudi Arabia, whereas ours is on the major oil importing country India. Trabelsi (2017) explores the potential asymmetry in tail dependency between the international oil market and the Saudi Arabian sectoral market using a time-varying copula. He reports an asymmetric effect of the oil price in the left tail in all sectors, except for the petrochemical, agricultural, and food sector. So far, there exists no study on an oil importing nation that explores the extreme asymmetry between oil and sectoral market returns. We use the dependence-switching copula to estimate the tail dependence asymmetry among oil prices and16 sector pairs. Moreover, based on the best fit copula results, the study is the first to estimate systemic downside oil price risk spillovers to different sectors using the CoVaR and delta CoVaR approach by following Adrian and Brunnermeier (2016). Though very limited, the copula approach has been applied in the financial literature in the context of BRICS stock and foreign exchange markets (Kumar et al., 2019), symmetric tail dependence to the crude oil market (Reboredo, 2011), the crude oil and Asia–Pacific stock market (Zhu et al., 2014), the Chinese and US stock markets (Wen et al., 2012), and the oil and European equity markets (Aloui et al., 2013).

3 Methodology

3.1 Copula specification

As mentioned at the outset, the dependence structure between the oil price (X_1) and sectoral equity index (X_2) is examined using the copula in a time-varying and dependence-switching framework. Then the risk spillover between the oil price and sectoral equity market is estimated using the CoVaRs and delta CoVaRs from their joint distribution.

The bivariate joint distribution function $F_{X_1X_2}(x_1, x_2)$ for two random variables is examined using a copula. According to Sklar's theorem (Sklar, 1959), this copula function is obtained by transforming the marginal distributions into uniform distributions. Thus, a copula function C can be represented as:

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

where $F_K\left(X_{K,t}; \delta_K\right)$, with K = 1, 2, is the marginal cumulative distribution function of $X_{K,t}$ and δ_K, while θ^c are the parameter sets of $F_K\left(X_{K,t}; \delta_K\right)$ and C.

If each of the cumulative distributions are differentiable, then

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

where $f\left(X_{1,t}, X_{2,t}; \delta_1, \delta_{2;}\theta^c\right) = \partial F^2\left(X_{1,t}, X_{2,t}; \delta_1, \delta_{2;}\theta^c\right)/\partial X_{1,t}\partial X_{2,t}$ is the joint density of $X_{1,t}$ and $X_{2,t}$. $u_{k,t}$ is the probability integral transformation of $X_{K,t}$ based on $F_K\left(X_{K,t}; \delta_K\right)$, with K = 1, 2. $C\left(u_{1,t}, u_{2,t}; \theta^c\right) = \partial C^2\left(u_{1,t} - u_{2,t}, \theta^c\right) = \partial C^2\left(u_{1,t}, u_{2,t}; \theta^c\right)/_{\partial u_{1,t}\partial u_{2,t}}$ is the copula density function, and, finally, $F_K\left(X_{K,t}; \delta_K\right)$ is the marginal density of $X_{K,t}$,where K = 1, 2.

The co-movement of the oil price and sectoral index prices can be positive (Return chasing) or negative (Portfolio rebalancing). One of the effects can potentially be dominant at different times, implying that the two series under consideration may switch from a positive to a negative dependence regime or vice-versa. In order to account for the two dependence regimes, we use the Markov-switching copula model, where the latent variables are set in both the copula function and the marginal models.

The designed copula model looks as follows:

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

where S_t is an unobserved state variable, whereas $C_1\left(u_{1,t}, u_{2,t}; \theta_1^C\right)$ and $C_0\left(u_{1,t}, u_{2,t}; \theta_0^C\right)$ are two copula functions, which mix the Clayton Copula (C^c) and the Survival Clayton copula (C^{SC}) with the positive and negative dependence structures correspondingly.[2] Hence,

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

and

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

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

[2] Wang et al. (2018) argued that, although as a substitute, the Gumbel copula could be explored, but it was not found to be suitable according to the AIC.

$\rho_2(\rho_3)$ estimates the dependence of a high oil price and high (low) sectoral equity index, and $\rho_1(\rho_4)$ estimates the dependence of a low oil price and low (high) sectoral equity index. Consequently, $\varphi_2(\varphi_3)$ estimates the dependence of very high oil prices with very high (low) sectoral equity index prices. $\varphi_1(\varphi_4)$ estimates the dependence of very low oil prices with very low (high) sectoral equity index prices.

The transition probability matrix of the latent variable S_t, which follows the Markov-switching process, is depicted below:

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

where $p_{ij} = 1 - p_{11}\Pr[S_t = j|S_{t-1} = i|]$ for I, j = 0, 1. S_t changes between the two regimes explained above. Its bivariate density function is:

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

Transforming Eq. (5) into log-likelihood gives:

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

where $\vartheta = \left(\theta_c^1, \theta_c^0, \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, p_{11}, p_{00}\right).L_c(\varphi_1)$ and $L_k(\varphi_{2,k})$ standforthe log of the copula density and the marginal density of X_k, respectively. They can be represented as:

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

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

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

3.2 Marginal models

The ARFIMA (p, dm, q) model for a stationary time series r_t, $t = 1, \ldots, T$ may be expressed as follows:

$$\varphi(L)(1 - L)^d (r_t - \gamma) = \omega(L) \in_t, \quad \in_t \sim i.i.d.\left(0, \sigma_\in^2\right) \tag{7}$$

where $\epsilon_t = \zeta_t\sigma_t; \zeta_t \sim (0, 1)$. γ is the restrictive average, L is the backward-shift operator and $(1 - L)^d$ is the fractional differencing operator. $\varphi(L) = \varphi_1 L + \varphi_2 L^2 + \cdots + \varphi_T L^T$ and $\omega(L) = \omega_1 L + \omega_2 L^2 + \cdots + \omega_s L^s$ are the AR and MA polynomials. When dm > 0, in Eq. (7), we say that the process has a long memory. When $0 \le dm \le 0.5$, we say that the series is covariance stationary and mean reverting. If $0.5 \le dm \le 1.0$, the series is mean reverting but not covariance stationary, because no long run effect of a novelty on future values of the process is seen. Finally, if $dm > 1.0$, we say that the series is non-stationary and non-mean reverting, and if $-0.5 \le dm \le 0.0$, the series is known to display transitional memory.

The GARCH (p,q) model of Bollerslev (1987) may be written as:

$$r_t = \phi + \in_t$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \in_{t-\mathrm{i}}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{8}$$

where ϕ is the likely return and ϵ_t is an IID term. The ω is a constant, ϵ_{t-i} is the ARCH and σ_{t-j}^2 is the GARCH component, and the number of lags (p, q) are chosen using the AIC.

3.3 Computation methodology

According to the Canonical Maximum Likelihood (CML) approach, the standardized residual is transformed into an identical distribution as:

$$F_i(\omega) = \frac{1}{T+1} \sum_{i=1}^{T} I\left(\upsilon_{i,t}^{S_t} \leq \omega\right) \tag{9}$$

where I(·) is a dual function, which is equal to 1 when $\upsilon_{i,t}^{S_t} \leq \omega$ holds or 0 otherwise. Subsequent to this, the function is estimated for all parameters $\hat{\upsilon}_{i,t}^{S_t}$ and denoted by $\hat{\mu}_{i,j}^{S_t} = \widehat{F}_k\left(\hat{\mu}_{i,j}^{S_t}\right)$, with $i = 1,2; j = 1, 2,\ldots, T$; and $S_t = 0, 1$.

We apply the Hamilton's filtered technique and the process is shown as:

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

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

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

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

where "o" is defined as the Hadamard product and μ^{S_t} indicatesthe density function for S_t = 0, 1. The parameters' vector $\theta = \left(\theta_c^1, \theta_c^0, \delta_1^1, \delta_1^0, \delta_2^1, \delta_2^0, p_{11}, p_{00}\right)$ is then estimated by maximizing $L(\theta)$:[3]

$$\theta = \arg\max_{\theta} \sum_{t=1}^{T} L(\theta) \tag{10}$$

Sequel to the estimation of the parameters, the time-varying dependence of the oil prices and sectoral index prices can be formed. We hypothesize that $E(c_1(u_1, u_2)) = \int_0^1\int_0^1 c_1(u_1, u_2) dc_1(u_1, u_2)$, and Kendall's τ in the positive correlation regime is:

$$\tau^1 = \omega_1[\propto_1 /2+ \propto_1] + (1-\omega_1)[\propto_2 /2+ \propto_2] \tag{11}$$

Similarly, the Kendall's τ in the negative correlation regime is:[4]

$$\tau^0 = \omega_2[\propto_3 /2+ \propto_3] + (1-\omega_2)[\propto_4 /2+ \propto_4] \tag{12}$$

[3] Wang et al. (2018) argued that it is better to use the simplex search method, in order to avoid an arbitrary initial value to obtain the $\theta\left(\hat{\theta}_0\right)$. We can then use the initial value of the MLE estimates of $\theta\left(\hat{\theta}_0\right)$.

[4] For a comprehensive derivation of the Kendall's correlation and smoothing correlation of the mixed copula, see Wang et al. (2013, 2018).

During dissimilar correlation regimes, the correlation coefficient is computed as $\rho^j = \sin\left(\pi * \tau^j/2\right)$ for $j = 0, 1$, while the smoothing correlation ρ_{sm} is estimated as:

$$\rho_{sm} = \rho_{1,sm}\rho^1 - \rho_{0,sm}\rho^0 = \rho_{1,sm} * \sin(A) - \rho_{0,sm} * \sin(B) \tag{13}$$

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

3.4 Measures of systemic oil price risk spillover

Based on the copula results, the VaR and CoVaR are estimated. In line with the general literature, we limited our analysis to the downside risk (Girardi & Ergün, 2013; Ji et al., 2018). The VaR for the sectoral index return is computed as the worst loss for a fixed horizon that will be within the band of a pre-fixed level of confidence $1-\alpha$, where α denotes the tail probability. Hence, the downside VaR for a sectoral index return may be measured as $pr\left(r_{sec,t} \le VaR^{\alpha}_{sec,t}\right) = \alpha$. The first assumption is to put $\alpha = 0.05$. Using the GJR-GARCH (p,q) skewed-t model for sectoral stock markets, we estimate the $VaR^{\alpha}_{sec,t} = \mu_{sec,t} + \sigma_{sec,t}.t^{-1}_{\upsilon,\eta}(\alpha)$, where $t^{-1}_{\upsilon,\eta}(\alpha)$ is the α quantile of Eq. (8).

