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Dynamic dependence and extreme risk comovement: The case of oil prices and exchange rates

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Abstract

This paper aims at investigating the dynamic dependence and extreme risk comovement of oil price and exchange rates in seven oil-importing and seven oil-exporting countries. For this purpose, we use six representative time-varying copula models and four types of tail dependences to assess the downside and upside conditional value-at-risk measures (CoVaRs). Our findings indicate that the dependence of crude oil returns and exchange rates is negative for most pairs, i.e., the rise (fall) in oil prices was accompanied by the appreciation (depreciation) of foreign currency against the US dollar. The oil price – exchange rate dependences in oil exporters are slightly larger than in oil importers, even though the dependence is weak in general. More interestingly, we find strong evidence of significant risk comovement between crude oil returns and exchange rates through the analysis of downside and upside CoVaRs. This comovement particularly showed asymmetric effects.

Keywords: time-varying copulas; tail dependence; CoVaR; oil price; US dollar exchange rate.

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1. Introduction

The comovement between crude oil prices and US dollar has been extensively debated in financial economics (e.g., Krugman, 1983; Reboredo, 2012; Aloui et al., 2013; Chen et al., 2013). Owing to its role as the major invoicing and also settlement currency, the movements in the price of US dollar relative to other currencies are directly linked to oil prices. A robust modeling of their links is thus an important input for improving investment decision making and portfolio risk management. Particularly, the current literature on crude oil price and exchange rate shows that their links are not alike for oil-exporting and oil-importing countries mainly due to the different trading characteristics, and oil price shocks can be transmitted to real economy of oil-related countries (Golub, 1983; Krugman, 1983; Reboredo, 2012). As increasing oil prices may benefit the oil exporters, while decreasing oil prices benefiting oil importers, research on the relationship between crude oil price and exchange rates especially on oil extreme risks has important implications for oil-related economies and financial institutions in identifying oil risk spillover, financial contagion and systemic risk.

In this study, we provide a comprehensive investigation of the dynamic dependence between crude oil returns and exchange rates in major oil trading countries over the last seventeen years, with the main focus placed on their time-varying dependence structure and extreme risk comovement. By doing so, our research extends the previous literature by assessing the nonlinear and dynamic dependences between crude oil prices and exchange rates in seven oil importers and seven oil exporters. The utilization of six time-varying copula models allows us to compare dynamic dependence patterns between sample countries. Recent papers in quantitative and mathematical finance have shown that copula models are flexible enough for modeling nonlinear dependence and tail risk (e.g., Grundke and Polle, 2012; Al Janabi et al., 2017; Irresberger et al., 2018). When fitting copula functions, we particularly suggest a new forcing variable to better model the dependence parameter of the 90-degree rotated Clayton and 270-degree rotated Clayton copulas.

Furthermore, we employ the copula estimation results to evaluate the comovement of extreme risks between crude oil returns and foreign exchange rates based on the concept of the conditional value-at-risk (CoVaR), in the spirit of Adrian and Brunnermeier (2016). Here, CoVaR is defined as the VaR of the foreign exchange market conditional on the extreme movement of the crude oil market. We indeed propose four types of extreme risk comovement between market pairs with respect to oil risk of sample countries: i) the upside and downside CoVaR conditional on the upside VaR of oil returns for oil importers; and ii) the upside and downside CoVaRs conditional on the downside VaR of oil returns for oil exporters. Studies such as Girardi and Ergünwhile (2013) and Cai et al. (2018) show that the CoVaR is useful and enhances our understanding of joint extreme risks across financial markets.

The remainder of this paper is structured as follows. Section 2 presents the literature review on the relationship between crude oil prices and exchange rates. Section 3 focuses on the theoretical framework of the time-varying copulas and CoVaRs. Section 4 analyzes the empirical results for 14 oil-trading countries. Section 5 concludes the paper.

2. Literature review

Golub (1983) and Krugman (1983) were among the first studies discussing the theoretical relationships between oil prices and exchange rates. Subsequent studies have investigated their empirical links through a wide range of econometric models, including, among others, cointegration, causality tests, error-correction model, VAR model, panel cointegration, and copula models, in the context of both bilateral and multilateral exchange rates. Table 1 summarizes relevant studies of this literature as well as their sample data, empirical method, and main findings. We notice three common effects in this relationship: i) there exists a long-term equilibrium between crude oil price and exchange rates; ii) the nonstationary behavior of crude oil prices can contribute to the nonstationarity of exchange rates; and iii) the rise of crude oil prices is usually accompanied by the depreciation of the dollar.

Table 1 about here

Our literature review also reveals several gaps in the relevant research. First, most studies concentrated on the co-movement between crude oil prices and exchange rates of a single country or a single class of countries. Aloui et al. (2013), among others, shows the dependence of oil prices–exchange rate pair on the oil-trading characteristics of different countries. Their findings suggest that oil price increases may cause the US dollar depreciation against the currencies of net oil exporters, such as Canada, Mexico and Russia but appreciate against the currencies of net oil importers, such as Japan.

Second, most studies focused on pre-crisis relationships, although the relationships between oil prices and exchange rates could structurally differ under the extreme market risks since 2010. In particular, international oil prices have decreased sharply since 2014, and the oil market has entered a “new normal”. New evidence should be investigated in order to contribute to the empirical research.

Finally, little is known about the joint occurrence of extreme risks (also referred to as systemic risk) between these two markets, while it became a concern of market participants and policymakers, to the extent that both financial and economic uncertainty increased (Baker et al., 2016). In extreme market situations such as financial distress and contagion, the oil price – exchange rate may be not only nonlinear but also time-varying (Reboredo, 2012). The high frequency of large changes in the oil prices and significant depreciations of the currencies of Russia, Brazil and South Africa especially when the Federal Reserve started its program of quantitative easing (QE) withdrawal. This situation motivates the understanding and quantification of the extreme risk co-movement between the oil price and exchange rates of oil-trading countries.

To date, some studies have investigated the nonlinear dependence between oil price and exchange rates through various copula models. Reboredo (2012), Aloui et al. (2013), and Brayek et al. (2015) use data of major oil-trading countries and mainly find that the dependences between crude oil price and exchange rates are generally weak, and that there is no significant evidence for asymmetric dependence. More specifically, Aloui et al. (2013) and Brayek et al (2015) use static copulas to measure the dependence. Reboredo (2012) consider a larger sample of eight major oil-trading countries, but the author only uses the time-varying elliptical copula functions such as normal and Student-t copulas, which could not capture the asymmetric dynamic tail dependence. The dependence modeling in previous studies, which mainly focuses on positive dependence, could be improved to accommodate both the positive and negative dynamics of the dependence structure (Liu et al., 2017).

Overall, this study explores the new dependence mechanisms between oil returns and exchange rates under the situation of extreme market risks, while considering the economic properties of oil-trading countries and extreme market situations. It uses the exchange rates of 14 countries from different universes (emerging, OECD, OPEC, and non-OPEC oil supply countries) to compare their similarities and differences.

3. Methodological Framework

Section 3.1 presents, based on conditional copula theory, the six time-varying copulas employed to measure the dynamic nonlinear dependence across crude oil and foreign exchange markets. A new forcing variable is introduced to efficiently drive the dynamic dependence of the time-varying 90-degree rotated Clayton (R1 Clayton) and 270-degree rotated Clayton (R2

Clayton) copulas. Section 3.2 develops four types of upside and downside CoVaRs used to explore the comovement of extreme risks.

3.1 Time-varying copula-based dependence modeling

For two asset returns, r_1 and r_2, we employ Kendall τ to measure the dependence between r_1 and r_2 as follows:

$$\tau_{r_1,r_2} = Pr\left(\left(r_{1,1} - r_{1,2}\right) \cdot \left(r_{2,1} - r_{2,2}\right) > 0\right) - Pr\left(\left(r_{1,1} - r_{1,2}\right) \cdot \left(r_{2,1} - r_{2,2}\right) < 0\right) \quad (1)$$

where $\left(r_{1,1}, r_{2,1}\right)$ and $\left(r_{1,2}, r_{2,2}\right)$ denote pairs of random variables obtained from the joint distribution of (r_1, r_2). The positive Kendall τ_{r_1,r_2} means that positive dependence exists between r_1 and r_2, and vice versa.

Previous studies employed tail dependence to investigate extreme comovement across markets. According to Joe (1997) and Liu et al. (2017), for a given real α, such as 0.01, the lower tail, upper tail, lower-upper tail and upper-lower tail dependence are given as follows:

$$\tau^{LL}(\alpha) = Pr\left(r_1 < F_1^{-1}(\alpha) | r_2 < F_2^{-1}(\alpha)\right) = \frac{C(\alpha,\alpha)}{\alpha}, \quad (2)$$

$$\tau^{UU}(\alpha) = Pr\left(r_1 > F_1^{-1}(1-\alpha) | r_2 > F_2^{-1}(1-\alpha)\right) = \frac{C(1-\alpha,1-\alpha)+2\alpha-1}{\alpha}, \quad (3)$$

$$\tau^{LU}(\alpha) = Pr\left(r_1 < F_1^{-1}(\alpha) | r_2 > F_2^{-1}(1-\alpha)\right) = \frac{\alpha - C(\alpha,1-\alpha)}{\alpha}, \quad (4)$$

$$\tau^{UL}(\alpha) = Pr\left(r_1 > F_1^{-1}(1-\alpha) | r_2 < F_2^{-1}(\alpha)\right) = \frac{\alpha - C(1-\alpha,\alpha)}{\alpha}. \quad (5)$$

3.1.1 Copulas

A copula is defined as a multivariate distribution function with margins that are uniform distributions on the interval (0, 1). For bivariate asset returns $\boldsymbol{r}_t = \left(r_{1,t}, r_{2,t}\right)$, given the information set at time $t-1$, $\mathcal{F}_{t-1} = \{\boldsymbol{r}_{t-1}, \boldsymbol{r}_{t-2}, \cdots, \boldsymbol{r}_1\}$, the conditional joint distribution at time t can be represented as follows:

$$F_t(x_1, x_2; \theta | \mathcal{F}_{t-1}) = C_t\left(F_{1,t}(x_1; \theta_1 | \mathcal{F}_{t-1}), F_{2,t}(x_2; \theta_2 | \mathcal{F}_{t-1}); \theta_c | \mathcal{F}_{t-1}\right), \quad (6)$$

where parameter $\theta = (\theta_1', \theta_2', \theta_c')'$, $C_t(\cdot,\cdot | \mathcal{F}_{t-1})$ is the conditional copula dependence structure, and $F_{1,t}(\cdot | \mathcal{F}_{t-1})$ and $F_{2,t}(\cdot | \mathcal{F}_{t-1})$ are conditional marginal distributions.

