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## On the intraday dynamics of oil price and exchange rate: What can we learn from China and India?

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# On the Intraday Dynamics of Oil Price and Exchange Rate: What Can We Learn from China and India?

## *Abstract*

The main aim of this paper is to investigate the volatility determinants of crude oil and foreign exchange markets and jump spillover between them. We consider currencies of two major oil-importing countries (India and China) over the sample period of January 1, 2013 to October 31, 2019. We find evidence of positive return spillover from the oil to the foreign exchange market; however, there is a lack of return spillover in the other direction. Oil jumps appear to have a negative impact on exchange rate conditional volatility, and the latter responds asymmetrically to disentangled (positive and negative) oil price jumps. We also report disentangled exchange rate jumps' significant impact on conditional oil price volatility. These results, however, are asymmetric based on the nature of jumps and alternative oil price series. Finally, we do not find evidence of co-jump between the oil and foreign exchange markets. These results have important implications for investors and policymakers.

**JEL Classification:** C2, C15

**Keywords:** Oil price volatility, Realised volatility, Intraday jumps, Exchange rate, Intraday data

## 1. Introduction

Crude oil (oil, hereafter) is a vital input for driving global economic growth, and oil price shocks can jeopardize this growth prospect. Researchers provide evidence of a negative impact of oil price shocks on future economic growth (Hamilton, 1983) and stock market returns (Driesprong, Jacobsen, and Maat, 2008). An inflationary pressure of rising oil prices on other commodities (such as industrial and precious metals) is also well documented in the literature (Hammoudeh and Yuan, 2008; Uddin, Rahman, Shahzad, and Rehman, 2018). More recently, researchers tend to examine the interaction between oil prices and exchange rates, particularly for two reasons. First, these two variables exhibit a co-movement in recent years. For instance, in 2007, the oil price rise was followed by a depreciation of the US dollar and other major currencies. On the other hand, the US dollar appreciated in 2016 when oil price declined to US\$30 per barrel compared to US\$140 per barrel in June 2008. Second, information relating to volatility and jump spillover between these two markets is important for formulating (i) portfolio strategies, and (ii) efficient monetary and energy policies.

The main objective of this paper is to examine the determinants of intraday volatility and identify the presence of jump spillover and co-jumps between exchange rates and oil prices. Several factors motivate the expectation that there can be jump pass through between exchange rates and oil prices. First, there is strong theoretical reasoning that oil prices have a role in determining exchange rates, while exchange rates can also affect oil prices.<sup>1</sup> Second, oil prices

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<sup>1</sup> Theoretically, oil prices can affect exchange rate movements due to an asset market disequilibrium (Golub, 1983; Krugman, 1983). With an increase in oil price, wealth is transferred from oil-importing countries to oil-exporting countries, which can create an asset market disequilibrium. For the time being, an oil price rise may result in a current-account surplus (deficit) for oil-exporting (oil-importing) countries, which can ultimately affect exchange rates due to differential portfolio preferences. For example, if increased demand for dollars from oil-exporting countries cannot offset decreased demand for dollars from oil-importing countries, the dollar value will tend to depreciate due to the excess supply of dollars. On the other hand, exchange rates can also affect oil prices. Since oil is typically traded in the US dollar, a depreciation in the US dollar results in lower oil prices for non-US oil-importing countries. This phenomenon can increase oil demand and price in terms of the US dollar

and currencies other than the US dollar are typically quoted and traded in terms of US dollars. Thus, common information affecting the US dollar exchange rate can be simultaneously transmitted to both markets. Third, in the case of a country that is heavily dependent on oil import or export should exhibit jump spillover between oil prices and exchange rates since countries tend to adjust their energy and foreign exchange policies in response to extreme conditions in these markets.

Although the interaction between exchange rates and oil prices has been extensively studied, the literature has several limitations. First, the literature is over-represented by studies examining oil prices' link with the US dollar, other major currencies (such as Euro, Great Britain Pound, Canadian Dollar, etc.) and currencies of major oil-exporting countries (such as Russia, Mexico, and the Middle Eastern countries).<sup>2</sup> Despite China and India, among the largest oil importers, the Chinese Yuan's (CNY) and the Indian Rupee's (INR) interaction with oil prices has received less attention. Second, the literature mostly focuses on Granger causality-type relationship between the oil price-exchange rate and provides inconclusive results.<sup>3</sup>

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<sup>2</sup> For instance, Jawadi, Louhichi, Ameer, and Cheffou (2016), Reboredo (2012), Wu, Chung, and Chang (2012), among others, investigate the relationship between oil prices and the US dollar exchange rates. de Truchis and Keddad (2016) consider Canadian dollar, Euro, Japanese Yen, and Great Britain Pound; Bouoiyour, Selmi, Tiwari, and Shahbaz (2015) analyse Russian exchange rates; Brahmasrene, Huang, and Sissoko (2014) consider currencies of Canada, Mexico, Colombia, the UK, and Venezuela; Yousefi and Wirjanto (2004) consider OPEC currencies. Malik and Umar (2019) and Xu, Han, Wan, and Yin (2019) respectively consider currencies of major oil-importing countries and major industrialized countries, including India and China. Huang, An, and Lucey (2020) investigate the Euro and British Pound per US dollar.

<sup>3</sup> For example, Benhmad (2012) and Tiwari, Dar, and Bhanja (2013) examine the causal link between oil prices and exchange rates. While Tiwari et al. (2013) find a unidirectional causality from exchange rates to oil prices in India, Benhmad (2012) finds evidence of bidirectional causality between these two variables. Sadorsky (2000) also shows that the exchange rate movement causes movement in the oil market. Zhang, Fan, Tsai, and Wei (2008) report unidirectional mean spillover from the US dollar exchange rate to the oil market and bidirectional risk spillover between the two. Huang and Feng (2007) show that the real oil price causes Chinese exchange rates. Reboredo (2012), however, finds weak dependence between oil prices and exchange rates. Similarly, Bal and Rath (2015) do not find evidence of linear causality between these two variables. Hussain, Zebende, Bashir, and Donghong (2017) find a weak relationship between oil price and exchange rate in India. Zhu and Chen (2019) document an asymmetric impact of the Brent prices on the Chinese exchange rates. Tiwari, Trabelsi, Alqahtani, and Bachmeier (2019) reveal a negative association between the oil prices and the exchange rates of India, Brazil, and South Africa. Kumar (2019) suggests a strong bidirectional linkage between the oil price and the exchange rate in India. Boqiang and Tong (2020) confirm that oil price shocks may affect the Indian exchange rate in the short and long-term however the Chinese exchange rate is immune to such shocks.

Although volatility dependence between oil prices and exchange rates has been examined by several studies (for example, Salisu and Mobolaji, 2013; de Truchis and Keddad, 2016), the determinants of exchange rate and oil price volatility, jumps spillover and the existence of co-jumps between exchange rates and oil prices are still under-researched. Third, most of the studies examining the relationship between oil prices and exchange rates are based on low-frequency data (such as daily and monthly). Thus, the nature of the interaction between these two variables in intraday or high-frequency data is still an open question.

Accordingly, our first contribution in this paper is the selection of currencies. We initially consider the exchange rates of Chinese and Indian currencies against the US dollar. We also consider the Japanese currency exchange rates as a robustness check. Therefore, unlike previous studies that mostly focus on either developed or major oil-exporting countries, our paper focuses firstly on two major oil-importing countries, and secondly, provides a comparison of the volatility and jump spillover between oil and currency markets of both emerging and developed countries. Examining the exchange rate-oil price nexus in the context of India and China can be interesting for several reasons. First, as indicated earlier, very little research has been conducted focusing on the intraday volatility determinants and jump spillover between the oil prices and the Chinese and Indian exchange rates.<sup>4</sup> Second, China (India) is the largest (fourth largest) importer of oil in 2017, importing 8.4 million (3 million) barrels per day (EIA, 2017). Both countries import more than 60% of their domestic oil demand. Thus, oil price fluctuation in the world market is expected to have an impact on macroeconomic dynamics, including the exchange rates of these two countries. Third, China and India, respectively, are the second (US\$14 trillion) and seventh (US\$2.85 trillion) largest

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<sup>4</sup> One notable study in the context of these two currencies is Bal and Rath (2015). Although the authors find significant relationship between oil prices and exchange rates, their main focus is detecting non-linear Granger causality rather than volatility determinants and jump spillover. Additionally, the authors use monthly data, thus do not examine intraday jump spillover.

economies in the world, sharing 14.84% and 2.83% of the global economy (Smith, 2018). Therefore, changes in the Chinese and Indian currency values may have an impact on the global commodity market, including oil prices. Fourth, the oil price-exchange rate relationship reported in the literature for the major currencies may not hold in the case of Chinese and Indian currencies. This is because, unlike the developed markets, the respective governments in India and China frequently intervene to insulate the energy sector from extreme volatilities in the international market (Ghosh, 2011; EIA, 2017). Fifth, the central bank's intervention in the foreign exchange market (for example, buying and selling foreign currencies, specifying a daily central parity rate, and moral persuasion) is common in both the countries (see Dua and Ranjan, 2012; Li, Yu, Zhang, and Zhang, 2017).<sup>5</sup> This phenomenon may have an impact on the interdependence between oil prices and exchange rates.

Our second contribution is the use of three oil price series, namely, West Texas Intermediate (WTI) Cushing oil futures, Brent Crude Oil futures (Brent), and Oman Crude Oil Energy Futures (DME). While previous relevant studies on the Asian market mostly concentrate on WTI crude oil prices (for example, Hussain et al., 2017; Bal and Rath, 2015), we argue that WTI price is not a good barometer for the oil price in Asia as most of the oil transactions take place on Dubai and Brent oil prices. We, therefore, address this issue and provide a comprehensive picture of the volatility spillover between oil price and exchange rate considering all the relevant oil price series.