Subsequent to the VaR, the CoVaR is used to compute the risk spillover from the oil to the sectoral markets. The CoVaR is the VaR for sectoral market returns based on severe oil price fluctuations, captured in the VaR. The advantage of the CoVaR over the VaR is the ability of the former in measuring the tail dependence and severe risk spillovers.

In addition, the upside and downside CoVaRs are computed as the VaR of sectoral market returns based on unknown severe fluctuation in the oil price returns. Given a bivariate time series $r_t = (r_{sec,t}, r_{oil,t})$, the downside CoVaR of sectoral returns conditional on severe downward fluctuation of the oil price returns and the upside CoVaR of sectoral returns conditional on severe upward oil price returns are determined using lower and upper tail dependences:

$$pr\left(r_{sec,t} \le CoVaR^{D,\alpha}_{secoil.D,t|}|r_{oil,t} \le VaR^{D,\beta}_{oil,t}\right) = \alpha \tag{14}$$

and

$$r\left(r_{sec,t} \ge CoVaR^{U,\alpha}_{sec|oil.U,t}|r_{oil,t} \ge VaR^{U,\beta}_{oil,t}\right) = \alpha, \tag{15}$$

where $pr\left(r_{oil,t} \le VaR^{D,\beta}_{oil,t}\right) = \beta$ and $pr\left(r_{oil,t} \ge VaR^{U,\beta}_{oil,t}\right) = \beta$, while β represents the tail probability of uncertainty changes $r_{oil,t}$. We represent the CoVaR for sectoral returns in the copula form below:

$$C\left(F_{sec,t}\left(CoVaR^{\alpha}_{sec,t}\right), F_{oil,t}\left(VaR^{\beta}_{oil,t}\right)\right) - \beta\alpha = 0, \tag{16}$$

where $F_{sec,t}$ and $F_{oil,t}$ are the marginal distribution of the sectoral prices and oil prices, respectively.

Further, we use the delta CoVaR as another measure of risk spillover from oil returns to sectoral market returns that is defined as:

$$deltaCoVaR^{\alpha}_{sec,t} = \frac{\left(CoVaR^{\alpha}_{sec,t} - CoVaR^{\alpha\beta=0.5}_{sec,t}\right)}{CoVaR^{\alpha\beta=0.5}_{sec,t}}, \tag{17}$$

where the $CoVaR^{\alpha\beta=0.5}_{sec,t}$ satisfies that $pr\left(r_{sec,t} \le CoVaR^{\alpha}_{sec,t}\middle|F_{oil,t}(r_{oil,t}) = 0.5\right) = \alpha$, with $F_{oil,t}(.)$ being the distribution function of $r_{oil,t}$.

We perform three statistical tests. First and second, we analysethe two risk spillover impacts with $H_{11}: CoVaR^{D,\alpha}_{sec|oil.D} < VaR^{D,\alpha}_{sec}$ and $H_{12}: CoVaR^{U,\alpha}_{sec|oil.U} < VaR^{U,\alpha}_{sec}$. $H_{11}(H_{12})$ assumes considerable differences between the CoVaR and the respective VaR. Third, we test for an asymmetric effect using $H_{13}: \frac{CoVaR^{D,\alpha}_{sec|oil.U}}{VaR^{D,\alpha}_{sec}} > \frac{CoVaR^{U,\alpha}_{sec|oil.U}}{VaR^{U,\alpha}_{sec}}$. H_{13} suggests that the rise in downside sectoral market risk is comparatively higher than the upside risk, when the likelihood of uncertain price changes in the oil market is very high.

4 Data and preliminary statistics

Daily closing price data of 16 sectoral indices are taken from the Bombay Stock Exchange (BSE) of India for the period starting from the date of their availability up to May 21, 2018 (Refer to Table 1). The daily WTI crude oil prices are extracted from the U.S. Energy Information Administration (2018). We calculate the daily returns by subtracting the natural log of the previous prices from the natural log of the current prices. Table 1 presents the descriptive statistics for the oil and sectoral returns series. The standard deviations for all returns series are larger compared to their respective average values, indicating larger risks in these indices. The skewness values are less than zero for every index, except for GreenX and Capital goods, and the kurtosis is greater than three, implying asymmetric and fat tails. In addition, the Jarque–Bera test significantly rejects the normality hypothesis. We use the ADF and PP unit root tests and the KPSS stationarity test to check the stationarity of the selected series. All return series are found to be stationary. Since the data might have undergone structural changes due to economic or geopolitical factors in the global context, we further check the stationarity using a structural break unit root test, i.e. the Zivot-Andrew (1994) test. The results, as shown in the last two columns in the Table, pass the stationarity test even under structural breaks in the data.

5 Main empirical results

5.1 GARCH estimation results for the marginal distribution models

It is highly important to identify the best specification of the marginal copula model, as we otherwise may not obtain unbiased estimations. Therefore, we examine various lags of the ARFIMA (p,d_m,q)-GARCH (1,1) model, to investigate empirically the dynamic behaviour of the volatility of each of the 16 sectoral indices of the BSE with the oil price. The best order of p and q is selected based on the AIC and correlation in the standardized error terms ($Q(10)$) as well as in the squared standardized error terms ($Q^2(10)$), by keeping the maximum order of p as 10 and for q as 5. Table 2 presents the findings. The restricted mean factor is significant at the 5% level in more than half of the cases and the slope factors in the restricted variance equation are also significant. The null hypothesis of $d_m = 0$, i.e. short term memory in the mean, is rejected for five out of 16 sectors, namely for the Metal, Bank, Energy, Carbon, and Capital sectors. This shows the short efficiency in those five sectors, which could be attributed to active trading in the component stocks and high correlation with the economy. The presence of autocorrelation is ruled out through the results of the $Q(10)$ and $Q^2(10)$ values. The result of the ARCH-LM statistic fails to reject the null hypothesis of no ARCH effect for any of the 16 sectors. Overall, the reported diagnostic results on the residual show that, except for one series, autocorrelation and heteroscedasticity have been correctly

Table 1 Summary statistics

Indices	Sample period starts on	Mean	Max	Min	SD	Skew	Kurt	J–B	N	Zivot–Andrews	*p*-value
Carbon	04/10/2010	− 0.0003	0.035	− 0.064	0.010	− 0.285	4.770	263.67***	1830	− 38.958	0.030**
GreenX	06/10/2008	0.0000	0.152	− 0.122	0.013	0.087	17.29	19,612***	2305	− 23.159	0.006***
Power	05/01/2005	0.0000	0.167	− 0.177	0.017	− 0.249	13.78	15,558***	3208	− 52.491	0.001***
Utility	20/09/2005	0.0001	0.153	− 0.262	0.017	− 1.143	27.81	78,782***	3045	− 52.706	0.000***
Material	20/09/2005	− 0.0002	0.124	− 0.185	0.018	− 0.539	10.92	8103.4***	3045	− 36.125	0.010**
Industrial	20/09/2005	0.0000	0.166	− 0.136	0.017	− 0.097	10.19	6568.1***	3045	− 47.521	0.007***
Energy	20/09/2005	0.0000	0.174	− 0.226	0.018	− 0.802	19.84	36,318***	3045	− 33.897	0.000***
CDG	20/09/2005	− 0.0004	0.111	− 0.185	0.014	− 0.997	17.99	29,022***	3045	− 34.721	0.000***
Bank	04/01/2002	− 0.0003	0.171	− 0.135	0.019	− 0.059	9.357	6625.5***	3933	− 29.884	0.011**
Metals	03/02/1999	0.0000	0.147	− 0.197	0.022	− 0.268	7.796	4497.3***	4634	− 61.873	0.015**
IT	03/02/1999	− 0.0003	0.175	− 0.223	0.023	− 0.259	11.37	13,584***	4634	− 30.860	0.004***
Oil & Gas	03/02/1999	− 0.0001	0.174	− 0.230	0.018	− 0.572	14.83	27,262***	4634	− 31.762	0.002***
FMCG	03/02/1999	− 0.0002	0.115	− 0.141	0.014	− 0.174	9.907	9234.6***	4634	− 31.083	0.030**
Consumer	03/02/1999	− 0.0004	0.121	− 0.170	0.019	− 0.251	8.048	4969.7***	4634	− 36.868	0.005***
Capital	03/02/1999	− 0.0003	0.193	− 0.147	0.018	0.105	9.294	7657.3***	4634	− 32.015	0.000***
Auto	03/02/1999	− 0.0002	0.104	− 0.137	0.015	− 0.233	7.166	3392.4***	4634	− 60.579	0.000***
Oil	03/02/1999	− 0.0002	0.166	− 0.153	0.024	− 0.056	7.522	3353.6***	4634	− 69.914	0.028**

J–B is the Jarque–Bera normality test. ***denotes rejection of the null hypothesis at the 1% level of significance. The Zivot–Andrews unit root test is a test of stationarity with the null hypothesis that there exists a unit root with structural breaks in the intercept and trend. ** and *** indicate the rejection of the null hypothesis at the 5% and 1% level of significance. The sample period ends on May 21, 2018 for each time-series