Accordingly, the conditional joint density can be written as follows:

$$f_t(x_1, x_2; \theta | \mathcal{F}_{t-1}) = c_t\left(F_{1,t}(x_1; \theta_1 | \mathcal{F}_{t-1}), F_{2,t}(x_2; \theta_2 | \mathcal{F}_{t-1}); \theta_c | \mathcal{F}_{t-1}\right) \cdot f_{1,t}(x_1; \theta_1 | \mathcal{F}_{t-1}) \cdot f_{2,t}(x_2; \theta_2 | \mathcal{F}_{t-1}), \quad (7)$$

where $c_t(\cdot,\cdot|\mathcal{F}_{t-1})$ is the conditional density of copula function, while $f_{1,t}(\cdot|\mathcal{F}_{t-1})$ and $f_{2,t}(\cdot|\mathcal{F}_{t-1})$ are the conditional marginal densities.

Following Liu et al. (2017), we select six representative copula dependence structures: Normal, Student-t, Clayton, R1 Clayton, rotated Clayton (R Clayton) R2 Clayton, which capture various structures of dependence and tail dependence. Then, the dynamic joint distribution is modeled with respect to each of these six time-varying copula models:

$$F_t(x_1,x_2;\theta|\mathcal{F}_{t-1}) = C_t^j(u_1,u_2;\theta_c|\mathcal{F}_{t-1}),\ u_i = F_{i,t}(x_i;\theta_i|\mathcal{F}_{t-1}),\ i = 1,2,$$
$$j \in \{N,t,C,R_1C,RC,R_2C\} \tag{8}$$

Liu et al. (2017) claimed that the half-rotated copulas (90-degree and 270-degree rotated copula) perform well to measure asymmetric negative dependence across markets. However, Liu et al. (2017) modeled the time-varying copula process based on the rolling window method, which is sensitive to the length of the chosen windows. Following the conditional copula theory (Patton, 2006; Patton, 2009; Patton, 2012), a new forcing variable is proposed to model the dependence parameter of copula and to construct time-varying 90-degree and 270-degree rotated copulas.

Recall that Patton (2006) proposed a time-varying copula (TVC) assuming that the copula parameters would vary following an ARMA-type process. This assumption arises from the difficulty in specifying how the forcing variable is defined to drive the dynamics of the copula dependence parameter's evolution equation. Hence, two forcing variables were proposed, which are widely applied in empirical finance. Following Patton (2006), we employ $\frac{1}{m}\sum_{j=1}^{m}\phi^{-1}(u_{1,t-j})\cdot\phi^{-1}(u_{2,t-j})$ and $\frac{1}{m}\sum_{j=1}^{m}t_n^{-1}(u_{1,t-j})\cdot t_n^{-1}(u_{2,t-j})$ as the forcing variables for time-varying Normal (TVN) and time-varying Student-t (TVt) copulas, respectively.

Figure 1 about here

However, neither of these two forcing variables is suitable for the half-rotated copulas, i.e., 90-degree and 270-degree rotated copulas. As shown in Figure 1, when the dependence of the random variables U_1 and U_2 is positive, their joint observations u_1 and u_2 are distributed along the main diagonal in a larger probability, i.e., the distance from the point (u_1,u_2) to the main diagonal, $d_1 = \frac{1}{\sqrt{2}}|u_1 - u_2|$ tends to be smaller. Inversely, when the dependence of the random variables U_1 and U_2 is negative, their joint observations, u_1 and u_2, are distributed along the minor diagonal in a larger probability, i.e., the distance from the point (u_1,u_2) to the minor diagonal, $d_2 = \frac{1}{\sqrt{2}}|u_1 + u_2 - 1|$ tends to be smaller. Thus, for the time-varying R1 Clayton and R2 Clayton, we use $\frac{1}{m}\sum_{j=1}^{m}\left|u_{1,t-j} + u_{2,t-j} - 1\right|$ as the forcing variable:

$$\delta_t = \Lambda\left(\bar{\omega} + \bar{\beta}\cdot\delta_{t-1} + \bar{\alpha}\cdot\frac{1}{m}\sum_{j=1}^{m}\left|u_{1,t-j} + u_{2,t-j} - 1\right|\right),\ u_{i,t} = F_{i,t}\left(r_{i,t};\theta_i|\mathcal{F}_{t-1}\right),\ i = 1,2,$$

$$\theta_c = \left(\bar{\omega},\bar{\beta},\bar{\alpha}\right)' \qquad (9)$$

where the transformation function $\Lambda(x) = x^2$ holds the parameter δ_t within the interval $(0,\infty)$.

Finally, we employ $\frac{1}{m}\sum_{j=1}^{m}\left|u_{1,t-j} - u_{2,t-j}\right|$ as the forcing variable for the time-varying Clayton and the time-varying rotated Clayton.

3.1.2 Conditional margins

According to the conditional Sklar theorem (Patton, 2006), the joint distribution of an asset portfolio is composed of the conditional copula and conditional margins. Since asset returns are characterized by stylized facts such as autocorrelation and volatility clustering, we use an ARMA(m,n)–GARCH(p,q) model with standard Student-t distribution to construct the conditional marginal distribution as follows:

$$r_{i,t} = \varphi_0 + \sum_{j=1}^{m}\varphi_j r_{i,t-j} + \varepsilon_{i,t} + \sum_{j=1}^{n}\psi_j\varepsilon_{i,t-j} = \mu_{i,t} + \varepsilon_{i,t},\ i = 1,2 \qquad (10)$$

$$\varepsilon_{i,t} = \sigma_{i,t}z_{i,t},\ z_{i,t}\sim i.i.d.\,t_{v_i}(0,1) \qquad (11)$$

$$\sigma_{i,t}^2 = \alpha_0 + \sum_{j=1}^{p}\alpha_j\varepsilon_{i,t-j}^2 + \sum_{j=1}^{p}\beta_j\sigma_{i,t-j}^2 \qquad (12)$$

where $\mu_{i,t} = E\left(r_{i,t}|\mathcal{F}_{t-1}\right)$, $\sigma_{i,t}^2 = Var\left(r_{i,t}|\mathcal{F}_{t-1}\right)$.

Then the conditional marginal distribution can then be derived as follows:

$$F_{i,t}(x_i;\theta_i|\mathcal{F}_{t-1}) = Pr\left(r_{i,t} \le x_i|\mathcal{F}_{t-1}\right) = Pr\left(\varepsilon_{i,t} \le \frac{x_i - \mu_{i,t}}{\sqrt{h_{i,t}}}|\mathcal{F}_{t-1}\right) = F_i\left(\frac{x_i - \mu_{i,t}}{\sqrt{h_{i,t}}}|\mathcal{F}_{t-1}\right) \qquad (13)$$

3.1.3 Estimation

We estimate the parameter θ via inference using Joe and Xu's (1996) margins (IFM) method as follows. First, we estimate the parameter θ_i $(i = 1,2)$ of the conditional marginal distributions:

$$\hat{\theta}_i = \underset{\theta_i}{argmax}\sum_{t=1}^{T} lnf_{i,t}\left(r_{i,t};\theta_i|\mathcal{F}_{t-1}\right) \qquad (14)$$

Second, we estimate the parameter θ_c of the time-varying copula:

$$\hat{\theta}_c = \underset{\theta_c}{argmax} \sum_{t=1}^{T} lnc_t\left(F_{1,t}\left(r_{1,t}; \hat{\theta}_1 | \mathcal{F}_{t-1}\right), F_{2,t}\left(r_{2,t}; \hat{\theta}_2 | \mathcal{F}_{t-1}\right); \theta_c | \mathcal{F}_{t-1}\right) \quad (15)$$

Joe (1997) shows that the IFM estimation $\hat{\theta} = \left(\hat{\theta}_1', \hat{\theta}_2', \hat{\theta}_c'\right)'$ verifies the following property:

$$\sqrt{T}\left(\hat{\theta} - \theta\right) \rightarrow N\left(0, G^{-1}(\theta)\right) \quad (16)$$

where $G(\theta)$ is the Godambe information matrix.