The next contribution of the paper is the use of intraday data. In the finance literature, the availability of low-cost intraday data has made high-frequency finance as one of the leading areas in finance. The use of high-frequency data (HFD) has further magnified the

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<sup>5</sup> For example, China unofficially reinstated the dollar peg in the mid-2008 until the mid-2010 (Li et al., 2017) and the Reserve Bank of India sold US\$20.6 billion in the foreign exchange market during October 2008 (Dua and Ranjan, 2012) to fight against the contagion of global financial crisis.

understanding of market microstructure and extreme comovement. In this regard, some of the early studies which provide a perspective on high-frequency finance includes Engle (2000), Andersen (2000), and Christensen, Oomen, and Podolskij (2014). However, we find following intraday studies covering various segments of financial market: Wang et al., (1994) and Będowska-Sójka (2016) for the stock market, Duong and Kalev (2008) for commodity derivatives, Ye and Karali (2016) and Inci and Seyhun (2018) for crude oil, and Frömmel, Han, and Van Gysegem (2015) and Lee and Wang (2020) for currency markets

Although few papers use intraday data to examine the interaction between oil prices and the US dollar exchange rates (for example, Jawadi et al., 2016), our paper is a pioneering attempt to provide novel evidence of intraday volatility dynamics of oil prices and emerging market currencies. Our final contribution is the research approach. We estimate oil price and exchange rate jumps, disentangle them to positive and negative jumps, compute bi-power variations, and use them to explain oil price and exchange rate volatility. We also estimate a Tobit model to identify the presence of co-jump between oil price and exchange rate changes taking into account several control variables. Although our paper is the closest to Jawadi et al. (2016), the latter study is different from our one in some ways. First, the authors do not consider the Chinese or Indian exchange rates; instead, they focus on the US dollar/Euro exchange rates. Therefore, intraday dynamics of oil price – exchange rate relationship is highly regulated emerging market context is still unknown. Second, while they examine the driver of oil price volatility, and unidirectional jump spillover from the exchange rate to oil prices, we investigate the drivers of both oil price and exchange rate volatility and bidirectional jump spillover between oil prices and exchange rate changes. Third, they rely only on the WTI crude oil prices, whereas we consider three relevant oil price series. Finally, they also do not provide a comparison of the oil price – exchange rate dynamics in emerging and developing market context.

We report several key findings in this paper. First, we find a positive return spillover from the Brent (DME) to the Indian (Chinese) currency market. This result indicates that an increase in Brent (DME) oil prices lead to an appreciation of Indian (Chinese) currency. This result, however, does not hold for the Japanese currency. We also find a lack of return spillover from the currency to oil markets except for some negative return spillover from the Chinese exchange rates to DME oil prices.

Second, it is observed that oil jumps have a negative impact on the exchange rate conditional volatility of the Chinese and Japanese exchange rates (in the cases of Brent and WTI), implying that large shocks in the oil market reduce exchange rate volatility in China and Japan. This result does not hold in India. On the other hand, exchange rate jumps are found to have a negative (positive) impact on oil price conditional volatility of the Indian (Chinese) exchange rates. This result is found for Brent and DME but not for WTI. These results indicate that abrupt shocks in the oil and currency markets are immediately transmitted to each other.

Third, we find that positive oil jumps have a negative impact on the Chinese exchange rate conditional volatility, implying that an abrupt increase in oil price reduces exchange rate volatility. While this result is found for all the three oil price series, a similar result for India is reported only for Brent. With regard to negative oil jumps, a positive (negative) impact is observed on the Indian (Chinese) exchange rates for Brent (WTI). As we focus on disentangled exchange rate jumps' impact on oil price volatility, we only find a statistically significant result for DME but not for Brent or WTI. Overall, this result implies the asymmetric impact of currency (oil) price appreciation or depreciation on the other market.

Finally, our Tobit model shows that oil or exchange rate jumps do not explain the corresponding jumps in the other market. Overall, there is significant evidence of return and volatility spillover as well as co-jumps between the oil prices and the US dollar exchange rates



reported in the literature. We, however, argue that such a result is conditional on the nature of jumps, oil price series considered, and the underlying economy. We further contend that previous studies focusing on one oil price series provide only a partial picture of the oil price – exchange rate nexus. Therefore, our results make an important addition to the link, particularly by complementing the results of Jawadi et al. (2016) and Bal and Rath (2015).

The rest of the paper proceeds as follows. Methodological aspects are presented in Section 2. Section 3 describes the data, time-trends, and descriptive statics. Empirical results and interpretation are provided in Section 4. Section 5 concludes by providing a summary of the paper.

## 2. Methodology

In this section, we discuss in brief the method used to analyze the intraday data. We begin with a basic understanding of the jump process.

### 2.1 Jumps

In the finance literature, we assume that the returns of a financial asset belong to an underlying continuous-time process. Let's define the underlying model in terms of log(price) of a continuous sample-path. Then standard stochastic of returns under general assumptions is written as,

$$dP(t) = \mu(t)dt + \sigma(t)dX(t) + s(t)dJ(t), t \geq 0, \quad (1)$$

where  $dP(t)$  is the logarithmic price increment of sample series, and  $\mu(t)$  refers to the drift that captures locally bounded variations.  $\sigma(t)$  is the point-in-time or spot volatility which is strictly positive.  $X(t)$  denotes a standard Brownian motion.  $J(t)$  represents a pure jump process with jump size  $s(t)$ . This jump process is a counting process with  $dJ(t) = 1$  corresponding to a jump at time  $t$  and  $dJ(t) = 0$  corresponding to a jump at time  $t-1$ . According to Galeano and Tsay

(2009), heavy-tailed series obtained from second-moment models often do not explain all the characteristics of an asset return. Consequently, jump-diffusion and stochastic volatility models have been proposed to overcome this limitation. We assume that the logarithmic prices belong to either Brownian Semi-Martingale or Brownian Semi-Martingale with jumps families of models. Andersen, Bollerslev, and Dobrev (2007) provide a realistic model for the price series of many financial assets.

## 2.2. Bi-Power Variation(BV)

Barndorff-Nielsen and Shephard (2004) show that the normalized sum of product of absolute values of continuous returns can be used as a consistent estimator for the integrated volatility. It is known as bi-power variation (BV), and defined as:

$$BV_t(\Delta) \equiv \mu_1^{-2} \frac{H}{H-1} \sum_{i=2}^H |r_{t,i-1}| |r_{t,i}| \quad (2)$$

where  $\mu_1 \equiv \sqrt{2/\pi} \approx 0.79788$  and  $H = 1/\Delta$ .  $\Delta$  represents sampling frequency within each day,  $H$  is number of observations occurring every day and as  $\Delta \rightarrow 0$ , we have  $H \rightarrow \infty$ .  $r_{t,i}$  is the  $i$ -th return of day  $t$  and it can be written as:

$$r_{t,i} = p(t+i\Delta) - p(t+(i-1)\Delta), \text{ where } i = 1, 2, \dots, H. \quad (3)$$

The bi-power variation is designed in such way that it is robust to jumps. Product of current return and lagged return make it robust to jump while realized variance is vulnerable to jumps as we use square of current return. In  $BV$ , if current or lagged return has a jump component and other one follows diffusion process, then product will have small impact on bi-power variation. When  $\Delta \rightarrow 0$  (or equivalently  $H \rightarrow \infty$ ):

$$p \lim_{\Delta \rightarrow 0} BV_t(\Delta) = \int_{t-1}^t \sigma^2(s) ds \quad (4)$$

where  $\sigma^2(s)ds$  is the realized volatility which becomes a consistent estimate of integrated volatility when a series does not exhibit jump or serial correlation in the intraday returns.

### 2.3. Intraday Jump Tests

Evidently, the difference between realized variance ( $BV_t$ ) and any robust jumps estimator denoted by  $IV_t$ , is an estimate of the jump contribution or realized jumps. More specifically,

$$RJ_t(\Delta) = BV_t(\Delta) - IV_t \rightarrow \sum_{t-1 < s \leq t} c^2(s) \quad (5)$$

where  $IV_t$  is for instance  $BV_t(\Delta)$  or any other approximation like realized outlyingness weighted variation ( $ROWVar_t(\Delta)$ ). Following Andersen et al. (2007), we also use  $Z_t$  statistics to test for the presence of jumps in data. We use this statistic for our five-minute intraday data which has the following form:

$$Z_t = \frac{BV_t(\Delta) - \hat{IV}_t(\Delta)}{(\theta - 2) \frac{1}{H} I\hat{Q}_t} \quad (6)$$

where,  $I\hat{Q}_t$  is a robust jumps estimate of the integrated quarticity  $IQ_t \equiv IQ_t \equiv \int_{t-1}^t \sigma^4(s) ds$ .

To calculate jump size, we assume that there is at most one jump/day and this jump size dominates the return. Daily realized jump sizes is

$$\hat{J}(t, \alpha) = \text{sign}(r(t)) \times \sqrt{(RV(t) - BV(t)) \times I_{(z(t) \geq \Phi^{-1}(\alpha))}} \quad (7)$$

where  $I_{(z(t) \geq \Phi^{-1}(\alpha))}$  is an indicator function which takes the value of one if there is a jump on a given day, and zero otherwise.  $\Phi(\cdot)$  is the cumulative distribution function of normal distribution and  $\alpha$  is the level of significance. We use  $\alpha$  equal to 5% for all of our estimations in this paper.