Table 2 Parameter estimates for the marginal distribution models

	Carbon	Oil	GreenX	Oil	Power	Oil	Utility	Material	Industrial	Energy	CDG	Oil
Cst(M)	0.00***	0.000	0.00***	0.000	0.000	0.000	0.000	0.001**	0.001***	0.00***	0.00***	0.000
	(0.001)	(0.841)	(0.003)	(0.639)	(0.338)	(0.201)	(0.393)	(0.033)	(0.006)	(0.006)	(0.000)	(0.314)
d-Arfima	− 0.08**	0.014	− 0.051	0.008	0.00	0.013	− 0.01	0.012	− 0.002	− 0.044*	− 0.007	0.016
	(0.046)	(0.663)	(0.125)	(0.808)	(0.929)	(0.601)	(0.625)	(0.646)	(0.934)	(0.083)	(0.809)	(0.551)
AR(1)	0.17***	− 0.039	0.13***	− 0.015	0.08***	− 0.032	0.07**	0.077**	0.144***	0.09***	0.14***	− 0.036
	(0.000)	(0.338)	(0.001)	(0.706)	(0.006)	(0.320)	(0.030)	(0.013)	(0.000)	(0.005)	(0.000)	(0.263)
Cst(V)	0.591	0.023	0.01***	0.024**	0.05***	0.026**	0.03***	0.06***	0.063***	0.04***	0.04***	0.028**
	(0.095)	(0.097)	(0.007)	(0.040)	(0.001)	(0.028)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.030)
ARCH($\alpha 1$)	0.04***	0.06***	0.05***	0.06***	0.10***	0.05***	0.08***	0.09***	0.112***	0.07***	0.10***	0.06***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GARCH($\beta 1$)	0.96***	0.94***	0.94***	0.94***	0.88***	0.94***	0.91***	0.89***	0.867***	0.91***	0.88***	0.94***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asymmetry	− 0.051	− 0.1***	− 0.07**	− 0.07**	− 0.13***	− 0.048*	− 0.13***	− 0.11***	− 0.11***	− 0.050	− 0.12***	− 0.054
	(0.085)	(0.010)	(0.025)	(0.013)	(0.000)	(0.055)	(0.000)	(0.000)	(0.000)	(0.081)	(0.000)	(0.054)
Tail	8.88***	6.44***	8.44***	7.36***	5.90***	7.70***	6.05***	7.50***	6.66***	7.18***	6.72***	8.30***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LL	5979	4730	7200	5751	9198	7958	8850	8472	8615	8618	9259	7580
Q(10)	4.771	9.882	10.11	8.673	19.10**	7.253	25.8***	21.92***	16.62	15.68	22.67***	8.394
	(0.854)	(0.360)	(0.342)	(0.468)	(0.024)	(0.611)	(0.002)	(0.009)	(0.055)	(0.074)	(0.007)	(0.495)
$Q^2(10)$	11.71	7.292	14.08	7.474	4.924	6.588	1.924	6.869	7.911	8.444	10.11	6.774
	(0.165)	(0.505)	(0.080)	(0.486)	(0.766)	(0.582)	(0.983)	(0.551)	(0.442)	(0.391)	(0.257)	(0.561)
ARCH (5)	0.7913	0.8553	0.3364	1.1413	0.1593	1.157	0.0931	1.1607	0.8988	1.509	1.7242	1.1403

Table 2 (continued)

	Carbon	Oil	GreenX	Oil	Power	Oil	Utility	Material	Industrial	Energy	CDG	Oil
	(0.558)	(0.511)	(0.891)	(0.336)	(0.977)	(0.3278)	(0.9933)	(0.3261)	(0.481)	(0.1835)	(0.1255)	(0.3366)
N	1831	1831	2306	2306	3209	3209	3046	3046	3046	3046	3046	3046

	FMCG	Consumer	Capital	Auto	Metals	IT	Oil & Gas	Oil	Bank	Oil
Cst(M)	0.00***	0.001***	0.00***	0.00***	0.001	0.00***	0.001***	0.001**	0.00***	0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.105)	(0.000)	(0.000)	(0.046)	(0.000)	(0.090)
d-Arfima	− 0.030	0.018	0.036**	0.002	0.035	− 0.029	− 0.025	0.000	− 0.040	0.012
	(0.103)	(0.314)	(0.041)	(0.902)	(0.068)	(0.123)	(0.197)	(0.988)	(0.077)	(0.604)
AR(1)	0.058**	0.052**	0.07***	0.11***	0.06**	0.07***	0.086***	− 0.027	0.14***	− 0.044
	(0.015)	(0.018)	(0.001)	(0.000)	(0.013)	(0.002)	(0.000)	(0.280)	(0.000)	(0.123)
Cst(V)	0.06***	0.073***	0.07***	0.05***	0.13***	0.038	0.051***	0.029**	0.03***	0.031**
	(0.002)	(0.005)	(0.000)	(0.002)	(0.000)	(0.141)	(0.000)	(0.011)	(0.008)	(0.015)
ARCH(α1)	0.09***	0.096***	0.11***	0.15***	0.10***	0.085**	0.079***	0.049***	0.07***	0.05***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH(α2)				− 0.07**						
				(0.016)						
GARCH(β1)	0.88***	0.89***	0.87***	0.91***	0.87***	0.91***	0.90***	0.95***	0.92***	0.94***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asymmetry	0.000	0.001	− 0.003	− 0.028	− 0.032	0.026	− 0.008	− 0.08***	0.023	− 0.06***
	(0.994)	(0.942)	(0.900)	(0.177)	(0.109)	(0.205)	(0.722)	(0.000)	(0.299)	(0.005)
Tail	5.16***	4.93***	6.21***	8.01***	6.40**	4.65***	6.45***	6.90***	6.83***	7.70***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 2 (continued)

	FMCG	Consumer	Capital	Auto	Metals	IT	Oil & Gas	Oil	Bank	Oil
LL	13,831	12,380	12,612	13,228	11,772	12,117	12,750	11,183	10,695	9645
Q(10)	10.69	16.56	22.67	13.01	18.38**	10.19	17.120**	4.459	14.95	5.928
	(0.298)	(0.056)	(0.007)	(0.162)	(0.031)	(0.335)	(0.047)	(0.879)	(0.092)	(0.747)
$Q^2(10)$	14.71	6.931	14.79	5.658	10.26	6.372	12.63	14.05	12.23	7.941
	(0.065)	(0.544)	(0.063)	(0.580)	(0.247)	(0.606)	(0.125)	(0.081)	(0.141)	(0.439)
ARCH (5)	1.9585	0.9516	1.9033	0.95235	1.9185	0.51759	2.1554	2.1929	1.3106	1.1678
	(0.0816)	(0.4462)	(0.0904)	(0.4458)	(0.0879)	(0.7632)	(0.0562)	(0.0523)	(0.2563)	(0.3244)
N	4635	4635	4635	4635	4635	4635	4635	4635	3934	4635

The numbers in parentheses are *p*-values. *** and ** denote significance at the 1% and 5% level of significance, respectively. Because Utility, Material, Industrial, Energy and CDG have the same number of observations, the single GARCH model for Oil with 3046 observations is estimated and presented in the last column of this Table

The numbers in parentheses are *p*-values. *** and ** denote significance at the 1% and 5% level of significance, respectively. Because FMCG, Consumer, Capital, Auto, Metals, IT, and Oil &Gas have the same number of observations, the single GARCH model for Oil with 4635 observations is estimated and presented in the third-last column of this Table removed in the selected ARFIMA (p, $d_{m,}q$)–GARCH (1,1) specification. Therefore, we now assess the copula models.

5.2 Estimating the copula functions

In this section, we first estimate various single-copula functions. Specifically, these are the Normal copula, Student-t copula, and 4 different specifications of the Clayton copula, namely the Clayton copula, the Rotated Clayton copula, and two Rotated Clayton copulas (half rotated). Table 3 reports the findings and, as a measure of the evaluation, the log-likelihood value (LL), AIC, and BIC. When the Normal and Student-t copula are computed, the parameter estimates ρ of the copula are significant for all BSE sectoral indices at least at the 1% level. Conversely, for the single Clayton copulas, a measure of lower tail dependency, each parameter estimate α is significant for all indices. However, the dependency in the upper tail is counter-intuitive; because the parameter estimate α is significant for the Rotated Clayton copula for each of the sixteen sectors, while it is not significant for the half rotated Clayton copulas.

Out of all the copula models estimated, the half rotated Clayton copulas generate the highest log likelihood values while the Student-t copula has the smallest AIC and BIC for all sectoral indices and oil as found in Wang et al. (2013). The Student-t copula, however, is subject to the following two limitations. First, it assumes symmetric tail dependency, which is rejected by the Clayton copula. Second, it ignores the dynamics of positive and negative relationship regimes between the oil price and sectoral equity markets. Consequently, in order to allow for asymmetry and regime switching dependency, we study the dependence structure among the sectoral indices and the oil market using the dependence-switching copula model.

The results, which are presented in Table 4, indicate that the α_i are large for each sectoral index under the negative correlation regime. Nonetheless, almost half of them are insignificant in the positive correlation regime. It is noteworthy that almost all computed log-likelihood functions are larger compared to those reported in Table 3 for the single copula models for all sectoral indices. Similarly, all corresponding AIC and BIC estimates in Table 4 are smaller compared to those in Table 3. This adds more affirmation to our argument of applying a dependence-switching copula, rather than the single copula models, to understand the dependence framework among sectoral indices and the oil price. Moreover, the high values of the estimated transition probabilities P_{11} and P_{00} indicate longer durations of the correlation regimes.

An additional improvement is that this framework allows us to examine the dependence (ρ_i) and tail dependence (φ_i) for four market states, i.e. (a) bear oil markets coupled with bear stock markets, (b) bull oil markets coupled with bull stock markets, (c) bear oil markets coupled with bull stock markets, and (d) bull oil markets coupled with bear stock markets. A considerable tail dependence, measured by φ_i, would suggest a greater likelihood of extreme events, implying a higher approximation of the VaR compared to what is obtained from a Gaussian distribution. Therefore, not considering tail dependence may result in an underestimation of risk and knowledge about significant tail dependences is crucial for the estimation of the true VaR.