3.2 VaRs and CoVaRs

VaRs and CoVaRs can be computed based on the constructed time-varying copulas and then used to explore the comovement of extreme risks for pairs of crude oil returns and exchange rates. VaR is usually employed to measure the risk loss for financial position. For asset return r_t, the VaR of a long position is defined as $Pr\left(r_t \leq -VaR_{\alpha,t}^{long}\right) = \alpha$, and the VaR of a short position is $Pr\left(r_t \geq VaR_{\alpha,t}^{short}\right) = \alpha$. The downside risk can be defined as $VaR_{\alpha,t}^{D} = -VaR_{\alpha,t}^{long}$ and the upside risk $VaR_{\alpha,t}^{U} = VaR_{\alpha,t}^{short}$. The following condition is verified:

$$Pr\left(r_t \leq VaR_{\alpha,t}^{D}\right) = \alpha,\ Pr\left(r_t < VaR_{\alpha,t}^{U}\right) = 1 - \alpha. \quad (17)$$

By construction, the CoVaR can be used to measure the extreme risk comovement between crude oil returns and exchange rates. It is defined as the VaR for the exchange rate in each country conditional on oil returns exhibiting an extreme movement. In previous studies such as Reboredo and Ugolini (2015, 2016) and Mensi et al. (2017), only two types of CoVaRs are defined, and both of them maintain a consistent risk direction of the VaRs. For example, the downside CoVaR is $Pr\left(r_{1,t} \leq CoVaR_{\alpha|\beta,t}^{1,D} | r_{2,t} \leq VaR_{\beta,t}^{2,D}\right) = \alpha$ and the upside CoVaR is $Pr\left(r_{1,t} \geq CoVaR_{\alpha|\beta,t}^{1,U} | r_{2,t} \geq VaR_{\beta,t}^{2,U}\right) = \alpha$.

In our study, since the exchange rates in different countries may suffer from both upside risk and downside risk in response to asymmetric oil price shocks (oil price increase or decrease), two additional CoVaRs are proposed to measure the extreme risk comovement when one market is under upside risk and another market is under downside risk. Specifically, according to the countries' oil trade attributes, oil price upside risk is only considered for net oil importers, and oil price downside risk is only considered for net oil exporters. This specification is consistent with the fact that importers benefit when oil prices fall, whereas oil exporters benefit when oil prices increase. For oil importers, the upside and downside CoVaRs conditional on the upside VaR of oil returns can be written as follows:

$$Pr\left(r_{1,t} \le CoVaR^{1,D}_{\alpha|\beta,t} | r_{2,t} \ge VaR^{2,U}_{\beta,t}\right) = \alpha,\ Pr\left(r_{1,t} \ge CoVaR^{1,U}_{\alpha|\beta,t} | r_{2,t} \ge VaR^{2,U}_{\beta,t}\right) = \alpha \quad (18)$$

Similarly, for oil exporters, we measure the upside and downside CoVaRs conditional on the downside VaR of oil returns as follows:

$$Pr\left(r_{1,t} \le CoVaR^{1,D}_{\alpha|\beta,t} | r_{2,t} \le VaR^{2,D}_{\beta,t}\right) = \alpha,\ Pr\left(r_{1,t} \ge CoVaR^{1,U}_{\alpha|\beta,t} | r_{2,t} \le VaR^{2,D}_{\beta,t}\right) = \alpha \quad (19)$$

4. Empirical Results and Discussions

Our sample includes the currencies of 14 major representative oil-trading countries according to their oil-dependence characteristics and the importance of their currencies in international trade. Seven net oil importers are China (CNY), European Union (EUR), South Africa (ZAR), Japan (JPY), India (INR), United Kingdom (GBP), and the United States (USDX). Seven net oil exporters are Brazil (BRL), Canada (CAD), Algeria (DZD), Kuwait (KWD), Nigeria (NGN), Norway (NOK) and Russia (RUB). We do not consider the currencies of other OPEC countries because they are pegged to the US dollar. The selected bilateral exchange rates are measured by the quantity of foreign currency per unit of the US dollar. Therefore, an increase of a bilateral exchange rate implies the appreciation of the US dollar. The WTI spot prices are used to represent crude oil prices. We employ daily observations from 3 January 2000 to 14 April 2017 (4,511 observations) in the analysis. All data were extracted from the Datastream database.[1]

4.1 Model estimations

First, we use the natural logarithm difference to compute the WTI returns and exchange rate returns of oil-trading countries. The descriptive statistics of return series are summarized in Table 2. Most exchange rates have positive mean values, except for CNY, EUR and CAD. The highest and lowest mean values are observed for NGN (0.025) and CNY (-0.004). Thus, sample statistics show that the US dollar has appreciated against almost oil-trading countries' currencies over a long period from 2000 to 2017. The foreign exchange markets are less volatile than the WTI oil market in view of their smaller standard deviations. Moreover, all return series exhibit asymmetric leptokurtic features evidenced by the fat tails and peakedness. The Jarque-Bera statistics accordingly indicate that all the returns do not follow a normal distribution.

[1] The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Moreover, all the return series are exposed to autocorrelation and ARCH effects, which are confirmed by the Ljung-Box Q, squared Q and Lagrange multiplier tests. It is thus opportune to use the ARMA (m, n)-GARCH (p, q) model to filter the return series.

Table 2 about here

Table 3 presents the optimal lagged order of ARMA (m,n)-GARCH (p,q) model based on the BIC information criterion and the estimated coefficients for each return series. As can be seen, the optimal order of ARMA (m,n)-GARCH (p,q) model differs across series, while all the standardized residuals are assumed to follow a standardized Student-t distribution. The high value of β_1 in most of the estimated models implies strong conditional volatility persistence. The degree-of-freedom values for the Student-t distribution measured by υ range from 2 to 10, indicating that the error terms do not follow normal distribution.

Table 3 about here

The estimation results of the conditional margins are then used to estimate the six representative time-varying copula models for all oil price–exchange rate pairs and the corresponding Kendall dependence coefficients. Table 4 reports the Kendall dependence and AIC values of copula models. Overall, all the Kendall dependence coefficients between oil returns and exchange rates are significantly different from zero, except for NGN–OIL pair. Only the JPY–WTI dependence is positive with a relatively small Kendall coefficient of 0.018, which suggests that the rise or fall in oil returns is only accompanied by the minor depreciation or appreciation of the JPY against the USD. This finding is not surprising since crude oil represents only 7% in the energy mix used to generate electricity in Japan according to the statistics by the International Energy Agency (IEA). The depreciation trend of the JPY against the USD over recent years is mainly due to expansionary monetary policy designed to stimulate economic recovery. Moreover, Japan has to import 90% of its oil consumption. If oil returns are high, the Japanese yen would also tend to depreciate against the US dollar to some extent because Japan needs to spend more yens to purchase crude oil denominated in US dollars.

Table 4 about here

The Kendall dependence, albeit weak in general, is larger for oil exporters than the one for oil importers. The negative dependence between crude oil returns and oil exporters' exchange rates indicates that the rise or fall in WTI returns is linked with the appreciation or depreciation of the currencies against the USD. This finding can support the theoretical results of Golub (1983) and Krugman (1983), and it is also consistent with the evidence of Reboredo et al. (2014). From the real-economy perspective, one explanation is that the currencies of oil exporters will appreciate against the USD because of their increasing purchasing power relatively to oil importers following a positive shock to oil returns. By contrast, a fall in oil returns would reduce the price level in the oil exporters, which results in the depreciation of their currencies relatively to the US dollar. Among the sample countries, the Kendall dependence in absolute value of the main oil exporters' exchange rate changes with oil returns (CAD–OIL, NOK–OIL and RUB–OIL) is relatively large. Obviously, oil price changes significantly affect the trade income of oil exporters, thereby affecting their exchange rates.

Similarly, the dependence between oil returns and exchange rates in the oil importers is negative. Thus, their exchange rates also tend to appreciate in response to rising oil prices, which generally reflects the decrease of the long-term purchasing power of the US dollar. Similar findings are found in Ji et al. (2015) and Basher et al. (2016).

Table 4 also indicates that the time-varying *t* copula is the optimal copula for most oil price-exchange rate pairs, based on the AIC values of the six time-varying copulas under consideration. Thus, asymmetric dependence is not an appealing and dominant relationship between crude oil returns and exchange rates. The CNY–OIL pair is an exception with the time-varying R_1C copula (90-degree rotated Clayton) as an optimal copula model showing evidence of asymmetric negative dependence between the two markets. The small AIC values of the CNY–OIL pair suggest that the time-varying 90-degree rotated and 270-degree rotated Clayton copulas perform better than time-varying Clayton and rotated Clayton copulas when the Kendall coefficient was negative. Another exception is the NGN–OIL pair in which the time-varying normal copula fits best. Table 5 reports the estimated coefficients of the corresponding optimal time-varying copula models. Given the values of associated standard errors, most parameters are statistically significant at conventional levels.

Table 5 about here

4.2 Analysis of dynamic dependence and tail dependence

The estimation results in Table 5 allow us to compute the dynamic Kendall dependence and four tail dependence coefficients for pairs of oil and exchange rate returns. In what follows, a thorough analysis of the dependence for oil importers and oil exporters is further provided.

4.2.1 Dependence in oil importers

Figure 2 depicts the dynamic Kendall dependence of oil-exchange rate pairs in oil importers along with their constant dependence. The dependence pattern is distinct across pairs of markets and varies through time. Among the seven oil importers, the JPY–OIL pair shows a positive and constant dependence over the entire sample, whereas its dynamic dependence fluctuates around zero. The dependence of the CNY–OIL pair fluctuates below the zero line. Its absolute value and its volatility for CNY–OIL are the smallest among the sample pairs. Huang and Guo (2007) also find that there is a long-term minor appreciation of CNY to USD exchange rate induced by oil price shocks, which is attributed to the RMB basket peg regime and energy price regulations by the government.

Figure 2 about here

For other oil importers and oil-importing economic union such as the European Union, India and South Africa, their dynamic dependence is not always negative, which mainly depends on the actual country-specific external economic circumstances and trade situation. The dynamic dependence of USDX–OIL is generally negative, with however some positive value before 2004. This finding makes clear suggestion that both positive and negative dependence results for the oil price–US dollar relationship could be found if one uses constant copula models over a specific time period. In the previous literature, Chen and Chen (2007) and Basher et al. (2012) support a positive relationship, whereas Yousefi and Wirjanto (2004) and Lizardo and Mollick (2010) document a negative relationship.