#### 2.4. GARCH (1,1) Models

To analyse the process of volatility between oil price and exchange rate changes, we consider the following GARCH (1,1) model proposed by Bollerslev (1986):

$$R(EX)_t = a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \quad (8)$$

$$VAR(\varepsilon_t | \varepsilon_{t-1}) = \sigma_t^2$$

$$\sigma_t^2 = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

$$R(OIL)_t = a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \quad (9)$$

$$VAR(\varepsilon_t | \varepsilon_{t-1}) = \sigma_t^2$$

$$\sigma_t^2 = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where  $R(EX)_t$  and  $R(OIL)_t$  are current and lagged currency returns while  $R(OIL)_t$  and  $R(OIL)_{t-1}$  are the current and lagged oil returns series. The parameters  $a_0, a_1, a_2, \alpha_0, \alpha, \beta$  are the coefficients to be estimated. The innovations  $\varepsilon_t$  are assumed to be identically and independently distributed (i.i.d). All returns are calculated as the logarithmic difference between the prices at time  $t$  and  $t - 1$ . The sum of coefficients  $\alpha$  and  $\beta$  measures the degree of volatility persistence. As  $\alpha + \beta$ , the magnitude of persistence, approaches to 1, the persistence of shocks to volatility increases.

To test for volatility spillover between oil price and exchange rate changes, we adopt an approach in line with the one used by Hamao, Masulis, and Ng (1990), Baur and Jung (2006), Miralles-Marcelo, Miralles-Quiros, and Miralles-Quiros (2010) and Jawadi et al.

(2016). We introduce the jump of oil returns (exchange rate returns) as an exogenous variable for the conditional variance equation of the exchange rate returns (oil returns). We use the GARCH (1,1) model with lagged returns from oil, and both currencies return into the mean equation to capture persistence and memory effects in the return dynamics. GARCH (1,1) model has the following specifications:

$$\begin{aligned} R(EX)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma Jump_{OIL,t-1} \end{aligned} \quad (10)$$

$$\begin{aligned} R(OIL)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma Jump_{EX,t-1} \end{aligned} \quad (11)$$

where  $Jump_{OIL,t-1}$  and  $Jump_{EX,t-1}$  are lagged oil and exchange rate jumps, respectively. The parameters  $\mu_0, a_1, a_2, \alpha_0, \beta, \lambda$  are the coefficients to be estimated.

Next, we further extend the GARCH model and introduce the negative and positive jumps of the return series to test volatility spillover. We use the intensity of positive and negative intraday jumps as an exogenous variable in the conditional variance equation in line with Jawadi et al. (2016). The GARCH specification takes the following form:

$$\begin{aligned} R(EX)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma_1 PosJ_{t-1}(OIL) + \gamma_2 NegJ_{t-1}(OIL) \end{aligned} \quad (12)$$

$$\begin{aligned} R(OIL)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma_1 PosJ_{t-1}(EX) + \gamma_2 NegJ_{t-1}(EX) \end{aligned} \quad (13)$$

where  $PosJ_t(OIL)$  and  $NegJ_t(OIL)$  refer to the intensity of the positive and negative current oil jumps, respectively and  $PosJ_t(EX)$  and  $NegJ_t(EX)$  reflect the intensity of positive and negative current exchange rate jumps. The parameters  $\mu_0, a_1, a_2, \alpha_0, \alpha, \beta, \lambda_1$  and  $\lambda_2$  are the coefficients to be estimated.

Further, we explain the spillover effects of  $BV$  between the oil and foreign exchange market. We start by introducing  $BV_{OIL,t-1}$  in the variance equation.

$$\begin{aligned} R(EX)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \varphi BV_{OIL,t-1} \end{aligned} \quad (14)$$

$$\begin{aligned} R(OIL)_t &= a_0 + a_1 R(OIL)_{t-1} + a_2 R(EX)_{t-1} + \varepsilon_t \\ VAR(\varepsilon_t | \varepsilon_{t-1}) &= \sigma_t^2 \\ \sigma_t^2 &= \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \varphi BV_{EX,t-1} \end{aligned} \quad (15)$$

### 3. Data, time-trends and descriptive statistics

#### 3.1 Data

This study uses five-minute interval data on oil prices and exchange rates for a sample period of January 1, 2013, to 31 October 2019. This sample period covers several economic and geopolitical events. For instance, in the post-global financial crisis (GFC) period, the quantitative easing approach taken by various governments has resulted in expansionary monetary policies and very low-interest rates, which also have influenced currency exchange rates (Aloui, Aïssa, and Nguyen, 2013). Oil prices fluctuated much during the sample period. In 2016, the price per barrel reached to US\$30 (compared to a US\$140 per barrel in June 2008), while on September 2019, oil price increased the most on record after a devastating attack on Saudi Arabia (Jawadi et al., 2016; Tobben, 2019). With regard to exchange rates, in June 2018, the Indian rupee collapsed to the all-time low value against the US dollar, potentially due to an

increase in crude oil price and fiscal deficit (Singh and Gogoi, 2018). In August 2019, the Chinese Yuan's value was the weakest against the US dollar since early 2008, mostly due to the trade war between China and the USA (Phillips, 2019). Therefore, we have an ideal context to explore volatility and jump spillover between oil prices and exchange rates.

With regard to exchange rates, we primarily consider the Indian Rupee (USDINR) and the Chinese Yuan's (USDCNY) exchange rates against the US dollar. However, due to the rising financial influence of Japan in Asia and globally, we also consider the exchange rates of the Japanese Yen (USDJPY) against the US dollar. The aim is to provide (i) a comparison between the emerging and developed market contexts, and (ii) find whether the jumps in the Japanese exchange rates determine the volatility and jumps of the Indian and Chinese exchange rates.

For oil prices, we consider three oil price series critical to the oil basket of India and China. They are West Texas Intermediate (WTI) Cushing oil futures quoted on New York Mercantile Exchange (NYMEX), Brent Crude Oil futures traded at Intercontinental Exchange, and Oman Crude (DME) Oil Energy Futures traded at the Dubai Mercantile Exchange.<sup>6</sup> The Brent is a determining factor for global oil demand as it is widely exported to Europe and Asia. The WTI, on the other hand, has a large and concentrated market in Europe.

The inclusion of DME is justified because, over the years, it has become the regional benchmarks for the oil exports from the Middle East to Asia (Nakajima and Hamori, 2012).

We take an average of the bid and ask prices of all the intraday series to calculate the intraday returns. To examine the jump spillover between the oil price and exchange rate changes, we consider several control variables. These are the Euro-US dollar exchange rates (USDEURO), the volume of oil traded (VOL), the Chicago Board of Exchange (CBOE) Oil

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<sup>6</sup> We are thankful to one of the anonymous reviewers for suggesting us to incorporate it in our analysis.

Volatility Index (OVX) for Brent, CBOE/NYMEX WTI Volatility Index (OIV), and the 1-month Non-deliverable Forwards (NDFs) of USDINR and USDCNY. The use of these control variables are consistent with the prior literature (see, for example, Jawadi et al., 2016; Ahmad, Sadorsky, and Sharma, 2018). All data are obtained from Thomson Reuters DataStream.<sup>7</sup>

We follow a two-step procedure for data cleaning and generating continuous series. In the first step, we remove the data corresponding to the non-trading hours of WTI futures from all the oil prices and exchange rates data series. We also remove data for days corresponding to weekends and other holidays as trading does not take place during these days. In the second step, similar data manipulation is done for other oil price series and exchange rate observations. As a result, we get a continuous data series of oil prices and exchange rates for corresponding time and days. Five-minute returns for the oil prices and exchange rates are calculated as the logarithmic difference of the observations from time  $t-1$  to time  $t$ .

### ***3.2 Time-trends***

Figure 1 presents the time-trends of exchange rates and oil prices. We find that USDINR exhibits a major jump in its trading prices during 2013-2014 and 2018-2019. A major depreciation in USDINR took place during July-August 2013 when it was traded at as high as 68.85 per US dollar. This depreciation can be attributed to several reasons, such as (i) the Indian central bank's strategy to gradually reduce the amount of money they fed into the economy and subsequent market reaction, (ii) the rapid increases in the demand for the US dollar from importers, and (iii) capital outflows (see RBI, 2015; Hutchison and Pasricha, 2016). Since the middle of 2014, USDINR shows a gradual decline in its value until 2016 on account of capital outflow and weak export (Gurumurthy, 2018). USDINR, however, shows a stable pattern

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<sup>7</sup> We are thankful to the DataStream system administrators for providing with the intraday data for three years on a special request. A special thanks to Chetan Kajaria and Rohit Pujari of Thomson Reuters (now [www.refinitiv.com](http://www.refinitiv.com)).



between 2016 – 2017. In 2018-2019, USDINR depreciated, which may be attributed to the significant political developments in the US and China, the US fed rate policy, and trade restrictions. The USDINR return is found to be predominantly negative between the period of 2013 – 2014. However, from 2014 until early 2015, returns oscillate between positive and negative values. Since the middle of 2015 onwards, the return series has turned positive.

From Figure 1, we further observe that USDCNY remains relatively stable from 2013 until the middle of 2015. The episodes of upheavals and major jumps are seen during 2016-2018 and the mid of 2019. Major volatility is also observed during August 2015 that can be attributed to the devaluation of the Chinese Yuan (Renminbi) and fixation of the band of depreciation of the Chinese currency against the US dollar. For the rest of the episodes, the possible explanation could be the China-US trade dispute and the Chinese economic slowdown (CRS, 2019). With regard to USDJPY, a major jump is observed during the 2015-2016 and post-2017 period, which may be linked to the Bank of Japan's asset purchase plan, Brexit fears, and deflationary pressure (Harding and Jones, 2016).