A positive correlation state represents two of the four states of the market, namely bear oil markets coupled with bear stock markets and bull oil markets coupled with bull stock markets. The left tail dependence (φ_3) signifies the likelihood of a greater loss in a bear-bear market (Case a), and the right tail dependence (φ_4) shows the likelihood of higher gains in a bull-bull market (Case b). If φ_3 (φ_4) is large, a long (short) position in the two markets would

Table 3 Estimates of the single-copula models: oil and BSE sectoral indices

	Carbon	GreenX	Power	Utility	Material	Industrial	Energy	CDG
Normal copula								
ρ	0.145***	0.204***	0.163***	0.171***	0.196***	0.158***	0.176***	0.160***
SE	(0.023)	(0.020)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)
LL	− 19.56	− 48.85	− 42.99	− 45.39	− 59.54	− 38.47	− 48.16	− 39.39
AIC	− 37.12	− 95.69	− 83.98	− 88.78	− 117.08	− 74.93	− 94.32	− 76.79
BIC	− 31.60	− 89.95	− 77.91	− 82.76	− 111.06	− 68.91	− 88.30	− 70.77
Student's t copula								
ρ	0.144***	0.187***	0.160***	0.168***	0.188***	0.151***	0.168***	0.155***
SE	(0.024)	(0.022)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
DoF	14.91***	4.508***	8.074***	7.832***	7.142***	7.433***	8.049***	7.283***
SE	(5.746)	(0.540)	(1.345)	(1.330)	(1.112)	(1.169)	(1.412)	(1.146)
LL	− 23.32	− 92.70	− 65.00	− 66.62	− 83.90	− 62.63	− 67.80	− 63.90
AIC	− 44.64	− 183.4	− 128.0	− 131.2	− 165.8	− 123.3	− 133.6	− 125.8
BIC	− 39.12	− 177.7	− 121.9	− 125.2	− 159.8	− 117.2	− 127.6	− 119.8
Clayton (u, v)								
α	0.189***	0.296***	0.211***	0.214***	0.250***	0.224***	0.235***	0.218***
SE	(0.031)	(0.030)	(0.023)	(0.024)	(0.025)	(0.024)	(0.024)	(0.024)
LL	− 24.53	− 69.90	− 53.90	− 51.54	− 67.52	− 58.30	− 62.75	− 54.39
AIC	− 47.05	− 137.8	− 105.8	− 101.1	− 133.0	− 114.6	− 123.5	− 106.8
BIC	− 41.54	− 132.1	− 99.73	− 95.05	− 127.0	− 108.6	− 117.5	− 100.8
Rotated Clayton copula (with tail dependence in upper tail instead of lower):Clayton (1 − u, 1 − v)								
α	0.118***	0.195***	0.150***	0.169***	0.194***	0.129***	0.157***	0.140***

Table 3 (continued)

	Carbon	GreenX	Power	Utility	Material	Industrial	Energy	CDG
SE	(0.029)	(0.028)	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)
LL	− 9.746	− 30.68	− 26.27	− 31.53	− 40.74	− 19.06	− 27.46	− 22.48
AIC	− 17.49	− 59.35	− 50.53	− 61.06	− 79.47	− 36.12	− 52.92	− 42.95
BIC	− 11.98	− 53.61	− 44.46	− 55.04	− 73.45	− 30.10	− 46.90	− 36.93
Rotated Clayton copula (half rotated):Clayton (1 − u, v)								
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SE	(0.027)	(0.023)	(0.019)	(0.020)	(0.022)	(0.020)	(0.022)	(0.020)
LL	0.020	0.029	0.035	0.034	0.041	0.031	0.038	0.030
AIC	2.039	2.059	2.069	2.069	2.083	2.062	2.075	2.061
BIC	7.551	7.801	8.142	8.090	8.104	8.083	8.096	8.082
Rotated Clayton copula (half rotated): Clayton (u, 1 − v)								
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SE	(0.027)	(0.024)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
LL	0.019	0.030	0.035	0.036	0.040	0.033	0.037	0.034
AIC	2.038	2.059	2.070	2.073	2.081	2.066	2.074	2.068
BIC	7.550	7.802	8.143	8.094	8.102	8.087	8.095	8.089

	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
Normal copula								
ρ	0.120***	0.110***	0.062***	0.101***	0.052***	0.059***	0.068***	0.068***
SE	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
LL	− 28.55	− 28.29	− 9.05	− 23.72	− 6.22	− 7.95	− 10.63	− 10.72

Table 3 (continued)

	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
AIC	− 55.09	− 54.59	− 16.10	− 45.44	− 10.44	− 13.91	− 19.26	− 19.43
BIC	− 48.82	− 48.14	− 9.66	− 39.00	− 4.00	− 7.47	− 12.82	− 12.99
Student's t copula								
ρ	0.115***	0.107***	0.065***	0.097***	0.048***	0.055***	0.064***	0.064***
SE	(0.017)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
DoF	6.380***	9.818***	8.659***	11.31***	11.78***	15.04***	11.56***	11.55***
SE	(0.789)	(1.721)	(1.323)	(2.185)	(2.443)	(3.723)	(2.243)	(2.291)
LL	− 68.39	− 47.20	− 34.31	− 39.41	− 19.26	− 16.98	− 26.02	− 24.88
AIC	− 134.8	− 92.39	− 66.62	− 76.83	− 36.53	− 31.95	− 50.04	− 47.75
BIC	− 128.5	− 85.95	− 60.17	− 70.39	− 30.09	− 25.51	− 43.60	− 41.31
Clayton (u, v)								
α	0.166***	0.141***	0.094***	0.128***	0.073***	0.075***	0.104***	0.092***
SE	(0.020)	(0.018)	(0.017)	(0.018)	(0.016)	(0.016)	(0.017)	(0.017)
LL	− 44.50	− 38.30	− 18.23	− 32.73	− 11.46	− 12.44	− 23.05	− 17.87
AIC	− 87.00	− 74.60	− 34.45	− 63.46	− 20.91	− 22.88	− 44.10	− 33.74
BIC	− 80.72	− 68.16	− 28.01	− 57.02	− 14.47	− 16.44	− 37.66	− 27.30
Rotated Clayton copula (with tail dependence in upper tail instead of lower):Clayton (1 − u, 1 − v)								
α	0.108***	0.095***	0.050***	0.086***	0.045***	0.052***	0.044***	0.057***
SE	(0.020)	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)
LL	− 18.39	− 17.11	− 4.981	− 14.346	− 4.205	− 5.483	− 4.041	− 6.606
AIC	− 34.77	− 32.22	− 7.96	− 26.69	− 6.41	− 8.97	− 6.08	− 11.21
BIC	− 28.49	− 25.78	− 1.52	− 20.25	0.03	− 2.52	0.36	− 4.77

Table 3 (continued)

	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
Rotated Clayton copula (half rotated):Clayton (1 − u, v)								
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SE	(0.017)	(0.016)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
LL	0.029	0.035	0.015	0.033	0.017	0.016	0.018	0.018
AIC	2.059	2.069	2.030	2.065	2.034	2.032	2.035	2.035
BIC	8.336	8.510	8.471	8.506	8.475	8.473	8.476	8.476
Rotated Clayton copula (half rotated): Clayton (u, 1 − v)								
Para	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SE	(0.017)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)
LL	0.027	0.034	0.014	0.030	0.011	0.020	0.021	0.022
AIC	2.054	2.069	2.027	2.061	2.023	2.040	2.043	2.045
BIC	8.331	8.510	8.468	8.502	8.464	8.481	8.484	8.486

SE, LL, AIC and BIC represent the standard error, log-likelihood, Akaike information criterion, and Bayes information criterion, respectively. α is the shape parameter, while ρ is the correlation coefficient. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively

Table 4 Estimates of the dependence-switching copula model for the sectoral equity markets and oil price

	Carbon	GreenX	Power	Utility	Material	Industrial	Energy	CDG
A negative correlation regime—Panel A and Panel B								
Panel A: Bear oil markets coupled with bull stock markets								
α_1	0.45***	0.73***	0.65***	0.63***	0.699***	0.570***	0.656***	0.58***
	(0.096)	(0.097)	(0.106)	(0.116)	(0.128)	(0.082)	(0.113)	(0.073)
ρ_1	0.28***	0.41***	0.38***	0.37***	0.396***	0.341***	0.378***	0.35***
	(0.048)	(0.037)	(0.044)	(0.049)	(0.051)	(0.037)	(0.046)	(0.032)
φ_1	0.11***	0.19***	0.17***	0.17***	0.186***	0.148***	0.174***	0.15***
	(0.035)	(0.024)	(0.030)	(0.034)	(0.034)	(0.026)	(0.032)	(0.023)
Panel B: Bull oil markets coupled with bear stock markets								
α_2	0.19**	0.39***	0.187**	0.275***	0.190**	0.124*	0.225**	0.23***
	(0.081)	(0.103)	(0.086)	(0.096)	(0.086)	(0.065)	(0.084)	(0.000)
ρ_2	0.14**	0.25***	0.134**	0.189***	0.136**	0.091**	0.158***	0.16***
	(0.053)	(0.055)	(0.056)	(0.057)	(0.056)	(0.045)	(0.053)	(0.000)
φ_2	0.013	0.08***	0.012	0.040	0.013	0.002	0.023	0.03***
	(0.020)	(0.040)	(0.021)	(0.035)	(0.022)	(0.005)	(0.026)	(0.000)
A positive correlation regime—Panel C and Panel D								
Panel C: Bear oil markets coupled with bear stock markets								
α_3	0.067	1.95***	− 0.103*	− 0.096**	− 0.106	0.148	− 0.116*	0.37***
	(0.110)	(0.727)	(0.055)	(0.049)	(0.081)	(0.133)	(0.067)	(0.073)
ρ_3	0.051	0.70***	− 0.085*	− 0.079*	− 0.088	0.108	− 0.096*	0.24***
	(0.081)	(0.104)	(0.048)	(0.042)	(0.071)	(0.090)	(0.059)	(0.039)
φ_3	0.000	0.35***	417.1	675.1	340.9	0.005	201.55	0.08**
	(0.000)	(0.046)	(1492)	(2467)	(1699)	(0.019)	(702.5)	(0.028)
Panel D: Bull oil markets coupled with bull stock markets								
α_4	0.090	0.889	− 0.073	− 0.071	− 0.128**	− 0.047	− 0.055	− 0.16**
	(0.134)	(0.616)	(0.049)	(0.048)	(0.053)	(0.095)	(0.059)	(0.060)
ρ_4	0.067	0.46***	− 0.060	− 0.058	− 0.107**	− 0.037	− 0.045	− 0.14**
	(0.096)	(0.205)	(0.041)	(0.041)	(0.047)	(0.078)	(0.049)	(0.055)
φ_4	0.000	0.23*	6355	8913	113.41	1E + 06	1E + 05	39.99
	(0.003)	(0.124)	(40,169)	(6E + 04)	(253.9)	(4E + 07)	(2E + 06)	(66.05)
Panel E: Regime switching								
P_{11}	0.996	0.856	0.999	0.999	0.999	0.996	0.998	0.998
P_{00}	0.992	0.245	0.999	0.999	0.998	0.989	0.999	0.994
LL	3940	4907	6894	6537	6523	6540	6532	6544
AIC	− 7920	− 9853	− 13,828	− 13,114	− 13,086	− 13,120	− 13,103	− 13,128
BIC	− 8031	− 9968	− 13,949	− 13,234	− 13,207	− 13,241	− 13,223	− 13,248