Figure 3 about here

Figure 3 shows four types of dynamic tail dependences for oil price-exchange rate pairs in oil importers. With the exception of the CNY–OIL pair, the optimal copula for the remaining pairs is either the time-varying t copula or normal copula (NGN–OIL). Their tail dependence structure is thus symmetric, implying the equality of upper tail and lower tail dependence as well the equality of lower–upper tail and upper–lower tail dependence. Differently, the lower-upper tail dependence in the CNY–OIL pair has distinct coefficients with the upper-lower tail dependence with respect to its optimal time-varying 90-degree rotated Clayton copula. Hence, there is asymmetric effect between appreciation and depreciation of the CNY in response to the corresponding oil price increase or decrease. Except for JPY–OIL, the upper–lower (or lower–upper) tail dependence of each pair is obviously larger than the lower (or upper) tail dependence, verifying the negative dependence of oil price-exchange rate pair.

4.2.2 Dependence in oil exporters

The dynamic Kendall dependence of oil price-exchange rate pair in oil exporters is shown in Figure 4. It can be divided into two categories according to the dependence fluctuation characteristics. The first type, including the DZD–OIL and NGN–OIL pairs, shows a relatively stable and small negative dependence. The second type, including the remaining oil exporters, exhibits larger dependence in absolute values and greater variations. Similar to the oil importers (Figure 2), the dynamic dependence between oil returns and oil exporters' exchange rates alternates positive and negative values over time. In particular, the dynamic dependence for Russia is positive but irregular at some points in time. This finding suggests that rising oil prices do not always contribute to the appreciation of the RUB/USD. This finding supports the evidence provided by Sosunov and Zamulin (2006) that oil prices alone could not account for the appreciation of the Russian currency unless the oil price increases are assumed to be permanent.

Figures 4 and 5 about here

Figure 5 plots four types of dynamic tail dependences between crude oil returns and exchange rates in oil exporters. The tail dependence of the DZD–OIL and NGN–OIL pairs is the lowest and the least volatile, which is consistent with the findings shown in Figure 4. The dynamic tail dependence for other pairs, which is very similar to pattern observed for the oil importers, shows a large gap between the upper-lower tail dependence and the lower tail dependence.

4.3 Analysis of upside and downside CoVaRs

The VaRs and CoVaRs of all the exchange rates are calculated based on the optimal time-varying copulas at the 95% confidence level ($\alpha = \beta = 0.05$). Figure 6 and Figure 7 display the dynamics of the obtained CoVaRs for the oil importers and oil exporters, respectively. The shape of the CoVaR for each country is comparatively different, which means that the impact of oil market's extreme risk on extreme risk of foreign exchange markets tends to be country-specific.

For example, the CoVaR for the CNY/USD rate conditional on the VaR for the oil returns was almost zero before 2005. A possible reason is that China has abolished, since 2005, the original pegging exchange rate policy and has implemented a regulated floating exchange rate mechanism. The CoVaR for the CNY/USD was, however, still smaller than for the exchange rates of other oil importers, which indeed reflects more stringent exchange control measures implemented by the Chinese government. The CoVaR trend of the INR/USD exchange rate is similar to that of the CNY/USD rate, suggesting their similar market situations. The CoVaR for exchange rates of all oil importers had an extreme movement in 2008 where the recent global financial crisis entered into its most critical stage. This increased risk in the exchange rate market is thus attributed to not only the transmission of extreme risk from the oil market but also the impact of external macroeconomic shocks.

Figures 6 and 7 about here

For the oil exporters, Figure 7 shows that the dynamics of CoVaRs differs significantly. Specifically, the CoVaRs for the NGN/USD and KWD/USD rates occasionally show sudden hikes, but their values remain close to zero. The CoVaR for the RUB/USD rate has become increasingly larger following the global financial crisis 2008-2009, with a peak at the end of 2014. The continuous decline in oil returns and the outbreak of the Russia–Ukraine conflict in the second half of 2014 could partially explain this peak. The CoVaRs for the exchange rates of other non-OPEC supply countries (BRL/USD, CAD/USD, and NOK/USD) show similar characteristics.

Table 6 presents the testing results of extreme risk comovement and asymmetric effects between downside and upside CoVaRs, conditionally on the specific oil risk for oil-exporting countries (oil price decreases) and oil-importing countries (oil price increases). We first compare the downside and upside risk comovement (CoVaR) to the downside and upside VaRs of the exchange rate. Panel A shows that the downside and upside CoVaRs conditional on the upside VaR of oil returns are significantly smaller than downside and upside VaRs for the exchange rates of sample oil importers, except for the CNY/USD and JPY/USD rates. This finding is consistent evidence of the influence of upward movements in oil returns on downward movements in exchange rate returns. For oil exporters, the downside and upside CoVaRs conditional on the downside VaR of oil returns are significantly larger than the corresponding VaRs for the exchange rates of sample oil exporters (Panel B).

Table 6 about here

We then examine the asymmetric effects of downside and upside CoVaRs. The tests in Table 6 indicate that, given the upside VaR condition for oil returns in the oil importers, the upside CoVaR is significantly smaller than the downside CoVaR normalized by the corresponding VaR, with the exception of the JPY/USD rate. By contrast, the upside CoVaR is significantly larger than the downside CoVaR normalized by the corresponding VaR, given the condition of downside VaR for the oil returns in the oil exporters. The comparison of the difference in the results for the oil exporters and the oil importers shows the following: the oil importers' exchange rates are exposed to greater appreciation pressure in response to upward comovement in oil returns, whereas the oil exporters' exchange rates are exposed to greater depreciation pressure in response to a downside comovement in oil returns.

5. Conclusion

Various time-varying copula models are used to estimate the time-varying dependence between crude oil returns and returns on exchange rates of 14 major oil-trading countries. The extreme risk comovement, measured by the CoVaRs for exchange rates conditional on the VaRs for crude oil returns, is also calculated on the basis of optimal copula models for each oil-exchange rate pair under consideration.

Our empirical results show that the dependence of oil-exchange rate pairs is generally weak and negative for both oil importers and oil exporters. For example, the rise in crude oil prices is only accompanied by a minor appreciation of the foreign currency against the US dollar. The overall value of dependence for oil price–exchange rate pairs for the oil importers is smaller than the one for the oil exporters. Another interesting result is that the lower tail and upper tail dependence of all market pairs is close to zero, whereas the upper-lower (lower-upper) tail dependence varies greatly over time and increased significantly in times of the 2008-2009 global financial crisis. The dependence of oil price-exchange rate pairs for some emerging economies such as China and OPEC countries (Algeria and Nigeria) is characterized by weak values and small variations. Finally, there are significant asymmetric effects between downside risk and upside risk comovement for both oil exporters and oil importers, which implies that the extreme risk for sample foreign exchange markets conditional on the oil price fluctuations is not alike.

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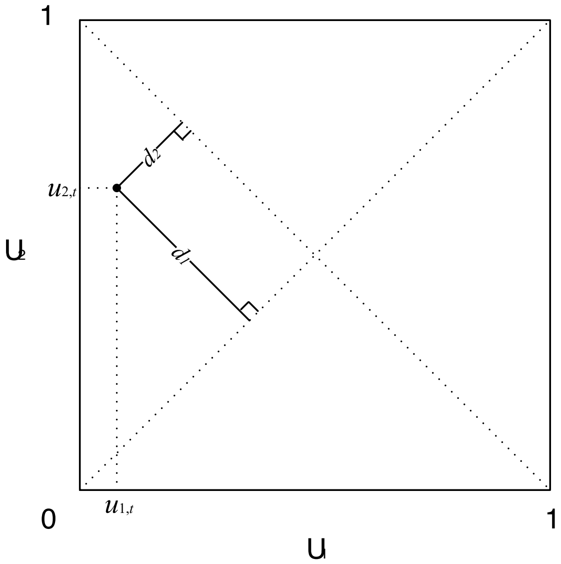