As we focus on the Brent prices, we observe the episodes of major upturns during 2013-2014 and 2018-2019. The plot also reveals a major decline during 2015-2016. The oil price was at its peak of US\$ 115 per barrel in June 2014, which declined to as low as US\$35 per barrel at the end of February 2016. The oil price slightly recovers afterward. The 2018-2019 spikes in prices could be attributed to geopolitical uncertainty in Middle-East (Tobben, 2019). A similar pattern is found for WTI prices.

To summarize, it is apparent that the intraday price variations coincide with the different economic events, which also may have caused extreme price movements in the respective markets.

[INSERT FIGURE 1 ABOUT HERE]

We plot the intraday jumps in the return series to identify sudden large changes (discontinuities) in returns in response to various exogenous events. The presence of jumps violates the assumption of the continuous diffusion process in asset prices. Identifying the existence of jumps in asset returns helps us to explain better the return distribution (particularly excess kurtosis and skewness) and its implied volatility (Lee and Mykland, 2007; Todorov, 2011; Bjursell, Gentle, and Wang, 2015). We also plot positive and negative jumps to identify the intensity of positive and negative extreme returns. Finally, we plot the bi-power variation (a common measure of continuous quadratic variation), which is a manifestation of integrated volatility in asset returns in the presence of jumps (Barndorff-Nielsen and Shephard, 2004).

Figure 2 (a-d) exhibits the intraday jumps, and bi-power variations in Brent returns. We find that oil returns experience smooth jumps from 2013 to 2015. However, major jumps are observed during 2015 – 2016 and 2018-2019. This result holds for the aggregate jumps as well as when aggregate jumps are segregated into negative and positive jumps (see Figure 2 (a-c)). Several large positive jumps appear to be higher than that of negative jumps. However, some negative jumps stand out in early 2017. Figure 2 (d) reveals that the oil returns exhibit major volatility between 2015 – 2016 and between 2018-2019, reaching up to the extent of 0.20 percent. The spikes in the bi-power variations capture the periods of major price decline described in the previous paragraphs. We find similar evidence for WTI and DME. However, the jumps in Brent seem to be more frequent than that of WTI.<sup>8</sup>

[INSERT FIGURE 2 ABOUT HERE]

Figure 3 (a-d) demonstrates jumps and bi-power variations in USDINR. The Indian currency reports a major decline in price in the mid-2014, indicated by large negative jumps. However, from 2015 onwards, it exhibits continuous large jumps, suggesting a sustained

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<sup>8</sup> To conserve space, we provide plots of WTI and DME in the Online Appendix A, Figures A1 (a-d) and A2 (a-d).

depreciation of the Indian rupee vis-à-vis the US dollar, and it is prominent during 2015-2016 and 2018-2019. The negative and positive jumps also clearly capture this phenomenon. However, as we look at the spikes of bi-power variations shown in Figure 3 (d), it appears that the major intertemporal variations take place during 2015-2016 and 2018-2019. The high exchange rate volatility is attributable to the tapering of quantitative easing by the US Federal Reserve, China-USA trade dispute, poor fiscal management, the outflow of foreign investment, and geopolitical uncertainty in the Middle-Eastern countries (Singh and Gogoi, 2018). This result supports Prakash (2012), who reports that the Indian Rupee faced a period of high volatility after May 2013.

With regard to USDCNY and USDJPY, we find that the jumps follow a similar pattern of USDINR.<sup>9</sup> Figure 4 (a-d) shows the USDCNY plots. The dominance of negative jumps is observed from the start of the sample period, and it appears to be more prominent during 2016-2017 and 2018-2019 for USDCNY and during 2013-2014 and 2016-2017 for USDJPY. For both the currencies, from 2015 onwards, the jumps are mostly positive, indicating a high depreciation. Overall, largely positive and negative jumps indicate both positive and negative extreme returns and high volatility. The frequency of the occurrence of positive jumps is higher than the negative jumps, indicating the weak currencies (USDCNY and USDJPY) against the US dollar.

[INSERT FIGURES 3 & 4 ABOUT HERE]

### ***3.3 Descriptive statistics***

Descriptive statistics are presented in Table 1. Panel A and Panel B respectively presents descriptive statistics of intraday price and return series. From Panel A, we find that average exchange rates are 6.558, 65.183, 1.188, and 109.270, respectively, for USDCNY,

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<sup>9</sup> Please refer to Figure A3 (a-d) of Online Appendix A for USDJPY's plot.

USDINR, USDEURO, and USDJPY, while average oil prices are USD 71.255, USD 65.481 and USD 85.618 per barrel for Brent, WTI and DME, respectively. The oil prices appear to be more volatile than the exchange rate series indicated by their high standard deviations. From Panel B, we observe that the average returns of oil price series and USDEURO are negative, implying high incidences of negative returns than the positive ones during the sample periods. On the other hand, the average returns of USDINR, USDCNY, and USDJPY are positive, indicating higher incidences of positive returns and persistent depreciation of these currencies against the US dollar. Higher Kurtosis and non-zero skewness imply deviation of the return series from normal distribution and chances of higher extreme returns compared to extreme returns we can expect from a normal distribution.

[INSERT TABLE 1 ABOUT HERE]

As we move to Table 2 (Panel A), we find that the mean negative jumps are lower than the mean positive jumps for USDINR and USDCNY, indicating that the frequency and magnitude of depreciation are higher than the appreciation during the sample period. This result confirms our findings in the previous subsection. Concerning the bi-power variation results (Panel B), we find that the average daily bi-power variations in USDINR, USDEURO, and USDJPY are substantially higher than that of USDCNY. The possible reason could be a higher degree of the devaluation of USDCNY compared to USDINR. Finally, we report descriptive statistics of the control variables in Panel C. In the case of trading volumes of Brent and WTI, high volatility in daily trade is indicated by a large variation between the minimum and maximum value and high standard deviation. A similar result is found for other control variables, including OIV and OVX series of WTI and Brent and NDFs of USDCNY and USDINR. Positive skewness for all the series represents the possibility of higher positive values without corresponding chances of negative values. However, kurtosis values three or less indicate less probability of extreme values in these series.

[INSERT TABLE 2 ABOUT HERE]

## 4. Empirical results

### *4.1 Measuring volatility spillover from oil markets to currency markets*

Panel A of Table 3 shows the estimated results of the GARCH (1,1) model specified in Equation 8 for Brent. Panel B, C, and D respectively show the estimation results pertaining to GARCH(1,1) model augmented by oil jumps (equation 10), positive and negative oil jumps (equation 12), and bi-power variation (equation 14). As indicated earlier, the mean equation of the model includes lagged returns of Brent and exchange rates. Based on Akaike and Schwarz information criteria, the GARCH (1,1) model appears to be the most suitable for explaining volatility spillover across the markets.

The results reveal that for USDINR, the currency return does not have a significant dependence on its past returns. However, the lagged Brent returns do have a statistically significant impact, implying that the Brent prices determine the performance of India's foreign exchange market. More specifically, the positive coefficient indicates that an increase in Brent oil prices leads to an appreciation of the Indian currency. In the case of USDCNY, the currency return is mostly found to be invariant to both its own lagged returns (the coefficient is only marginally significant) and the lagged oil returns. Overall, these results indicate that there is a return spillover from the oil market to the foreign exchange market only for USDINR.

In the variance equation, we find that ARCH and GARCH terms are statistically significant, indicating that the currency return volatility has a significant positive dependence on its prior period's shock (ARCH effect) and the previous period's forecast volatility (GARCH effect). For both the currencies, the coefficient of the GARCH term is larger than that of the ARCH term, implying that the currency markets have memory longer than one period, which is the high persistence of exchange rate volatility. This result further indicates

that currency return volatility is more sensitive to its own lagged volatility compared to lagged return shocks. The sum of the ARCH and GARCH coefficients is less than one indicating, firstly, the clustering pattern and persistence effect of both the currency futures and, secondly, the mean-reverting property of the return series. Overall, significant coefficients of the ARCH and GARCH terms suggest that current idiosyncratic currency variance depends on its previous level and past innovations. These results are robust for all the specifications of the GARCH (1,1) model presented in Panel A to Panel D.

From Panel B, we find that the coefficient of  $Jump_{oil, t-1}$  has a negative sign for both the currencies; however, it is significant for USDCNY only. This result (i) reveals an inverse relationship between exchange rate volatility and oil return jumps and (ii) provides evidence of volatility spillover from the oil market to exchange rates when there are strong variations in crude oil prices. In other words, this result manifests that in China, abrupt shocks in the crude oil prices are immediately transmitted to the foreign currency prices.

Although oil jumps appear to be an insignificant driver of USDINR conditional volatility, as we disentangled aggregate oil jumps into positive and negative jumps, Panel C shows that an increment in lagged negative jumps of oil increases the exchange rate conditional volatility of USDINR. However, a positive jump in oil leads to a decrease in the intraday volatility for both currencies. Overall, these results imply that the currency market upheaval both in India and China decreases with positive jumps in the oil market. However, negative jumps have an asymmetric effect in the Indian and Chinese currency markets. While exchange rate volatility increases in India with a positive jump in the Brent prices, it has an opposite effect on the Chinese currency market. These results are at odds with Hussain et al. (2017), who find a weak negative association between oil prices and exchange rates for major Asian economies, including India and China. This discrepancy may arise as the authors rely on daily

data, use a different sample period (May 2006 to May 2016) and focus only on WTI crude oil prices.