	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
A negative correlation regime—Panel A and Panel B								

Table 4 (continued)

	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
Panel A: Bear oil markets associated with bull stock markets								
α_1	0.53***	0.65***	0.88***	0.71***	0.28***	0.712***	0.52***	0.54***
	(0.084)	(0.105)	0.146	(0.120)	(0.062)	(0.152)	(0.081)	(0.090)
ρ_1	0.32***	0.38***	0.46***	0.40***	0.19***	0.401***	0.32***	0.33***
	(0.039)	(0.043)	(0.049)	(0.047)	(0.037)	(0.060)	(0.038)	(0.042)
φ_1	0.13***	0.17***	0.23***	0.19***	0.040*	0.189***	0.132***	0.14***
	(0.028)	(0.030)	(0.030)	(0.031)	(0.023)	(0.039)	(0.027)	(0.030)
Panel B: Bull oil markets associated with bear stock markets								
α_2	0.20***	0.31**	0.045*	0.201**	0.123**	0.270**	0.067	0.26***
	(0.072)	(0.113)	(0.086)	(0.081)	(0.058)	(0.114)	(0.056)	(0.080)
ρ_2	0.14***	0.21***	0.035*	0.14***	0.091**	0.186**	0.051	0.18***
	(0.047)	(0.065)	(0.064)	(0.052)	(0.040)	(0.068)	(0.041)	(0.049)
φ_2	0.014	0.052**	0.00***	0.016	0.002	0.038**	0.000	0.033
	(0.019)	(0.044)	(0.000)	(0.022)	(0.005)	(0.042)	(0.000)	(0.028)
A positive correlation regime—Panel C and Panel D								
Panel C: Bear oil markets associated with bear stock markets								
α_3	0.136	0.059	0.069*	− 0.031	0.017	0.053	0.123*	0.17**
	(0.089)	(0.053)	(0.041)	(0.043)	(0.048)	(0.044)	(0.064)	(0.064)
ρ_3	0.100*	0.045	0.052*	− 0.025	0.014	0.041	0.091**	0.12***
	(0.061)	(0.039)	(0.030)	(0.035)	(0.037)	(0.033)	(0.044)	(0.042)
φ_3	0.003	0.000	0.000	2E + 09	0.000	0.000	0.002	0.009
	(0.010)	(0.000)	(0.000)	(6E + 10)	(0.000)	(0.000)	(0.005)	(0.013)
Panel D: Bull oil markets associated with bull stock markets								
α_4	0.135	0.033	− 0.038	0.003	0.127*	− 0.015	0.006	0.017
	(0.106)	(0.055)	(0.035)	(0.044)	(0.069)	(0.039)	(0.051)	(0.051)
ρ_4	0.099	0.025	− 0.030	0.002	0.094*	− 0.012	0.005	0.013
	(0.073)	(0.042)	(0.028)	(0.034)	(0.048)	(0.031)	(0.040)	(0.039)
φ_4	0.003	0.000	5E + 07	0.000	0.002	8E + 19	0.000	0.000
	(0.012)	(0.000)	(9E + 08)	(0.000)	(0.006)	(0.411)	(0.000)	(0.000)
Panel E: Regime switching								
P11	0.990	0.995	0.999	0.998	1.000	0.994	0.998	0.993
P00	0.979	0.995	0.999	0.999	0.999	0.997	0.998	0.994
LL	8468	9973	10,004	9990	10,028	10,018	10,005	10,003
AIC	− 16,976	− 19,986	− 20,047	− 20,020	− 20,096	− 20,077	− 20,050	− 20,046
BIC	− 17,101	− 20,115	− 20,176	− 20,148	− 20,225	− 20,206	− 20,179	− 20,175

α_i is the shape parameter of the dependence-switching copula, and ρ_i and φ_i are the measures of dependence and tail dependence, respectively. The numbers in parentheses are standard deviations. *P11* and *P00* are the two transition probabilities. *, ** and, *** indicate significance at the 10%, 5%, and 1% level, respectively make investors experience large losses (gains). Hence, consideration of tail dependence is essential for managing the portfolio risk.

In Panel C, the estimates of the left dependence (ρ_3) are significant for GreenX, Power, Utility, Energy, Consumer discretionary goods, Banking, IT, Capital goods, and Auto. The left tail dependence (φ_3) is significant for GreenX and Consumer discretionary goods when both the oil and equity markets collapse. Conversely, in Panel D, the parameters of right dependency and right tail dependency, i.e.ρ_4 and φ_4 respectively, are found to be mainly insignificant when both markets are advancing. Exceptions are GreenX, Material, CDG, and FMCG for ρ_4 and GreenX for φ_4. Therefore, the significant left tail dependences and predominantly insignificant right tail dependencies confirm the asymmetric tail dependency between the oil price and sectoral equity markets in a positive correlation regime. From a portfolio management prospective, if investors hold both oil and sectoral equity in the portfolio, they are exposed to large losses in the bear-bear market state but not to correspondingly large gains in a bull-bull market.

Subsequently, we focus on the negative correlation regime associated with bear oil markets coupled with bull sectoral equity markets and bull oil markets coupled with bear sectoral equity markets. The left tail dependence (φ_1) represents the likelihood of suffering huge losses in a bearish oil market and at the time gaining huge profits in bullish sectoral equity markets. The opposite holds true for the right tail dependence (φ_2). A bigger value of $\varphi_1(\varphi_2)$ signifies the higher likelihood for an investor to suffer large losses if he is long (short) in the oil market and short (long) in the sectoral equity market. In Panel A, the estimates of the left dependence ρ_1 are significant for all sectoral indices and range from 0.19 to 0.46. The estimates of φ_1 are also significant for all sectoral indices and vary between 0.04 and 0.23. Panel B shows that, apart from capital goods, the estimates of ρ_2 are all significant and range from 0.035 to 0.25, whereas the estimates of φ_2 are large only for GreenX, CDG, Metals, IT, and Consumer durables, and vary between 0.000017 and 0.08.

Concerning the magnitude of the tail dependences, commonly larger values are estimated in the negative correlation regime when the oil market is in the bear phase. In such dynamics, FMCG and Carbon sectors are showing the lowest dependency with oil. Thus, an investor is exposed to the lowest systemic risk in the negative correlation regime if these two sectors are included in the portfolio along with a short position in the oil market. The heteroskedastic dependence structure between the sectoral equity and oil price is in confirmation with the findings of Ramos and Veiga (2011), and the reasons may depend on first, whether oil is an input or output to that particular sector, and second, whether the oil shock is due to demand or supply factors.

Next, we check the hypotheses of symmetric dependence and tail dependence using a Wald test. For the positive correlation regime, where both markets are rising or collapsing simultaneously, we test if $\rho_3 = \rho_4$ and if $\varphi_3 = \varphi_4$. The results from Panel A in Table 5 indicate that the hypothesis of symmetric dependence can be rejected for CDG, IT, and Auto, whereas the symmetric tail dependence cannot be rejected for any of the indices. Panel B in Table 5 presents the results under a negative correlation regime. As explained in Ning (2010), such a setting is not captured by a single copula model. Specifically, for the symmetric dependence we test the null hypothesis that $\rho_1 = \rho_2$, and for the symmetric tail dependence we test if $\varphi_1 = \varphi_2$. The results indicate that the symmetric hypothesis is rejected for all sectoral indices, except for FMCG. A number of studies have shown asymmetric tail dependence across stock and oil markets (e.g., see Mensi et al., 2017b; Oh & Patton, 2017; Raza et al., 2016; Jondeau, 2016; Reboredo, 2015). Our results of asymmetric tail dependence in a negative correlation regime between oil and the BSE sectoral indices add more evidence to this existing literature.