Figure 1. The diagram of forcing variables

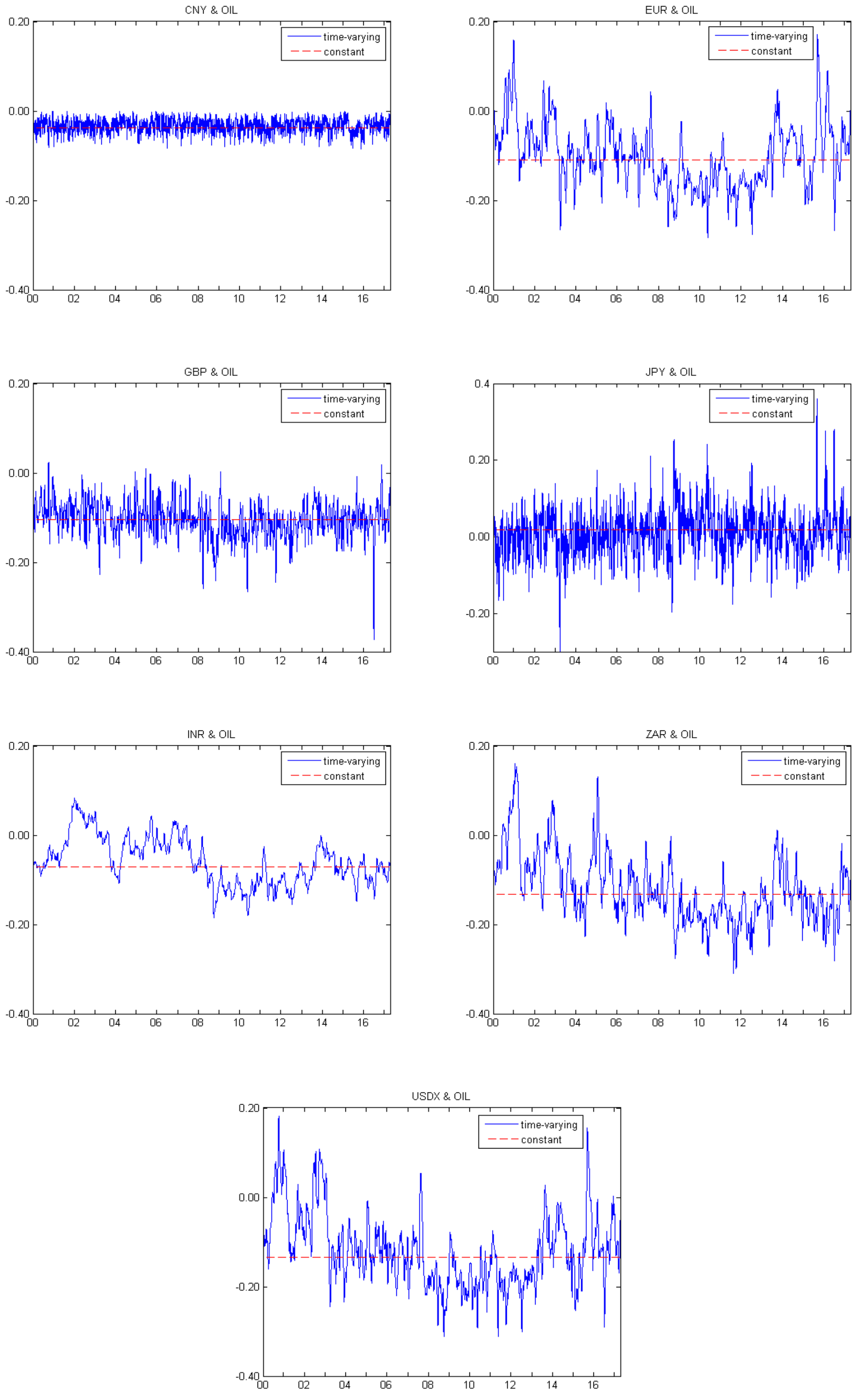

Figure 2. Dynamic dependences between oil returns and exchange rates in oil importers

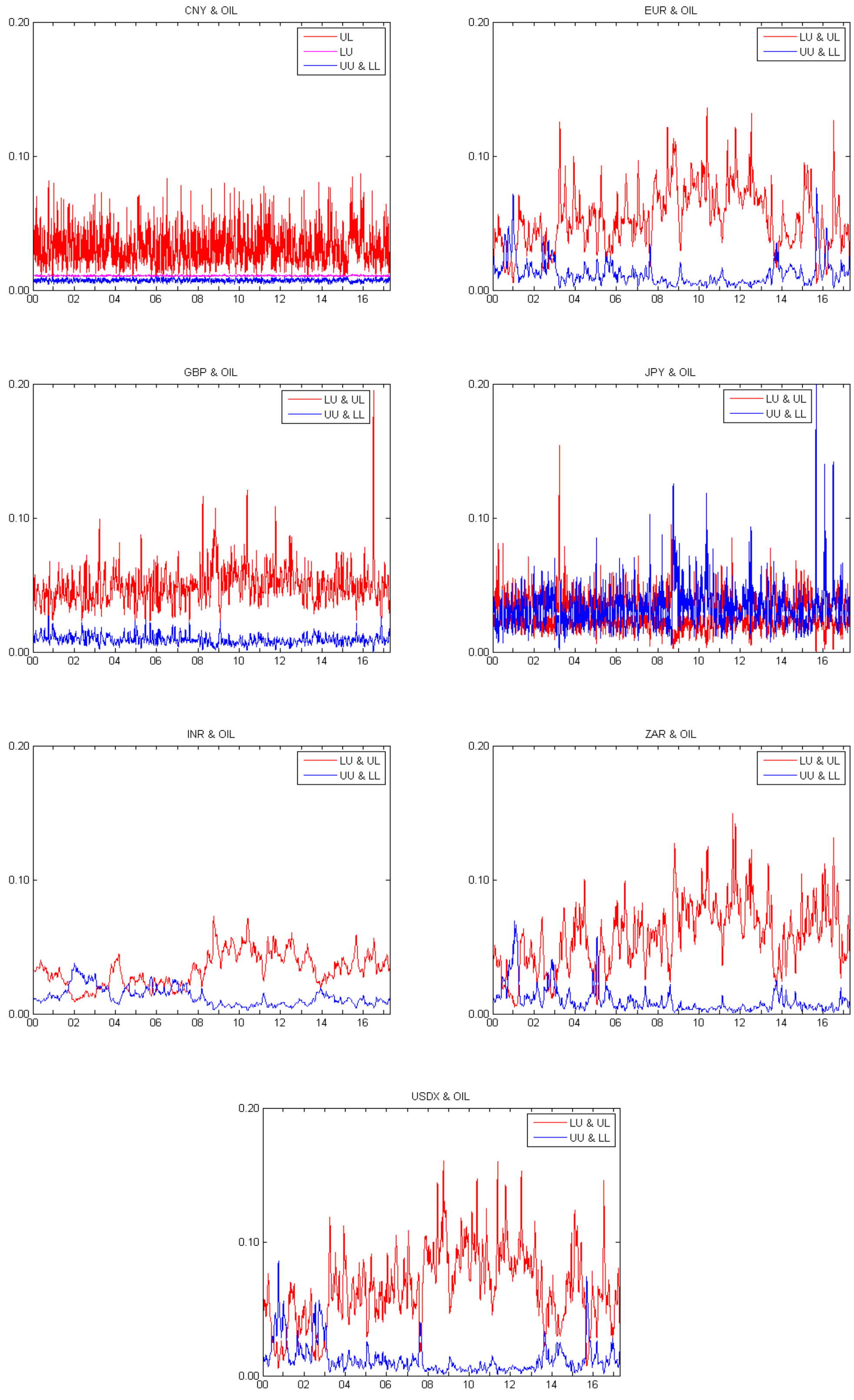

Figure 3. Dynamic tail dependences between oil returns and exchange rates in oil importers

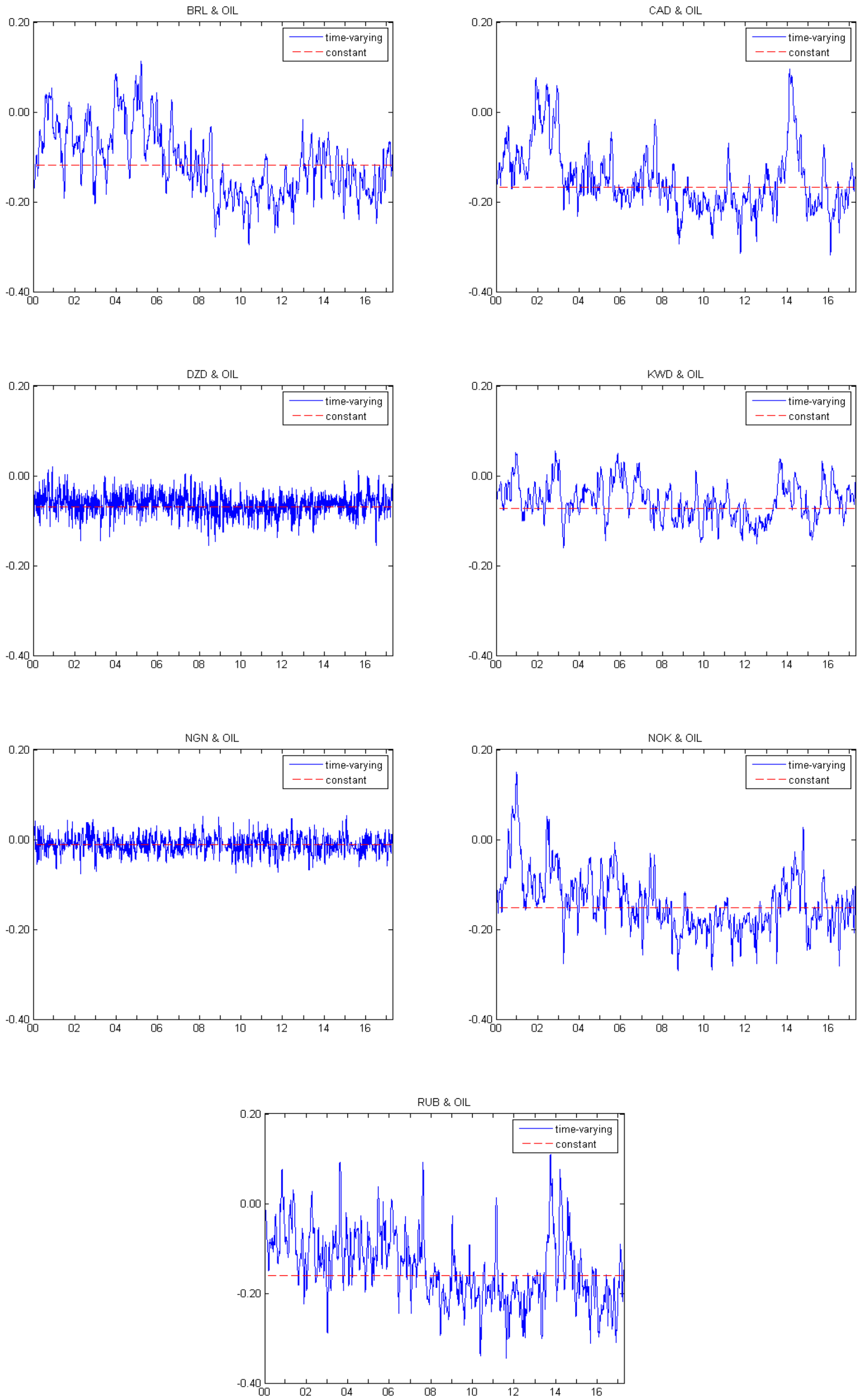

Figure 4. Dynamic dependences between oil returns and exchange rates in oil exporters