Finally, Panel D reports that in the case of USDINR (USDCNY), the coefficient of lagged bi-power variation is statistically insignificant (significant), implying that the Indian (Chinese) exchange rate volatility is invariant (sensitive) to realized volatility in the oil market. This result may indicate that the episodes of high volatilities in the Indian exchange rates are primarily attributable to capital outflows and the US-centric macroeconomic policies rather than the variations in oil prices. This result agrees with Tiwari et al. (2019), who find that the extreme variations in oil prices have no impact on the exchange rates for India. However, volatility in the oil market appears to be an important driver of conditional volatility in the Chinese exchange rates.

[INSERT TABLE 3 ABOUT HERE]

Table 4 shows the impact of WTI jumps on exchange rate returns. In the mean equations, the coefficients of lagged WTI return do not significantly explain the returns of either currency, indicating that change in WTI oil prices does not influence the Indian and Chinese currency prices. This result is in contrast with the results pertaining to Brent (Table 3), which exhibit a significant positive return spillover to USDINR. This finding implies that Brent is more important in determining USDINR compared to the role of WTI.

As we focus on the variance part of the model with different controls, we observe that unlike Brent, WTI's unsegregated jumps, positive and negative jumps, and bi-power variation do not have a statistically significant impact on USDINR. This result confirms our previous observation that Brent is more important than WTI in determining USDINR.<sup>10</sup> In line with the result presented in Table 3, we find that un-disentangled jumps, positive and negative jumps,

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<sup>10</sup> We are thankful to the anonymous referees for their useful suggestion to incorporate Brent in our analysis.

and bi-power variation of WTI have a statistically significant impact on USDCNY. Overall, these results imply that being the largest importer of crude oil, the exchange rate of China is equally sensitive to both Brent and WTI prices, which is, however, not applicable for the Indian counterpart. Our finding, although somewhat consistent with Tiwari et al. (2019), contradicts Malik and Umar (2019). They suggest the negligible impact of oil price shocks on the exchange rate volatility of major economies, including China and India. Malik and Umar (2019), however, derive their results from daily data and using a measure of connectedness different from the approach followed in this paper.

[INSERT TABLE 4 ABOUT HERE]

#### ***4.2 Measuring volatility spillover from currency markets to oil markets***

Based on our theoretical arguments and empirical evidence in the literature (presented in section 1) regarding a potential bidirectional causal relationship between oil prices and exchange rates, in this subsection, we examine volatility spillover from the currency markets to the oil markets.

From Table 5, we find that Brent's return is insensitive to its own lagged returns and lagged currency returns implying a lack of return spillover from currency to Brent prices. This result indicates that appreciation or depreciation of the Indian and Chinese currencies do not influence Brent oil prices. This result holds for different specifications of the GARCH (1,1) model. Our result is at odds with Jawadi et al. (2016) as the authors show that an appreciation (depreciation) of the US dollar leads to a decrease (increase) in oil prices.

In the variance equation, we observe that the coefficient of lagged exchange rate jumps of both currencies significantly explain the Brent returns. The coefficient of the lagged jumps of USDINR (USDCNY) exhibits a negative (positive) relationship with Brent returns (Panel B). This result indicates that although there is no return spillover from the foreign exchange



market to the Brent market, there is a significant jump spillover. That is, a general movement in the Indian and Chinese exchange rates do not drive volatility in the Brent oil returns. However, in the case of an abrupt move in the exchange rates, Brent returns' conditional volatility changes. Nonetheless, as we move to panel C and Panel D, we observe that lagged positive and negative jumps and bi-power variations in exchange rates mostly do not have a statistically significant impact on Brent return volatility. This result holds for both currencies.

[INSERT TABLE 5 ABOUT HERE]

Table 6 shows the impact of exchange rate jumps on WTI returns. While conducting this analysis, we observe that the WTI series is noisy, and consequently, the GARCH parameters do not confirm the specifications. To overcome this problem, we introduce an intercept term of the variance equation as a function of GARCH parameters and the unconditional variance of the residuals. Francq, Horvath, and Zakoïan (2011) argue that the variance targeting technique gives superior results compared to Quasi Maximum Likelihood (QML) estimates when series are noisy, and there are specification problems.<sup>11</sup>

Result reveals that the WTI return is significantly explained by its own lag return, indicating the memory effect. In line with the Brent result presented in Table 5, we find that the coefficient of lagged currency returns is statistically insignificant, implying a lack of return spillover from currency to the WTI market. This result holds for both the currencies and irrespective of including controls in the GARCH (1,1) model. We further observe that WTI returns are insensitive to exchange rate jumps (jump coefficients are statistically insignificant in Panel B and Panel C), indicating a lack of volatility spillover. This result holds for both currencies. However, when we introduce the lagged Bi-power variation in the variance equation (Panel D), we find that the coefficient of USDCNY is statistically significant. This

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<sup>11</sup> We also explore the Integrated GARCH process but the diagnostic test results are found to be unsatisfactory.

result suggests that there is a reinforcing effect of USDCNY on WTI volatility. In other words, any significant variations or policy decisions, such as the devaluation in the Chinese exchange rate against the US dollar, may lead to an increase the volatility of WTI.

[INSERT TABLE 6 ABOUT HERE]

Overall, we find several key results in subsection 4.1 and 4.2. First, there is a significant return spillover from Brent to USDINR. However, there is no return spillover from WTI to either currency and no evidence of return spillover from the foreign exchange markets to currency markets. Second, USDCNY conditional volatility responds negatively to Brent jumps, and both USDINR and USDCNY conditional volatility responds negatively to positive Brent jumps. A similar result holds only for USDCNY in the case of WTI. USDCNY also responds positively to bi-power variation in both oil returns. Third, there is almost no evidence of jump spillover from the foreign exchange market to the oil market. We, therefore, can conclude that Brent oil price is an important driver of the Indian exchange rates and their conditional volatility. WTI oil prices, however, do not have similar influences on USDINR. Further, both Brent and WTI oil jumps have a significant role in shaping up conditional volatility of the Chinese exchange rates. Our results complement Jawadi et al. (2016), who show that (i) oil returns depend on lagged US exchange rate returns, and (ii) both aggregate and negative and positive jumps in the exchange rate have a statistically significant impact on oil price conditional volatility.

Overall, our finding is somewhat at odds with several previous studies that find a strong causal relationship between oil and exchange rate returns. The reason could be because of the lack of intraday study on the Indian exchange rate. For instance, Bal and Rath (2015) conclude that under a non-linear setting, there is a bidirectional causal relationship between the oil (WTI) prices and the Indian exchange rate. Bal and Rath's (2015) finding, however, is later refuted

by Vita and Trachanas (2016). Our result is also in contrast with Ghosh (2011), who finds a positive relationship between oil (Brent Crude) and exchange rate volatility in the Indian market. Our results of volatility and jump spillover from Brent to USDCNY (Table 3) are in line with Huang and Feng (2007), who show that real oil price shocks lead to a minor appreciation of the Chinese exchange rate against the US dollar. Similarly, Ju, Zhou, Zhou, and Wu (2014) also find an inverse relationship between the Chinese exchange rate and oil volatility.

#### ***4.3 Explaining exchange rate and oil return volatilities: The cases of USDJPY and DME***

In this section, as a robustness exercise, we introduce two more variables viz., USDJPY and DME. More specifically, we explore return and volatility spillover between (i) USDJPY and oil (both Brent and WTI) and (ii) currencies (both USDINR and USDCNY) and DME. The purpose of this analysis is to check if we can confirm the results presented in the subsections 4.1 and 4.2 for USDJPY and DME. The USDJPY is chosen because of the rising influence of Japan in Asia and globally, and its economic dependence on both India and China. The inclusion of DME is justified because, over the years, it has become the regional benchmarks for oil exports from the Middle East to Asia.

Table A1 (Online Appendix A) presents the results relating to the impact of oil return volatility and jumps on USDJPY. In the mean equation, we find no evidence of return spillover from oil to USDJPY as the coefficient of lagged oil is statistically insignificant across the panels (A-D). This result indicates that a change in Brent or WTI oil prices does not have any influence on the Japanese currency exchange rates.

In the variance equation, we observe that the coefficients of lagged jumps, and both positive and negative jumps are negative and statistically significant. This result firstly holds for both Brent and WTI, and secondly, it is consistent with the impact of Brent and WTI jumps,

particularly on USDCNY. Overall, this result indicates that the negative jumps in oil put depreciating pressure on the Japanese Yen against the US dollar. This result further implies that the USDJPY exchange rates are immune to the general movement in oil prices. However, abrupt movements in oil prices are transmitted to the currency market. The coefficient of bi-power variation reinforces our previous result further as they are significant for both the oil series. Overall, we report that for Asian economies, including Japan, the jumps in Brent and WTI have a significant impact on exchange rate conditional volatility, and they have significant explanatory power for the exchange rate variations.

Next, we explore the return and volatility spillover from USDJPY to the oil markets (Brent and WTI). From Table A2 (Online Appendix A), we find evidence supporting a lack of return spillover from currency to oil markets except for the case of the statistically significant negative impact of lagged currency returns on Brent returns (Panel C). This result is consistent with our previous findings of the absence of return spillover from USDINR and USDCNY to the oil markets.