Table 5 Symmetric dependences under a positive and negative correlation regime

Panel A: Symmetric dependence under a positive correlation regime (both markets are advancing and collapsing)								
Wald test	Carbon	GreenX	Power	Utility	Material	Industrial	Energy	CDG
$\rho_3 = \rho_4$	0.012	1.196	0.111	0.098	0.042	1.144	0.344	26.7***
	[0.911]	[0.274]	[0.739]	[0.754]	[0.838]	[0.285]	[0.558]	[0.000]
$\varphi_3 = \varphi_4$	0.006	0.936	0.021	0.019	0.017	0.001	0.006	0.365
	[0.939]	[0.333]	[0.885]	[0.892]	[0.898]	[0.974]	[0.941]	[0.546]
	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
$\rho_3 = \rho_4$	0.000	0.102	2.922*	0.235	1.195	0.988	1.511	2.852*
	[0.993]	[0.750]	[0.087]	[0.628]	[0.274]	[0.320]	[0.219]	[0.091]
$\varphi_3 = \varphi_4$	0.000	0.009	0.003	0.001	0.115	0.000	0.118	0.452
	[0.993]	[0.924]	[0.953]	[0.974]	[0.734]	[0.994]	[0.732]	[0.501]
Panel B: Symmetric dependence under a negative correlation regime (one advancing market coupled with the other in collapsing)								
Wald test	Carbon	GreenX	Power	Utility	Material	Industrial	Energy	CDG
$\rho_1 = \rho_2$	3.738*	4.982**	7.79***	3.652*	7.46***	14.22***	6.485**	6.88***
	[0.053]	[0.026]	[0.005]	[0.056]	[0.006]	[0.000]	[0.011]	[0.009]
$\varphi_1 = \varphi_2$	4.732**	5.052**	13.1***	4.309**	12.1***	27.28***	8.89***	8.22***
	[0.030]	[0.025]	[0.000]	[0.038]	[0.001]	[0.000]	[0.003]	[0.004]
	Bank	Metals	IT	Oil & Gas	FMCG	Consumer	Capital	Auto
$\rho_1 = \rho_2$	6.96***	4.221**	18.9***	9.50***	2.087	4.028**	17.3***	4.731**
	[0.008]	[0.040]	[0.000]	[0.002]	[0.149]	[0.045]	[0.000]	[0.030]
$\varphi_1 = \varphi_2$	9.80***	4.759**	59.3***	14.8***	2.209	4.931**	23.2***	5.615**
	[0.002]	[0.029]	[0.000]	[0.000]	[0.137]	[0.026]	[0.000]	[0.018]

Numbers in brackets are *p*-values. ρ_i and φ_i measure the dependence and tail dependence of the oil and BSE sectoral indices under different market statuses

To further validate our application of the dependence-switching copula, we present the smoothing probability of the positive correlation regime and the corresponding smoothing correlation coefficients for each sector in Fig. 1. These smoothing probabilities indicate whether both of the markets stay in the regime or not. If they stay in the regime, it is an indication of opportunities for portfolio rebalancing between the two asset classes. The smoothing correlation coefficients reflect the correlation structure between the two markets throughout the sample period.

Except for FMCG and GREEN-X, the sectors tend to stay in the regime with the oil price for most of the time. During the financial crisis of 2008 and the European crisis of 2011–13, these sectors along with the oil price witness a simultaneous crash. Also a negative correlation regime is evident from Fig. 1 for these sectors during 2005–07 and 2014–16. The corresponding smoothing correlation coefficients further confirm the positive regime, where both the sectoral indices and the oil price stay in the regime and vice-versa. Our results on India are an indication that the dependency between the oil price and sectoral equity markets switches between the positive and negative correlation regime, hence, supporting the use of a dependence-switching copula.

5.3 Measures of oil price risk spillover

Following the estimation of tail dependences, the downside oil price risk spillovers to different sectors are measured using the VaR, CoVaR, and delta CoVaR. The results are presented graphically in Fig. 2 and the summary statistics are presented in Table 6.

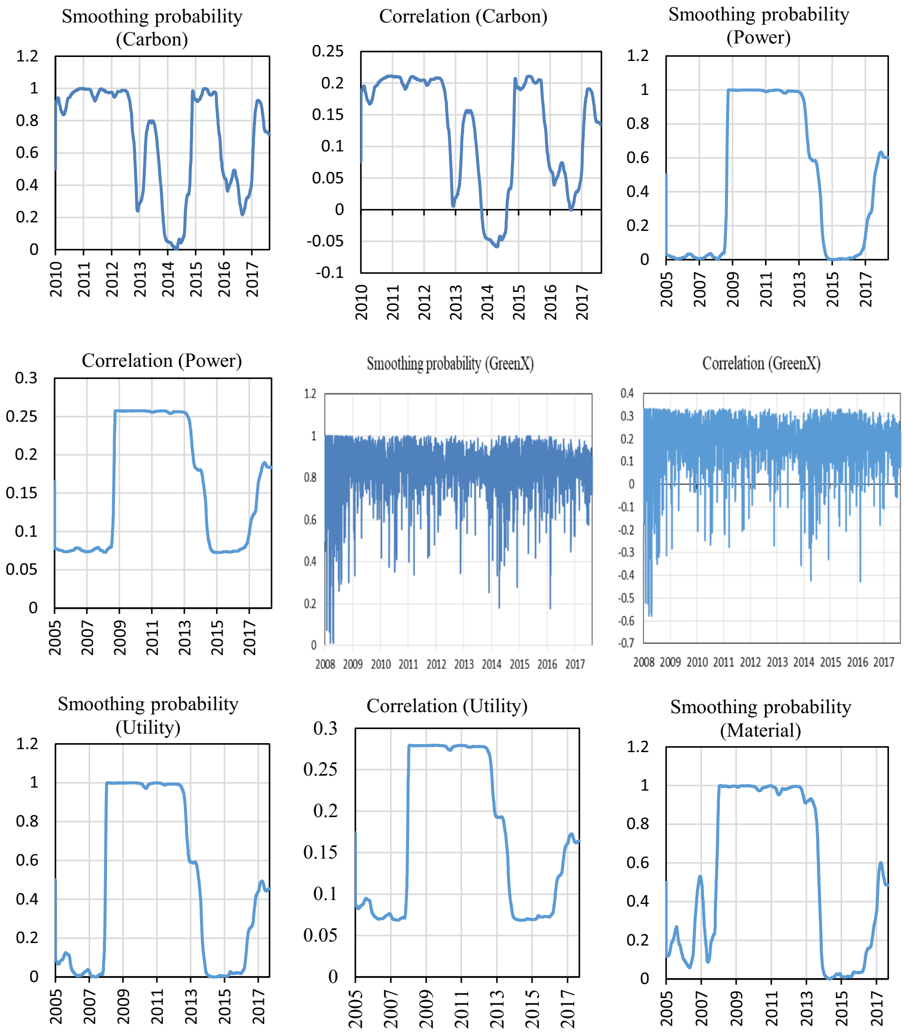

Fig. 1 Smoothing probability and smoothing correlation coefficients of the positive correlation regime between the oil returns and sectoral equity returns

In a bearish equity market, the IT sector is the riskiest sector with the highest VaR and the Carbon sector has the lowest VaR. Therefore, in such a market situation, the Carbon sector provides the opportunity for a safe haven investment. However, across the sectors the average sectoral CoVaR is positive, i.e. greater than the VaR. Given its minimum and maximum value, the CoVaR is fleeting over time. This suggests that when the sectoral equity market is bearish, a bearish oil market does not create any additional risk for the equity market. Similar to Demirer et al. (2015) and Christoffersen and Pan (2017) in the context of stocks, our findings reveal that the oil price risk is systemically priced across the sectors when both the sectoral equity and oil market are bearish.

The same phenomenon is observed for the delta CoVaRs for all sectoral indices over the sample period, i.e. the systemic oil price risk is time-varying. The maximum of 0.20%

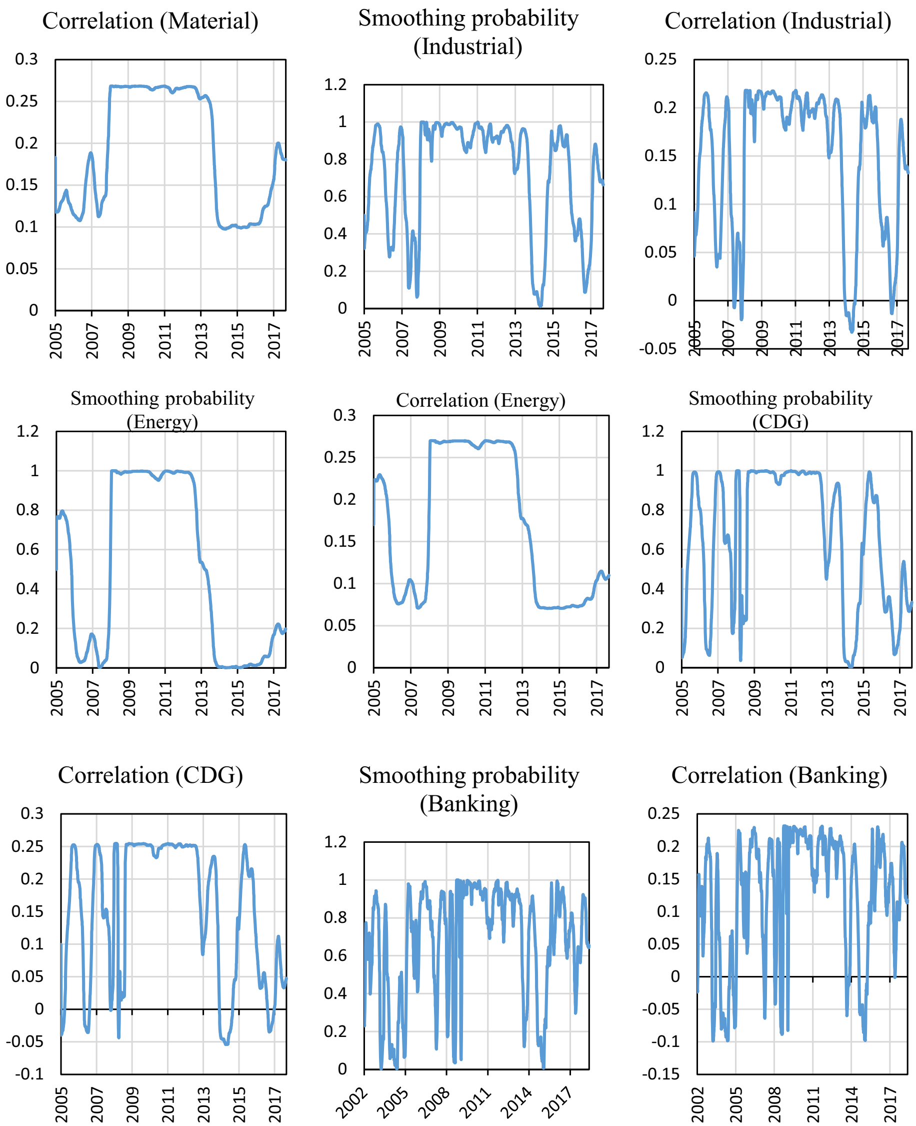

Fig. 1 continued

(minimum of 0.01%) systemic oil price risk is observed for the Industrial sector (Carbon sector). The implication for portfolio investing is that when the equity market is bearish, the oil price brings the diversification opportunity, and the best diversified portfolio that can be constructed is the combination of investments in the oil and carbon sector. Hence, the potential sectoral portfolio diversification as suggested by Degiannakis et al. (2013) and Nandha and Faff (2008) is limited to the carbon sector in a bearish market. Furthermore, highly positive correlations (more than 0.90) between the delta CoVaR and CoVaR indicate that for a given sector, the delta CoVaR does not bring any additional systemic risk over its VaR.