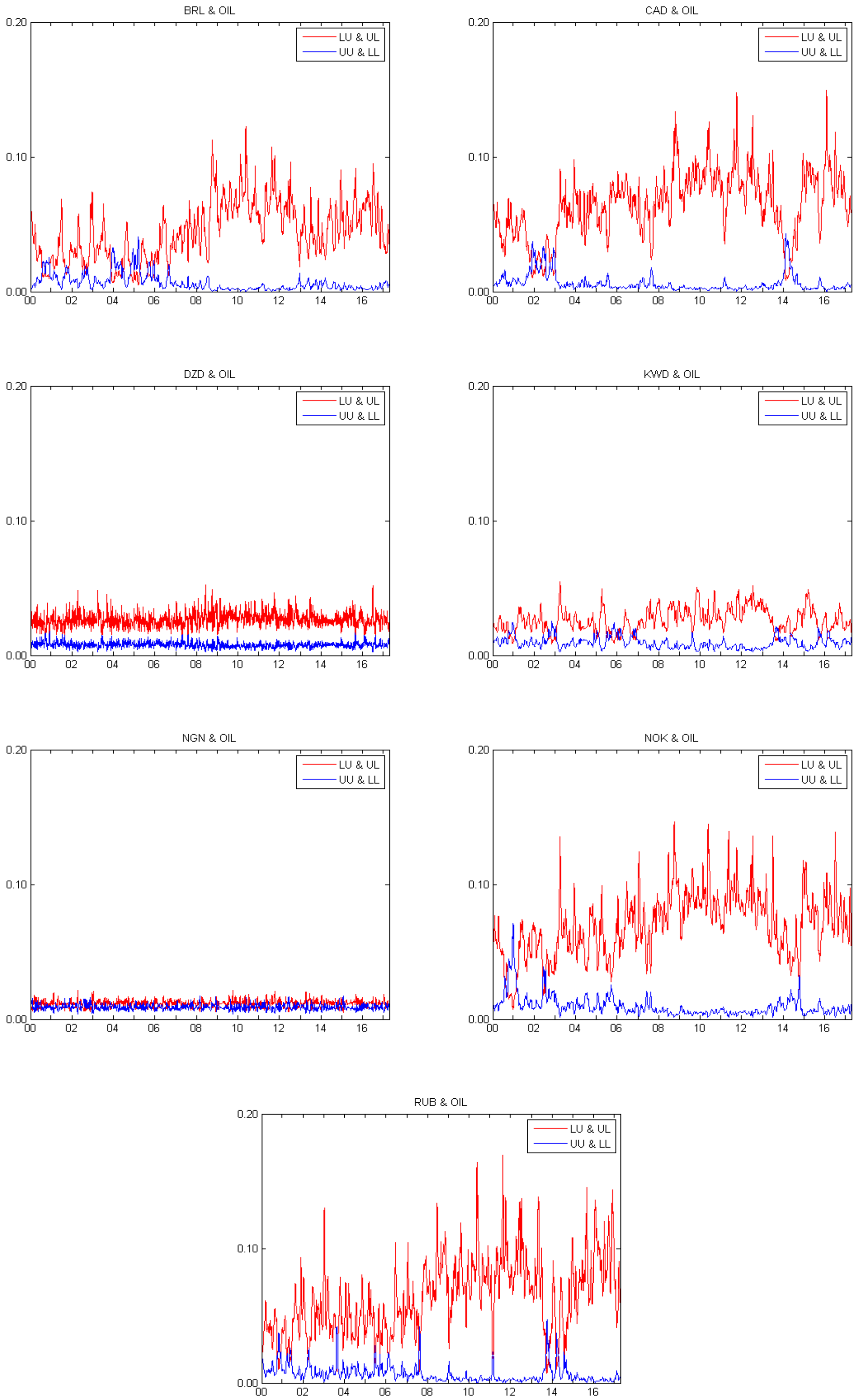

Figure 5. Dynamic tail dependences between oil returns and exchange rates in oil exporters

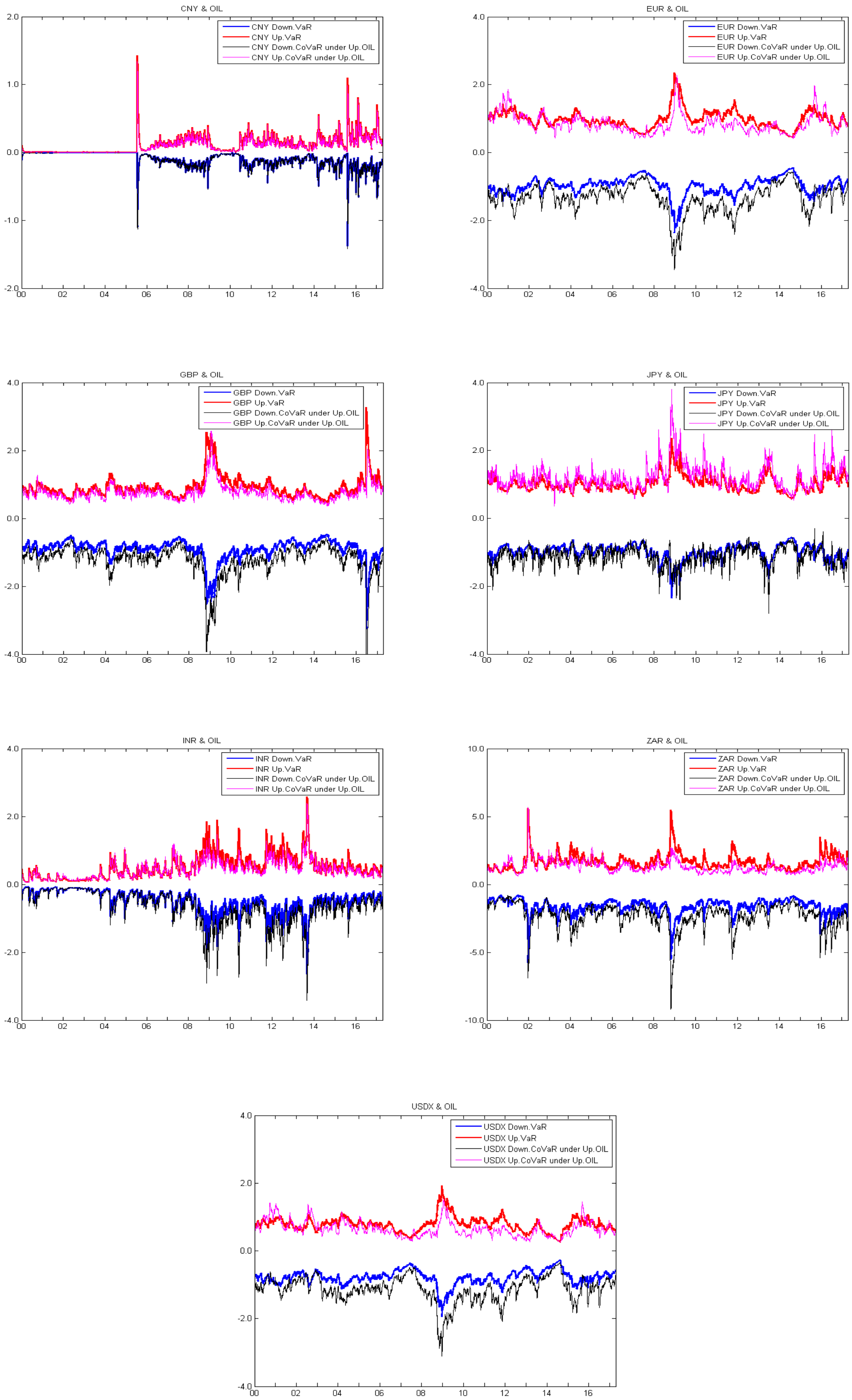

Figure 6. Upside and downside CoVaRs for exchange rates in oil importers conditional on upside VaRs for oil returns