As we look at the variance equation, we find significant evidence of the impact of USDJPY jumps on Brent. More specifically, the lagged jump in USDJPY has a negative and statistically significant impact on Brent. However, when we disentangle jumps into positive and negative jumps, we find that the negative (positive) jumps have a positive (negative) impact on the Brent. We also find a positive and significant impact of bi-power variations of USDJPY on WTI volatility. This result commensurate with that of USDCNY.

We now tend to provide a comparison between the results pertaining to India and China with that of Japan. We observe a positive return spillover from Brent to USDINR. However, no return spillover is found from the oil (either Brent or WTI) to the currency markets of China and Japan. Further, we find a negative impact of oil jumps (both Brent and WTI) on the

conditional volatility USDCNY and USDJPY. However, oil jumps' impact on the conditional volatility of the Indian exchange rate is mostly insignificant. Overall, these results imply that Brent price is an important determinant of the Indian exchange rates while the Chinese and Japanese exchange rate volatility is sensitive to both Brent and WTI oil price jumps.

Table A3 of Online Appendix A shows the results of the impact of DME jumps on exchange rate returns of USDINR and USDCNY. In the mean equation, we find a significant positive impact of lagged oil returns on USDCNY. While we previously found a lack of return spillover from Brent or WTI, this result indicates a significant return spillover from DME to USDCNY. The possible explanation could be a large volume of DME futures trade in the Chinese currency. The positive coefficient implies that an increase in DME oil prices leads to an appreciation of the Chinese currency. This result, however, does not hold for USDINR.

In the variance equation, we find high volatility persistence for both the exchange rates. However, the currency returns are found to be mostly insensitive to DME jumps and bi-power variations except for the negative impact of positive jumps on USDCNY, indicating an inverse relationship between positive jumps and USDCNY.

Overall, we conclude that the intraday dynamics of DME is only restricted to the Chinese currency as there is a negligible impact of DME on USDINR. This result further justifies the choice of oil series as there seems to be a role of market microstructure in the analysis. In other words, the asymmetric impact of different oil series on exchange rate returns further limits the universalization of oil price -exchange rate nexus debate. We, therefore, conclude that previous studies focusing on one oil price series provide only a partial picture of the oil price – exchange rate relationship.

We also examine the impact of exchange rate jumps (USDINR and USDCNY) on DME returns. Table A4 of Online Appendix A shows the results. In the mean equation, we find that

the coefficients of lagged returns of USDCNY are negative and statistically significant when we control for positive and negative jumps (Panel C) and bi-power variations (Panel D). This result provides some evidence of return spillover from the currency to oil markets.

In the variance equation, we find a high clustering effect but very low volatility persistence. The coefficients of lagged jumps of USDINR (USDCNY) have a negative (positive) impact on DME's volatility, indicating that an increase in jumps in USDINR (USDCNY) reduces (increases) DME's volatility. When we disentangle the jumps into negative and positive, the sign of the coefficient of USDINR is consistent with its aggregate jump as we find a statistically significant negative coefficient for both negative and positive jumps. However, the coefficients of disentangled jumps of USDCNY is only significant for negative jumps. The coefficient of the Bi-power variation of USDCNY shows a positive relationship with DME volatility. Overall, we observe that both currencies are crucial for determining the fair price of DME.

[INSERT TABLE 10 ABOUT HERE]

#### ***4.3 Modelling jump spillover between the exchange rate and currency returns***

In this subsection, we set-up a regression model to examine the sensitivity of intraday jumps between the foreign exchange and oil markets. That is, the main purpose of this analysis is to identify the existence of any co-jump between the oil price and exchange rate changes. To do this, we apply a Tobit model to take into account the presence of a large number of negative, positive, and a long-range of zero values in the jump series. Our analysis is worthwhile as the presence of co-jumps helps, firstly, to understand the speed of information incorporation across asset prices, and secondly, to comprehend if the point-of-interest variables (for example, exchange rates and oil prices) react to a common set of information (see Jawadi et al., 2016; Li et al., 2017).

To estimate the Tobit model, the intraday jumps of the exchange rate and oil returns are alternatively considered as dependent variables. The right-hand side variables include the jump series, the Euro-US dollar exchange rates (USDEURO), the volume of oil traded (VOL), the Chicago Board of Exchange (CBOE) Oil Volatility Index (OVX) for Brent, CBOE/NYMEX WTI Volatility Index (OIV), and the 1-month non-deliverable forwards (NDFs) of USDINR and USDCNY. Misra and Behera (2006) show that the non-deliverable forward (NDF) foreign exchange market reports a huge turnover, and NDF exchange rate plays a significant role in the fair price discovery of major currencies. A similar result is found by Hung-Gay, Leung, and Jiang (2004), Gu and McNelis (2013), Lien, Yang, Zhou, and Lee (2014) and Ho, Shi, and Zhang (2017) in the context of the Chinese market. To this vein, we introduce the EX(NDF) as an explanatory variable in the Tobit model. The intraday jump of USDEURO is included because of its high liquidity, and volatility series (OVX and OIV) are considered to control for the oil trading related uncertainty. The Tobit models are as follows:

$$Jump_{EX,t} = \alpha_0 + \gamma_t Jump_{OIL,t} + \omega Jump(USDEURO)_t + \theta Jump(USDJPY)_t + \phi EX(NDF)_t + \vartheta OIV_t \text{ or } OVX_t + \beta Volume(OIL)_t + \varepsilon_t \quad (18)$$

$$Jump_{OIL,t} = \alpha_0 + \gamma_t Jump_{EX,t} + \omega Jump(USDEURO)_t + \theta Jump(USDJPY)_t + \phi EX(NDF)_t + \vartheta OIV_t \text{ or } OVX_t + \beta Volume(OIL)_t + \varepsilon_t \quad (19)$$

where,  $Jump_{EX,t}$  = Jumps in USDINR and USDCNY and  $Jump_{OIL,t}$  represents intraday jumps in Brent, WTI and DME.

Relevant results are presented in Table 7. From Panel A, we find that the jumps in Brent and WTI do not have a statistically significant impact on the exchange rate jumps except the case of a marginally significant coefficient of WTI jumps for USDINR. This result indicates that the jumps in crude oil series are not a significant driver of jumps in the Indian and Chinese currency prices.

With regard to the control variables, although USDEURO jumps are found to have an insignificant influence on currency jumps, USDINR jumps respond negatively to USDJPY jumps. This result may be attributed to high financial and currency transactions between the two countries. For instance, India and Japan have signed a USD75 billion currency swap agreement in 2018 (Oberoi, 2018). However, the negative sign implies that an appreciation of the Indian currency leads to a depreciation in Japanese currency and vice-versa. The NDF exchange rate is found to have a major impact on currency jumps as the coefficients of NDF exchange rate are statistically significant for both currencies. The result indicates a strong and positive response of both currencies jump with a rise in the corresponding NDF exchange rate. Our result is in agreement with Misra and Behera (2006), who report that the role of NDFs in determining the fair value of Indian currency has increased after the introduction of currency futures in India. For China, Gu and McNelis (2013) show that NDFs market activities, especially forward premia, play a crucial role in the determination of USDCNY. While exchange rate jumps are invariant to oil price volatility (indicated by the statistically insignificant coefficient of OVX and OIV), volume growth of WTI has a negative impact on USDINR. This result suggests that higher growth in the trading volume of WTI has a stabilizing effect on USDINR. Overall, we do not find significant evidence of co-jump between oil and exchange rates. However, both USDINR and USDCNY jumps exhibit a significant dependence with NDF and, to some extent, with the trading volume.

As we move to Panel B, we find that exchange rate jumps do not influence oil jumps, reinforcing our finding of a lack of co-jumps between exchange rates and oil prices. However, the coefficient of USDINR jump is only a borderline significant for WTI jumps. The oil jumps are also found to be insensitive to the control variables, with two exceptions. The NDF exchange rates of USDCNY and oil volatility (both OVX and OIV) have a significant impact



on oil jumps. This result indicates that the increase in oil volatility reduces the intensity of oil jumps.

We also explore the potential co-jumps between DME and exchange rate returns by estimating the Tobit model. However, we do not report these results in this paper as they are qualitatively similar to the results presented earlier in this subsection. For instance, we find the statistically insignificant impact of the DME jumps on the exchange rate jumps, and the DME jumps are also found to be invariant to exchange rate jumps. These results hold for both USDINR and USDCNY.

[INSERT TABLE 7 ABOUT HERE]

## **5. Conclusion**

The main objective of this study is to examine the volatility and jump spillover between oil price and exchange rate changes. We contribute to the literature in several ways. First, we consider the Chinese and Indian exchange rates. Despite China and India, among the largest importers of oil, the interaction between their exchange rates and oil prices have not received attention in the literature. Second, we use high-frequency data to develop more accurate measures of continuous and discontinuous volatility. Third, we consider three globally traded oil products, namely, Brent, WTI, and DME. Fourth, to analyse the volatility and jump spillover, we undertake an approach different from the ones used by previous researchers. We initially estimate the conventional GARCH (1,1) model, then augment the model by lagged (i) aggregate jumps, (ii) negative and positive jumps, and (iii) bi-power variations in the variance equation. Finally, a Tobit model is estimated to identify the presence of co-jumps between oil price and exchange rate changes.