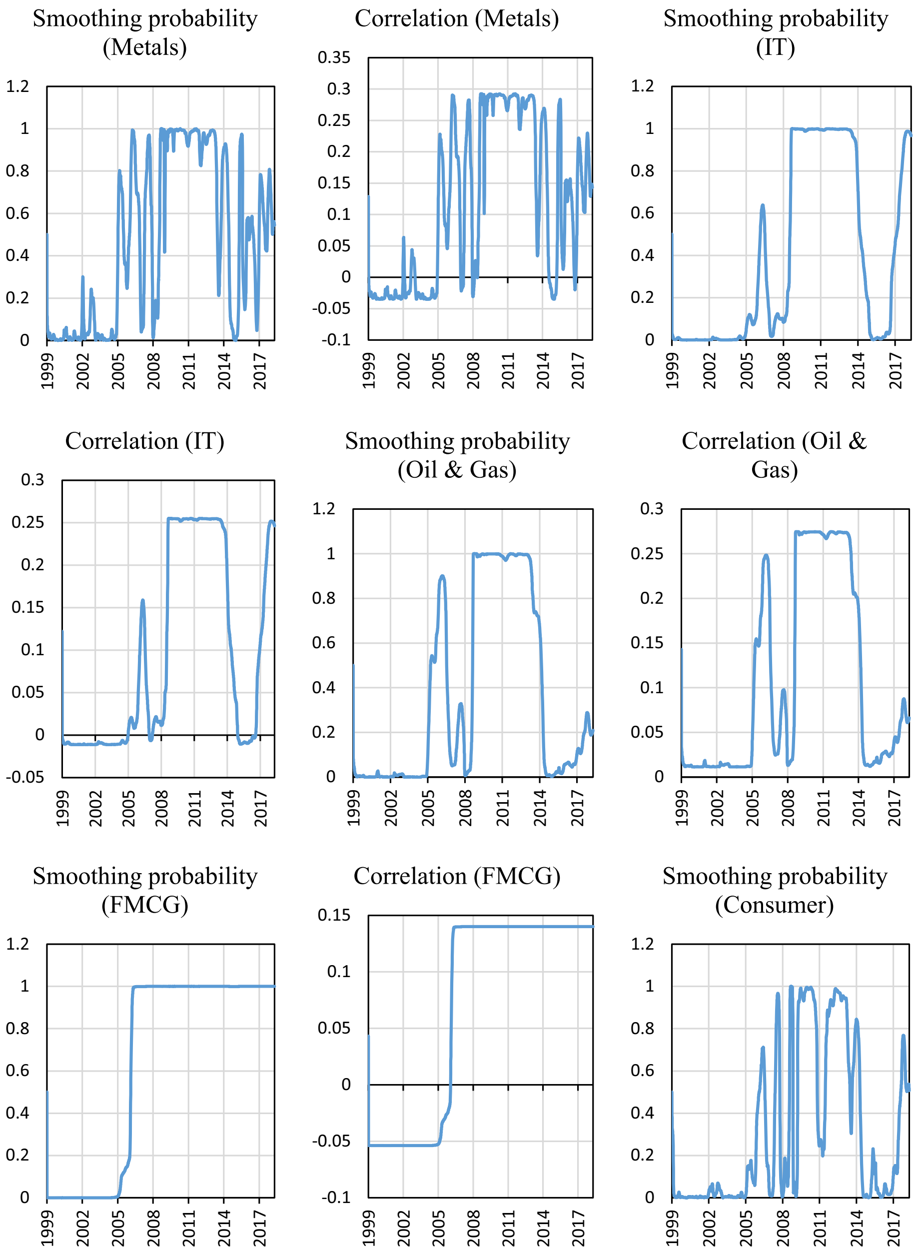

Fig. 1 continued

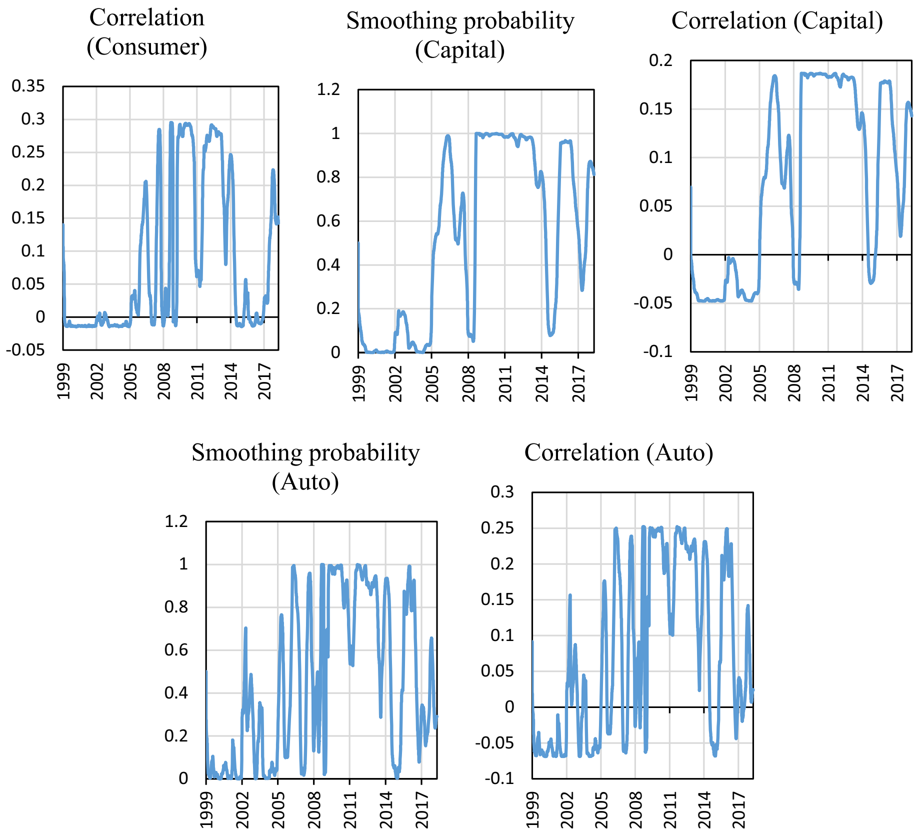

Fig. 1 continued

During a financial crisis period, a jump in both the sectoral VaR and delta CoVaR is observed. Although the CoVaR increased across the sectors during the period of a financial crisis, the increase is very marginal. This again signifies that the oil market does not contribute any additional systemic risk to the sectoral equity market during the crisis. This finding validates the sectoral equity market results of Aloui et al. (2012), who detect no impact of the oil price on the stock market in 25 emerging net oil importing countries including India.

6 Conclusions and policy implications

Highlighting the necessity to look at four diverse market conditions between the oil price and the sectoral equity markets, we have examined the dependence and tail dependence asymmetry using the novel dependence-switching copula methodology of Wang et al. (2013). Thereby, our focus on India and the sectoral equity markets is important. On the one hand, India is one of the fastest growing economies in the world and has become the major investment destination in the emerging market context. Though the IMF is also confident that the Indian growth continues in the long-run, rising oil prices are a major cause of concern due to India's high dependence on oil imports. On the other hand, sectoral investing has emerged as

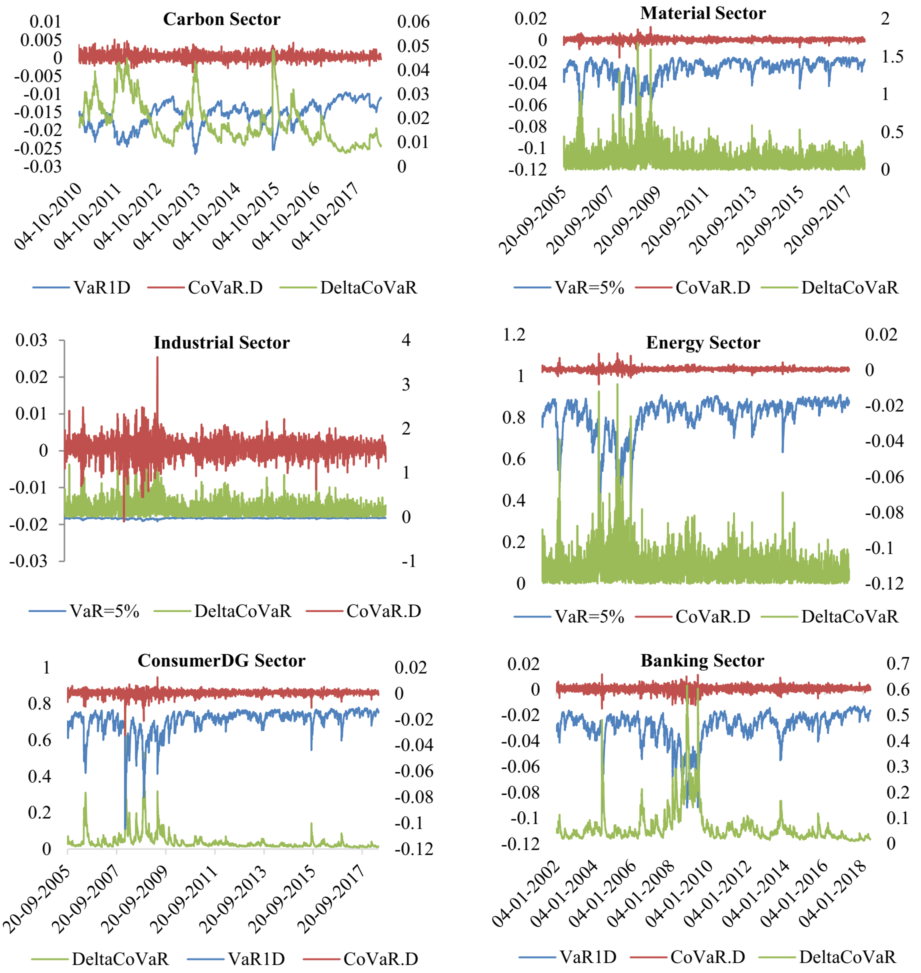

Fig. 2 Downside sectoral VaR, CoVaR and delta CoVaR

an investment strategy for two main reasons. First, given financial market integration, portfolio diversification opportunities at the aggregate market level have been reduced. Second, sectoral indices show varying degrees of exposure to oil price risk.