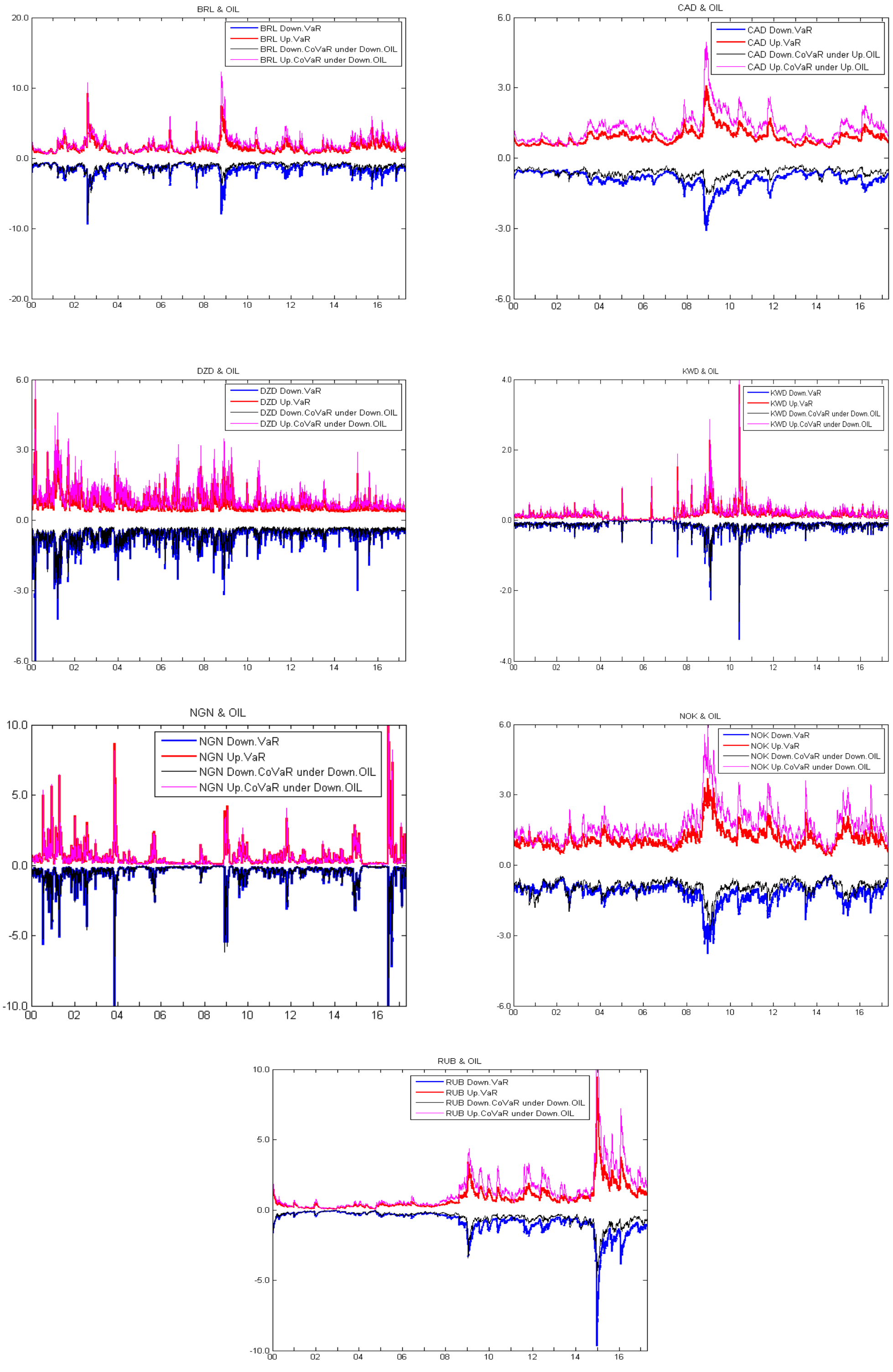

Figure 7. Upside and downside CoVaRs for exchange rates in oil exporters conditional on downside VaRs for oil returns

Table 1. Review of the literature on the relationships between oil returns and exchange rates

Authors	Country	Model	Period	Frequency	Results
Chaudhuri and Daniel (1998)	16 OECD countries	Cointegration, causality test	Most countries: 1973~1996	Monthly	The nonstationary of US dollar real exchange rates is due to the nonstationary of real oil prices during the post-Bretton Woods era.
Amano and van Norden (1998), Basher et al. (2012), Wu et al. (2012), Chen et al. (2013)	US	Cointegration, ECM, SVAR, Time-varying copula	1972~2011	Monthly, weekly	Positive oil price shocks tend to depress US dollars in the short run, and the dependence structure between oil price and USD becomes negative.
Huang and Guo (2007)	China	SVAR	1990~2005	Monthly	Real oil price rise causes RMB real exchange rate appreciation.
Chen and Chen (2007)	G7 countries	Panel cointegration	1972~2005	Monthly	The real oil prices have become the main determinant of exchange rate movements.
Narayan et al. (2008)	Fiji islands	GARCH	2000~2006	Daily	Oil price rise result in Fiji currency's appreciation.
Sari et al. (2010)	European Union	GVD, GIR	1999~2007	Daily	There is no stable relationship between oil price returns and exchange rates.
Lizardo and Mollick (2010)	Eight oil-trading countries	Cointegration	1975~2007	Monthly	Oil price rise may cause significant depreciation for the USD against currency in net oil exporters.
Nikbakht (2010)	7 OPEC countries	Panel cointegration	2000~2007	Monthly	There is a long-term relationship between real oil prices and real exchange rates.
Reboredo (2012)	7 OECD countries	Time-varying copula	2000~2010	Daily	Oil price-exchange rate dependence is in general weak.
Oriavwote and Eriemo (2012), Salisu and Mobolaji (2013)	Nigeria	VAR, VECM; VAR-GARCH	1980~2010; 2002~2012	Annual; daily	There exists a long-term equilibrium relationship between real oil prices and real effective exchange rates. The increase in oil price volatility may cause a depreciation in Nigerian currency relative to the USD.
Aloui et al. (2013)	5 OECD countries	Copula	2000~2011	Daily	There is a relationship between oil price rise and the dollar depreciation.
Turhan et al. (2014)	G20	cDCC model	2000~2013	Daily	There is an increasing negative relationship in the last decade between oil prices and exchange rates.
Atems et al. (2015)	7 OECD countries	VAR	1974~2013	Monthly	Oil-specific demand shocks and global aggregate demand shocks are associated with a depreciation of exchange rates.
Bal and Rath (2015)	China, India	Nonlinear Granger causality	1994~2013	Monthly	The nonlinearity of oil price influences the exchange rate.
Pershin et al. (2016)	3 African countries	VAR	2003~2014	Daily	No general rule exists on the relationship between oil prices and net oil-importing sub-Saharan countries' exchange rates.

Table 2. Descriptive statistics of oil and exchange rate return

		Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.
OIL	**WTI**	0.016	16.414	–17.092	2.437	–0.150	7.275
	CNY	–0.004	1.810	–2.031	0.101	–0.636	75.100
	EUR	–0.001	3.844	–4.617	0.625	–0.137	5.491
	GBP	0.006	8.312	–4.474	0.598	0.616	14.793
Oil importers	**JPY**	0.002	3.710	–4.610	0.647	–0.272	6.768
	INR	0.009	3.251	–3.064	0.383	0.274	10.631
	ZAR	0.017	9.808	–8.523	1.066	0.301	8.120
	USDX	0.000	2.524	–3.065	0.510	–0.081	4.561
	BRL	0.012	9.677	–11.778	1.020	0.084	14.536
	CAD	–0.002	4.338	–5.046	0.584	–0.093	8.149
	DZD	0.011	6.287	–5.109	0.558	0.474	16.623
Oil exporters	**KWD**	0.000	3.542	–3.610	0.162	0.081	133.573
	NGN	0.025	26.905	–7.710	0.735	12.218	437.231
	NOK	0.002	5.015	–6.458	0.766	–0.000	7.195
	RUB	0.016	14.268	–15.523	0.774	0.228	77.051

	Jarque-Bera	Q(8)	$Q^2(8)$	ARCH(8)
OIL	3449.746 **	28.368 **	1117.316 **	502.060 **
CNY	976952.531 **	50.083 **	80.068 **	77.613 **
EUR	1179.519 **	7.382	321.949 **	212.213 **
GBP	26414.686 **	27.635 **	380.930 **	235.088 **
JPY	2722.841 **	5.113	171.541 **	129.082 **
INR	10998.116 **	61.415 **	1896.949 **	717.237 **
ZAR	4992.246 **	22.031 **	1119.609 **	576.565 **
USDX	463.051 **	2.983	381.861 **	218.885 **
BRL	25009.617 **	47.560 **	2782.853 **	1130.277 **
CAD	4987.134 **	25.610 **	1008.334 **	476.079 **
DZD	35037.473 **	347.355 **	1572.124 **	832.883 **
KWD	3203121.071 **	279.930 **	899.068 **	953.091 **
NGN	35537278.618 **	51.821 **	34.434 **	33.730 **
NOK	3306.764 **	14.038	579.594 **	317.621 **
RUB	1030264.939 **	84.462 **	1946.754 **	1514.734 **

Note: * and ** denote significance at the 5% and 1% level, respectively.
Q(8) and $Q^2(8)$ denote the Ljung-Box statistics for returns and squared returns, respectively.
ARCH denotes the Lagrange Multiplier test for autoregressive conditional heteroscedasticity.