This study reports the following key findings. First, we find a positive return spillover from Brent (DME) to the Indian (Chinese) currency markets. However, there is a lack of return

spillover from the currency to oil markets except for some negative return spillover from the Chinese exchange rates to DME returns. Second, although oil jumps have a negative impact on exchange rate conditional volatility of the Chinese exchange rates (in the cases of Brent and WTI), this result does not hold in India. On the other hand, exchange rate jumps are found to have a negative (positive) impact on oil price conditional volatility of the Indian (Chinese) exchange rates. Third, positive oil jumps have a negative impact on the Chinese exchange rate volatility. With regard to negative oil jumps, a positive (negative) impact is observed on the Indian (Chinese) exchange rates for Brent (WTI). As we focus on disentangled exchange rate jumps' impact on oil price volatility, we only find a statistically significant result for DME returns but not for Brent or WTI returns. Finally, the Tobit model shows that oil or exchange rate jumps do not explain the corresponding jumps in the other market. Overall, in the case of India and China, volatility and jump spillover between oil prices and exchange rates is conditional on the nature of jumps and the oil price series considered.

The results of this paper have important implications for investors and policymakers. For instance, we find a lack of return spillover from Brent and WTI; however, significant positive return spillover from DME to the currency market in China. Further, positive oil price jumps are found to have a significant negative impact on Chinese currency returns. This result may imply that the current controlled exchange rate policy in China is sufficient to safeguard against the oil (Brent and WTI) volatility spillover to currency markets. However, this framework may not protect the currency market when DME prices are volatile or there is an abrupt change in the oil prices. Hence the findings could help them articulate policies seeking to evade the contagion risk emanating from the volatile energy market. The result of this empirical study can also be helpful to investors for devising their portfolio strategies. For instance, we find a positive relationship between lagged Brent and Indian exchange rate returns,

Będowska-Sójk, B. (2016). Liquidity dynamics around jumps: The evidence from the Warsaw Stock Exchange. *Emerging Markets Finance and Trade*, 52(12), 2740-2755.

indicating that an increase in oil price leads to a one-period-ahead increase in respective currency returns. Thus, investors can rebalance their portfolios in anticipation of oil price change in a particular direction to improve their portfolio performance.

The high-frequency analysis conducted in this paper opens a debate on whether oil price variations have a similar impact on emerging and developed country currencies. In our case, we are not able to distinguish significantly between the results of emerging (China and India) and developed (Japan) countries. These issues, however, warrant further investigation, which we leave for future research.

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**Simulation Code and Data (.ZIP)**  
**Data\_CODE.rar**

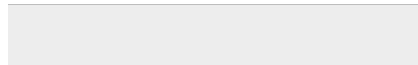
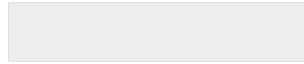


Table A1: The impact of oil return volatility and jumps on USDJPY returns

	Panel A: GARCH (1,1) model		Panel B: Impact of oil jumps		Panel C: Impact of positive and negative oil jumps		Panel D: Impact of bi-power variations	
Variable	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI
<i>Mean constant</i>	0.0096	0.0097	0.0097	0.0089	0.0097	0.0078	0.0093	0.0097
	[0.7900]	[0.7945]	[0.7959]	[0.7223]	[0.7941]	[0.6454]	[0.7639]	[0.7889]
$R(EX)_{t-1}$	-0.0181	-0.0204	-0.0186	-0.0208	-0.0195	-0.0228	-0.0189	-0.0212
	[-0.6735]	[-0.7620]	[-0.6943]	[-0.7805]	[-0.7243]	[-0.8682]	[-0.7048]	[-0.7889]
$R(OIL)_{t-1}$	-0.0075	0.0001	-0.0072	0.0001	-0.0066	0.0002	-0.0073	0.0000
	[-1.1700]	[0.0628]	[-1.1160]	[0.0810]	[-0.9936]	[0.1529]	[-1.0824]	[0.0262]
<i>Variance constant</i>	0.0027***	0.0026***	0.0027***	0.0029***	0.0019***	0.0007	0.0018***	0.0016***
	[3.6432]	[3.6450]	[3.5475]	[4.0946]	[2.6949]	[1.1509]	[2.4518]	[2.1574]
$\alpha$	0.0549***	0.0542***	0.0555***	0.0493***	0.0522***	0.0409***	0.0520***	0.0529***
	[7.4599]	[7.4325]	[7.4972]	[6.8949]	[7.0449]	[6.3287]	[6.7383]	[6.8409]
$\beta$	0.9375***	0.9384***	0.9372***	0.9423***	0.9366***	0.9494***	0.9387***	0.9384***
	[121.41]	[123.173]	[119.531]	[126.564]	[114.016]	[135.351]	[116.35]	[117.354]
$Jump_{OIL,t-1}$			-0.0084**	-0.0138***				
			[-1.8463]	[-3.1392]				
$NegJ_{t-1}(Brent, WTI)$					-0.0256***	-0.0813***		
					[-2.790]	[-5.934]		
$PosJ_{t-1}(Brent, WTI)$					0.0002	0.0137		
					[0.0310]	[1.2473]		
$BV_{OIL,t-1}$							0.0444***	0.0611***
							[2.7436]	[2.4982]
<i>Diagnostics</i>								
ARCH-LM (5)	1.3402	1.3322	1.6326	0.9082	1.6971	0.0844	1.3615	1.1878
Q-Statistics (5)	3.8797	3.8394	4.1825	3.8151	4.2053	4.4119	3.9434	3.8383
LL	-1357.65	-1358.31	-1356.70	-1355.52	-1354.11	-1345.57	-1355.38	-1356.66
DW	1.9905	1.9936	1.9879	1.9928	1.9886	1.9890	1.9891	1.9918

Note: USDJPY is the Japanese Yen exchange rate against the US dollar. Brent represents Brent crude oil futures returns and WTI represents the West Texas Intermediate Cushing oil futures returns. Statistical significance at the 10%, 5%, & 1% level is marked by (\*), (\*\*) & (\*\*\*) respectively.

Table A2: The impact of USDJPY return volatility and jumps on oil returns

	Panel A: GARCH (1,1) model		Panel B: Impact of oil jumps		Panel C: Impact of positive and negative exchange jumps		Panel D: Impact of bi-power variations	
Variable	Brent	WTI	Brent	WTI	Brent	WTI	Brent	WTI
<i>Mean constant</i>	-0.0051	0.0006*	-0.0039	0.0007	-0.0025	0.0007	-0.0049	0.0007*
	[-0.1428]	[1.5991]	[-0.1069]	[1.5699]	[-3.5915]	[1.5006]	[-0.1369]	[1.7095]
$R(EX)_{t-1}$	-0.0874	-0.0862	-0.0878	-0.0736	-0.0723**	-0.0681	-0.0872	-0.0008
	[-1.3836]	[-1.2912]	[-1.3685]	[-0.9380]	[-1.8857]	[-0.8975]	[-1.3792]	[-1.0882]
$R(OIL)_{t-1}$	-0.0163	0.0305***	-0.0146	0.0304***	-0.1290	0.0309***	-0.0163	0.0385***
	[-0.6368]	[2.0424]	[-0.5644]	[2.0292]	[-1.1205]	[2.0136]	[-0.6350]	[2.5540]
<i>Variance constant</i>	0.0263***	0.0010	0.0293***	0.0010	0.0002***	0.0010	0.0273***	0.0008
	[3.9839]	[-----]	[4.1527]	[-----]	[4.7569]	[-----]	[3.1957]	[-----]
$\alpha$	0.0649***	0.7733***	0.0688***	0.7725***	0.1555***	0.7799***	0.0649***	0.8144***
	[8.4087]	[36.947]	[8.3207]	[36.765]	[3.9860]	[36.867]	[8.3335]	[32.491]
$\beta$	0.9311***	0.0828***	0.9265***	0.0834***	0.4822***	0.0827***	0.9310***	0.0810***
	[123.325]	[3.4036]	[116.101]	[3.4148]	[4.6600]	[3.4298]	[121.597]	[3.4053]
$Jump_{EX,t-1}$			-0.3626***	-0.0198				
			[-2.5200]	[-0.5642]				
$NegJ_{t-1}(EX)$					0.0277***	-0.0928		
					[51.6197]	[-1.1977]		
$PosJ_{t-1}(EX)$					-0.0460***	0.1198		
					[-18.7149]	[0.8514]		
$BV_{EX,t-1}$							-0.3197	0.1234***
							[-0.1882]	[2.6260]
<i>Diagnostics</i>								
ARCH-LM (5)	1.5878	1.8193	1.7264	1.7943	4.4962	1.7772	1.5736	1.8749
Q-Statistics (5)	1.3492	33.31***	1.2317	33.159***	5.5417	32.8630***	1.3416	31.9541***
LL	-3357.103	2660.059	-3355.043	2660.128	4353.268	2661.136	-3357.094	2663.456
DW	2.0384	1.8193	2.0419	1.9057	1.9019	1.9066	2.0385	1.9199

Note: Brent represents Brent crude oil futures and West Texas Intermediate Crushing oil futures. USDJPY denotes the exchange rates of Japanese Yen per US dollar.  $Jump_{EX,t-1}$  denotes the daily jumps in exchange rate returns.  $PosJ_{t-1}$  and  $NegJ_{t-1}$  respectively indicate positive and negative jumps in the exchange rate returns. Statistical significance at the 10%, 5%, & 1% level is marked by (\*), (\*\*) & (\*\*\*) respectively.