Our results show that in a positive correlation regime, the dependence and tail-dependence between the sectoral indices and the oil price are asymmetric and symmetric, respectively. However, in a negative correlation regime, both dependence structures are asymmetric.The average sectoral CoVaR is positive across the sectors and greater than the corresponding VaR. Given its minimum and maximum value, the CoVaR fleets over time, this implies that a bearish oil market does not add additional systemic risk to a bearish sectoral equity market. When both equity and oil are in a downward phase, the carbon sector is found to be the safe haven investment. Thus, knowledge about the dependence structure across financial markets helps to understand the portfolio diversification opportunities, asset pricing, contagion and better risk management through VaR.

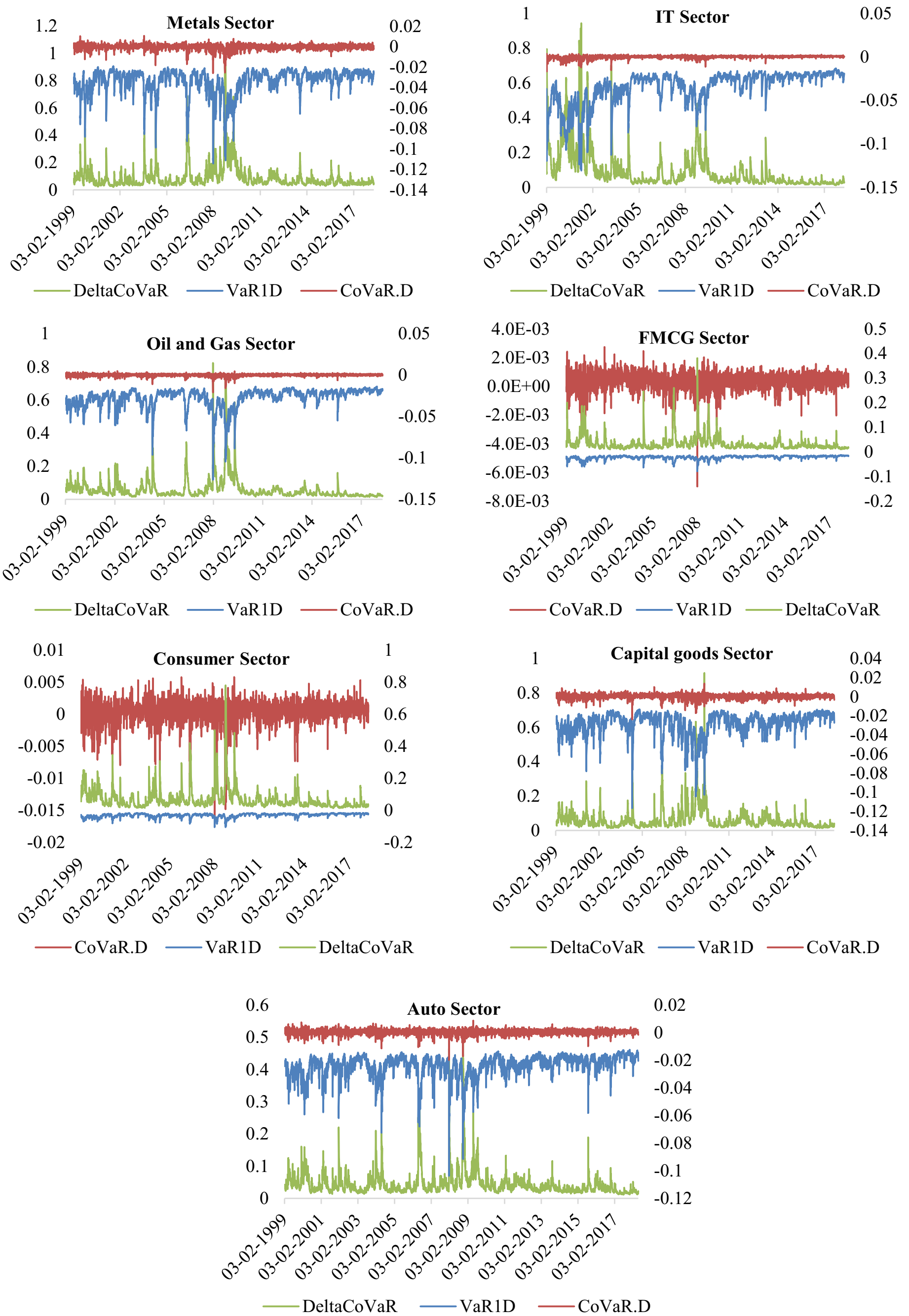

Fig. 2 continued

Table 6 Summary statistics of VaR, CoVaR and delta CoVaR for all sectors

Sectoral indices	VaR						CoVaR						Delta CoVaR					
	Mean	SD	Kurt	Skew	Min	Max	Mean	SD	Kurt	Skew	Min	Max	Mean	SD	Kurt	Skew	Min	Max
Carbon	− 0.02	0.00	− 0.19	− 0.55	− 0.03	− 0.01	0.00	0.00	1.52	0.23	− 0.01	0.01	0.02	0.01	0.45	1.00	0.01	0.05
Material	− 0.03	0.01	9.40	− 2.63	− 0.10	− 0.02	0.00	0.00	7.77	− 0.62	− 0.02	0.01	0.15	0.14	18.26	3.02	0.00	1.68
Industrial	− 0.03	0.01	7.46	− 2.39	− 0.10	− 0.01	0.00	0.00	7.54	− 0.06	− 0.02	0.03	0.20	0.19	26.79	3.40	0.00	3.18
Energy	− 0.03	0.01	11.14	− 2.89	− 0.11	− 0.01	0.00	0.00	12.03	1.05	− 0.01	0.01	0.08	0.08	23.24	3.43	0.00	0.96
CDG	− 0.02	0.01	14.17	− 3.05	− 0.10	− 0.01	0.00	0.00	29.25	− 2.77	− 0.03	0.01	0.03	0.05	66.06	6.63	0.81	123
Bank	− 0.03	0.01	4.95	− 2.02	− 0.10	− 0.01	0.00	0.00	6.53	− 1.12	− 0.02	0.01	0.06	0.07	16.92	3.60	0.01	0.62
Metals	− 0.03	0.01	6.85	− 2.25	− 0.11	− 0.02	0.00	0.00	5.98	1.11	− 0.01	0.02	0.09	0.09	25.16	4.30	0.02	1.00
IT	− 0.03	0.02	3.26	− 1.75	− 0.13	− 0.01	0.00	0.00	12.11	− 2.57	− 0.02	0.00	0.09	0.11	11.05	2.97	0.01	0.94
Oil & Gas	− 0.03	0.01	9.53	− 2.50	− 0.13	− 0.01	0.00	0.00	24.03	− 2.84	− 0.02	0.00	0.06	0.07	35.72	5.11	0.01	0.82
FMCG	− 0.02	0.01	7.01	− 2.28	− 0.08	− 0.01	0.00	0.00	10.80	− 1.72	− 0.01	0.00	0.03	0.03	27.03	4.27	0.01	0.38
Consumer	− 0.03	0.01	4.61	− 1.81	− 0.11	− 0.01	0.00	0.00	12.22	− 2.14	− 0.02	0.01	0.07	0.06	28.98	4.34	0.02	0.78
Capital	− 0.03	0.01	6.99	− 2.16	− 0.12	− 0.01	0.00	0.00	7.96	− 1.49	− 0.02	0.01	0.06	0.07	34.43	4.85	0.01	0.92
Auto	− 0.02	0.01	7.77	− 2.16	− 0.10	− 0.01	0.06	0.07	34.43	4.85	0.01	0.92	0.04	0.03	31.31	4.42	0.01	0.49

Max, Min, SD, Skew, and Kurt denote the maximum, minimum, standard deviation, skewness, and kurtosis of returns, respectively. J–B is the Jarque–Bera normality test

Our results have important practical implications for cross-market risk management and asset pricing. Our findings reveal that investors should not rule out the risks from one market to another, since there are significant tail dependences among the oil and sectoral equity markets. Moreover, the oil price risk is systemically priced across the sectors when both the sectoral equity and the oil market are bearish. The advantage of the CoVaR over the VaR is the ability of the former in measuring the tail dependence and severe risk spillovers. A practical implication of our results for portfolio investing is that when the equity market is bearish in India, the oil price provides a diversification opportunity. In such a market, the combination of investments in the oil and carbon sector gives the best diversified portfolio. Paradoxically, the chances of making profit are very limited when both markets are booming. As such, when stock and foreign exchange markets are moving in the same direction, there are higher chances of incurring simultaneous losses than of making simultaneous profits.

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