Table 3. Marginal distributions

	φ_0	φ_1	φ_2	ψ_1	ψ_2	α_0	α_1	β_1	υ
	ARMA(1,1)-GARCH(1,1)-t								
WTI	0.065	–0.033	--	–0.002	--	0.027	0.048	0.948	6.360
	(0.039)	(0.416)		(0.417)		(0.009)	(0.006)	(0.006)	(0.539)
	ARMA(1,1)-GARCH(1,1)-t								
CNY	–0.000	0.191	--	–0.283	--	0.000	0.167	0.833	3.884
	(0.000)	(0.137)		(0.134)		(0.000)	(0.011)	(0.007)	(0.109)
	ARMA(0,0)-GARCH(1,1)-t								
EUR	–0.005	--	--	--	--	0.001	0.032	0.967	7.904
	(0.008)					(0.000)	(0.005)	(0.005)	(0.988)
	ARMA(2,2)-GARCH(1,1)-t								
GBP	–0.014	–1.335	–0.366	1.349	0.387	0.002	0.042	0.952	9.208
	(0.020)	(0.512)	(0.496)	(0.507)	(0.487)	(0.001)	(0.006)	(0.006)	(0.963)
	ARMA(0,0)-GARCH(1,1)-t								
JPY	0.012	--	--	--	--	0.004	0.038	0.953	5.452
	(0.008)					(0.001)	(0.006)	(0.007)	(0.427)
	ARMA(0,1)-GARCH(1,1)-t								
INR	–0.003	--	--	–0.011	--	0.000	0.125	0.875	4.281
	(0.002)			(0.013)		(0.000)	(0.010)	(0.007)	(0.232)
	ARMA(2,2)-GARCH(1,1)-t								
ZAR	0.013	–0.211	–0.876	0.223	0.865	0.010	0.064	0.929	7.350
	(0.027)	(0.106)	(0.100)	(0.110)	(0.105)	(0.003)	(0.007)	(0.007)	(0.870)
	ARMA(0,0)-GARCH(1,1)-t								
USDX	–0.004	--	--	--	--	0.000	0.039	0.961	6.199
	(0.006)					(0.000)	(0.005)	(0.005)	(0.648)
	ARMA(2,0)-GARCH(1,1)-t								
BRL	–0.020	0.024	–0.030	--	--	0.010	0.131	0.868	7.067
	(0.010)	(0.016)	(0.015)			(0.002)	(0.012)	(0.010)	(0.727)
	ARMA(0,0)-GARCH(1,1)-t								
CAD	0.000	--	--	--	--	0.001	0.044	0.954	8.985
	(0.007)					(0.000)	(0.006)	(0.006)	(1.230)
	ARMA(1,2)-GARCH(1,1)-t								
DZD	0.006	–0.695	--	0.551	–0.132	0.021	0.303	0.697	2.782
	(0.006)	(0.147)		(0.146)	(0.020)	(0.003)	(0.045)	(0.020)	(0.142)
	ARMA(0,1)-GARCH(1,1)-t								
KWD	0.000	--	--	–0.162	--	0.000	0.287	0.713	3.532
	(0.000)			(0.012)		(0.000)	(0.014)	(0.006)	(0.095)
	ARMA(0,1)-GARCH(1,1)-t								
NGN	–0.001	--	--	–0.130	--	0.001	0.275	0.725	2.949
	(0.001)			(0.013)		(0.000)	(0.020)	(0.009)	(0.089)
	ARMA(0,0)-GARCH(1,1)-t								
NOK	–0.027	--	--	--	--	0.000	0.070	0.930	6.939
	(0.008)					(0.001)	(0.008)	(0.007)	(0.619)
	ARMA(1,1)-GARCH(1,1)-t								
RUB	0.006	–0.986	--	0.990	--	0.000	0.069	0.931	4.567
	(0.004)	(0.010)		(0.008)		(0.000)	(0.006)	(0.005)	(0.280)

Note: The values in parentheses denote the standard error.

Table 4. Selection of optimal time-varying copulas

Model	Kendall	TV-N	TV-t	TV-C	TV-R_1C	TV-RC	TV-R_2C
CNY-OIL	–0.038 ***	–16.516	–14.381	–3.020	**–26.860**	8.392	1.213
EUR-OIL	–0.110 ***	–186.151	**–199.041**	7.739	–137.490	7.052	–124.953
GBP-OIL	–0.105 ***	–144.114	**–153.805**	6.222	–123.234	6.217	–76.921
JPY-OIL	0.018 *	–43.716	**–61.813**	–18.380	–4.785	–2.867	4.666
INR-OIL	–0.071 ***	–90.093	**–97.367**	3.661	–72.488	6.488	–20.091
ZAR-OIL	–0.133 ***	–242.115	**–252.108**	6.656	–179.623	1.888	–139.630
USDX-OIL	–0.135 ***	–268.190	**–287.147**	6.653	–190.679	6.360	–198.390
BRL-OIL	–0.119 ***	–221.312	**–223.126**	–4.314	–140.915	7.708	–134.455
CAD-OIL	–0.167 ***	–360.500	**–366.339**	6.184	–268.434	4.773	–250.993
DZD-OIL	–0.069 ***	–47.182	**–47.730**	–10.216	–41.462	0.025	–22.987
KWD-OIL	–0.072 ***	–69.294	**–74.212**	6.397	–41.846	6.035	–32.858
NGN-OIL	–0.012	**–0.806**	1.691	--	--	--	--
NOK-OIL	–0.151 ***	–303.965	**–322.199**	6.617	–239.785	6.235	–187.496
RUB-OIL	–0.160 ***	–353.561	**–363.928**	7.189	–291.260	8.675	–256.701

Note: *, ** and *** denote the significant levels of 10%, 5% and 1% for the non-zero Kendall coefficient test. The values in bold denote the optimal copula model with the smallest AIC value.

Table 5. Optimal time-varying copulas

	Model	$\overline{\omega}$	$\overline{\beta}$	$\overline{\alpha}$	n
CNY-OIL	**TV-R$_1$C**	0.740***	–1.361***	–1.214**	--
		(0.151)	(0.196)	(0.498)	
EUR-OIL	**TV-t**	–0.005*	1.957***	0.045***	16.601
		(0.003)	(0.027)	(0.013)	(4.323)
GBP-OIL	**TV-t**	–0.103*	1.243***	0.131**	19.069
		(0.061)	(0.430)	(0.066)	(6.458)
JPY-OIL	**TV-t**	0.036	–0.558	0.517**	13.747
		(0.045)	(1.106)	(0.207)	(3.147)
INR-OIL	**TV-t**	0.000	1.993***	0.015***	24.111
		(0.000)	(0.005)	(0.004)	(6.851)
ZAR-OIL	**TV-t**	–0.002	1.985***	0.043***	18.642
		(0.002)	(0.019)	(0.011)	(6.321)
USDX-OIL	**TV-t**	–0.004	1.972***	0.046***	14.588
		(0.003)	(0.019)	(0.011)	(3.460)
BRL-OIL	**TV-t**	–0.003	1.983***	0.046**	36.846
		(0.003)	(0.030)	(0.019)	(18.898)
CAD-OIL	**TV-t**	–0.001	2.007***	0.041***	22.140
		(0.002)	(0.019)	(0.014)	(9.099)
DZD-OIL	**TV-t**	–0.278***	–1.071**	0.269**	43.863
		(0.062)	(0.443)	(0.110)	(19.575)
KWD-OIL	**TV-t**	–0.003	1.939***	0.024***	39.639
		(0.002)	(0.032)	(0.008)	(14.519)
NGN-OIL	**TV-N**	–0.023	0.796	–0.112	--
		(0.022)	(0.746)	(0.077)	
NOK-OIL	**TV-t**	–0.003	1.990***	0.038***	14.971
		(0.003)	(0.019)	(0.009)	(3.656)
RUB-OIL	**TV-t**	–0.006	1.959***	0.060**	21.975
		(0.007)	(0.054)	(0.025)	(5.709)

Note: *, ** and *** denote the significant levels of 10%, 5% and 1%, respectively. The value in the parentheses denotes the standard error. $\overline{\omega}$ is the intercept, $\overline{\beta}$ is the coefficient of dependence at time t-1, capturing the dependence persistence, $\overline{\alpha}$ is the coefficient of driven variable in the dynamic process of dependence coefficients at time t. n is the degree-of-freedom in t Copula.

Table 6. Tests of risk comovement and asymmetric effects of CoVaRs

Panel A: Oil importers			
Symbol 1|2	Downside risk comovement $H_{01}: CoVaR_{1\|2U}^{D} = VaR_1^D$ $H_{11}: CoVaR_{1\|2U}^{D} < VaR_1^D$	Upside risk comovement $H_{02}: CoVaR_{1\|2U}^{U} = VaR_1^U$ $H_{12}: CoVaR_{1\|2U}^{U} < VaR_1^U$	Asymmetry effect $H_{03}: \frac{CoVaR_{1\|2U}^{D}}{VaR_1^D} = \frac{CoVaR_{1\|2U}^{U}}{VaR_1^U}$ $H_{13}: \frac{CoVaR_{1\|2U}^{D}}{VaR_1^D} > \frac{CoVaR_{1\|2U}^{U}}{VaR_1^U}$
CNY|OIL(U)	0.015	0.037 ***	1.000 ***
EUR|OIL(U)	0.452 ***	0.285 ***	0.836 ***
GBP|OIL(U)	0.473 ***	0.277 ***	0.990 ***
JPY|OIL(U)	0.227 ***	0.002	0.000
INR|OIL(U)	0.176 ***	0.087 ***	0.698 ***
ZAR|OIL(U)	0.418 ***	0.273 ***	0.859 ***
USDX|OIL(U)	0.533 ***	0.345 ***	0.813 ***
Panel B: Oil exporters			
Symbol 1|2	Downside risk comovement $H_{01}: CoVaR_{1\|2D}^{D} = VaR_1^D$ $H_{11}: CoVaR_{1\|2D}^{D} > VaR_1^D$	Upside risk comovement $H_{02}: CoVaR_{1\|2D}^{U} = VaR_1^U$ $H_{12}: CoVaR_{1\|2D}^{U} > VaR_1^U$	Asymmetry effect $H_{03}: \frac{CoVaR_{1\|2D}^{D}}{VaR_1^D} = \frac{CoVaR_{1\|2D}^{U}}{VaR_1^U}$ $H_{13}: \frac{CoVaR_{1\|2D}^{D}}{VaR_1^D} < \frac{CoVaR_{1\|2D}^{U}}{VaR_1^U}$
BRL|OIL(D)	0.246 **	0.232 ***	0.814 ***
CAD|OIL(D)	0.432 ***	0.424 ***	0.905 ***
DZD|OIL(D)	0.205 ***	0.300 ***	0.991 ***
KWD|OIL(D)	0.088 ***	0.146 ***	0.788 ***
NGN|OIL(D)	0.024 *	0.023 *	0.454 ***
NOK|OIL(D)	0.344 ***	0.470 ***	0.928 ***
RUB|OIL(D)	0.213 ***	0.193 ***	0.904 ***

Note: *, ** and *** denote the significant levels of 10%, 5% and 1%, respectively. This table verifies the significance of risk spillover by testing whether there is significantly difference between VaR and its corresponding CoVaR. In the meantime, asymmetric effect is also verified by testing whether upside CoVaR normalized by the upside VaR is statistically different from the downside CoVaR normalized by the downside VaR.