Table A3: The impact of DME return volatility and jumps on exchange rate returns

	Panel A: GARCH (1,1) model		Panel B: Impact of oil jumps		Panel C: Impact of positive and negative oil jumps		Panel D: Impact of bi-power variations	
Variable	USDINR	USDCNY	USDINR	USDCNY	USDINR	USDCNY	USDINR	USDCNY
<i>Mean constant</i>	$1.46 \times 10^{-4}$	$-7.20 \times 10^{-6}$	0.0001	$-6.35 \times 10^{-6}$	0.0001	$-2.56 \times 10^{-5}$	$8.10 \times 10^{-5}$	$-6.81 \times 10^{-6}$
	[1.1817]	[-0.5078]	[1.0733]	[-0.4400]	[1.0805]	[-0.5767]	[0.8018]	[-0.4785]
$R(EX)_{t-1}$	0.0419	0.1551***	0.0382	0.1540***	0.0383	0.1911***	0.0216	0.1530***
	[1.1527]	[5.8170]	[1.0421]	[5.6180]	[1.0456]	[4.9821]	[0.7102]	[5.6673]
$R(OIL)_{t-1}$	0.0001	0.0004***	0.0004	0.0004**	0.0004	0.0005	-0.0003	0.0004***
	[0.1072]	[2.3147]	[0.3905]	[1.9905]	[0.3744]	[1.0238]	[-0.3206]	[2.3995]
<i>Variance constant</i>	$1.26 \times 10^{-6}$	$1.05 \times 10^{-8}$	$1.27 \times 10^{-6}$	$1.43 \times 10^{-8}$	$1.24 \times 10^{-6}$	$3.52 \times 10^{-7}$	$1.91 \times 10^{-6}$	$1.31 \times 10^{-8}$
	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]
$\alpha$	0.1645***	0.1849***	0.1639***	0.2158***	0.1618***	0.1008***	0.1768***	0.2095***
	[5.9237]	[6.6909]	[5.4297]	[7.1790]	[4.7411]	[4.3739]	[4.2734]	[6.8822]
$\beta$	0.7847***	0.8077***	0.7850***	0.7742***	0.7881***	0.6507***	$7.46 \times 10^{-1}$ ***	0.7812***
	[19.7994]	[27.694]	[18.043]	[24.287]	[17.001]	[11.422]	[12.148]	[24.1752]
$Jump_{OIL,t-1}$			$1.38 \times 10^{-5}$	$-2.14 \times 10^{-7}$				
			[1.0681]	[-1.1503]				
$NegJ_{t-1}(OIL)$					$1.37 \times 10^{-5}$	$6.15 \times 10^{-7}$		
					[0.9862]	[1.0586]		
$PosJ_{t-1}(OIL)$					$1.27 \times 10^{-5}$	$-3.63 \times 10^{-6}$ ***		
					[0.5604]	[-15.1033]		
$BV_{OIL,t-1}$							$-2.96 \times 10^{-6}$	$2.78 \times 10^{-7}$
							[-0.2784]	[0.5053]
<i>Diagnostics</i>								
ARCH-LM (5)	2.364	3.9745	2.5071	4.5211	2.5207	12.412*	2.4630	4.3905
Q-Statistics (5)	2.460	5.9281	2.5944	4.9307	2.5809	8.3460	3.5516	5.4398
LL	3245.431	4451.796	3246.743	4452.469	3246.691	4300.775	3238.461	4452.278
DW	1.9271	2.0188	1.9195	2.0163	1.9196	2.0961	1.8879	2.0143

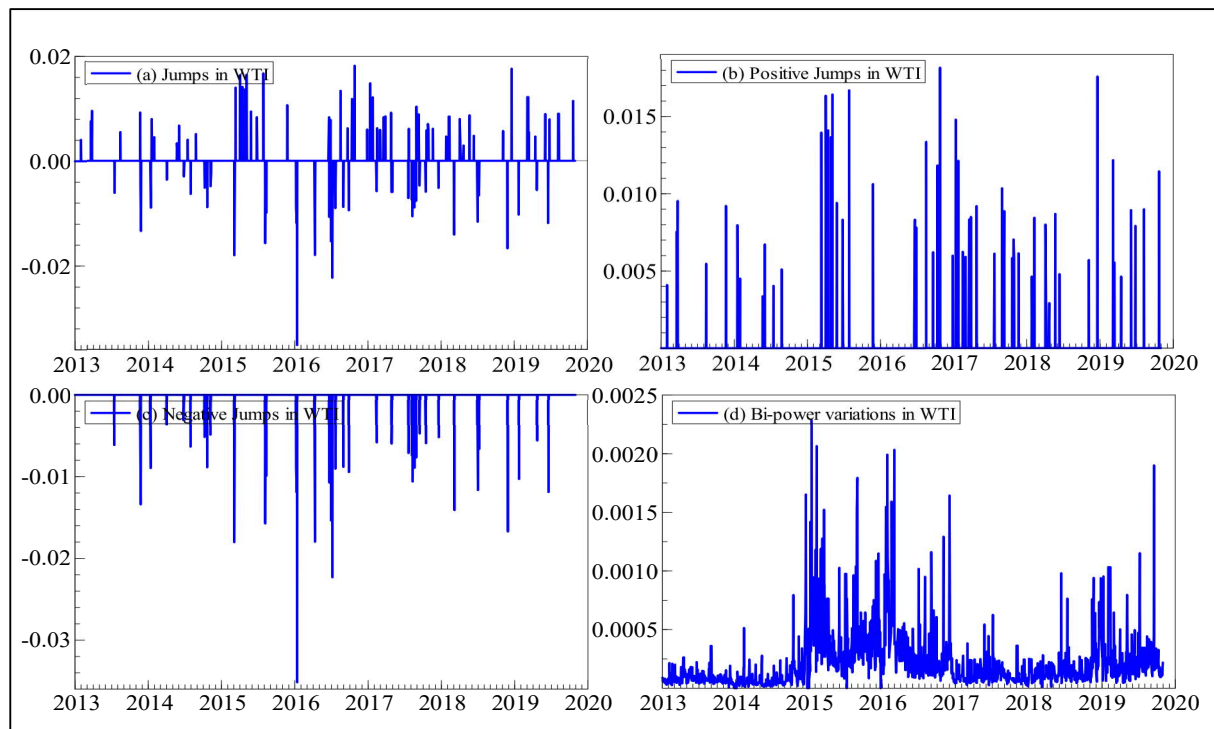
Note: DME represents Oman Crude Oil Energy Futures traded in Dubai Mercantile Exchange. Statistical significance at the 10%, 5%, & 1% level is marked by (\*), (\*\*) & (\*\*\*) respectively.

Table A4: The impact of exchange rate volatility and jumps on DME returns

	Panel A: GARCH (1,1) model		Panel B: Impact of oil jumps		Panel C: Impact of positive and negative exchange jumps		Panel D: Impact of bi-power variations	
Variable	USDINR	USDCNY	USDINR	USDCNY	USDINR	USDCNY	USDINR	USDCNY
<i>Mean constant</i>	0.0012	0.0008	0.0009	-1.06×10 <sup>-5</sup>	0.0014***	-0.0009	0.0013***	0.0012*
	[1.556]	[1.1012]	[1.2837]	[-0.0088]	[2.3732]	[-0.9424]	[2.6001]	[1.6020]
$R(EX)_{t-1}$	0.0821	-0.8341	0.0553	-1.0630	0.0964	-2.0550***	0.0424	-1.7461***
	[0.4694]	[-1.5791]	[0.3617]	[-1.2630]	[0.9119]	[-2.5403]	[0.4625]	[-2.2454]
$R(OIL)_{t-1}$	-0.1591***	-0.1551***	-0.1545***	-0.0863***	-0.0920***	-0.1632***	-0.1003***	-0.1665***
	[-5.9310]	[-5.1813]	[-5.1591]	[-3.1220]	[-3.3572]	[-4.8478]	[-4.2814]	[-6.1044]
<i>Variance constant</i>	0.0003	0.0003	0.0002	0.0012	0.0005	0.0002	0.0006	0.0002
	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]	[-----]
$\alpha$	0.8160***	0.8332***	0.8457***	0.7421***	0.5996***	0.3523***	0.7953***	0.8321***
	[49.104]	[34.735]	[44.857]	[27.238]	[76.8031]	[17.6538]	[28.8781]	[49.962]
$\beta$	0.1430***	0.1225***	0.1205***	0.0931***	0.3302***	0.6137***	0.1280***	0.1416***
	[8.0459]	[4.7450]	[6.0363]	[2.9369]	[26.2385]	[29.7360]	[4.2106]	[8.1690]
$Jump_{EX,t-1}$			-0.0215***	0.7442***				
			[-2.4614]	[8.2547]				
$NegJ_{t-1}(EX)$					-0.0140***	0.3071***		
					[-4.5560]	[4.5131]		
$PosJ_{t-1}(EX)$					-0.0008**	-0.2879		
					[-1.9078]	[-1.1909]		
$BV_{EX,t-1}$							-0.0185	1.2952***
							[-1.3433]	[4.7491]
<i>Diagnostics</i>								
ARCH-LM (5)	0.1119	0.1088	0.1315	0.1116	0.9312	0.2832	0.1291	0.0739
Q-Statistics (5)	9.4687*	9.7531*	9.0050	17.251**	15.4860***	9.8965**	12.1501***	7.8492
LL	1289.61	1409.752	1373.658	1367.278	1398.992	1321.680	1409.093	1298.65
DW	2.1892	2.1984	2.1977	2.3166	2.3033	2.1869	2.2898	2.1797

Note: DME stands for Oman Crude Oil Energy Futures traded in Dubai Mercantile Exchange.  $Jump_{EX,t-1}$  denotes the daily jump in the exchange rate returns.  $PosJ_{t-1}$  and  $NegJ_{t-1}$  respectively indicate the positive and negative jumps in the exchange rate returns. Statistical significance at the 10%, 5%, & 1% level is marked by (\*), (\*\*) & (\*\*\*) respectively. See notes to Table 3 for further details.

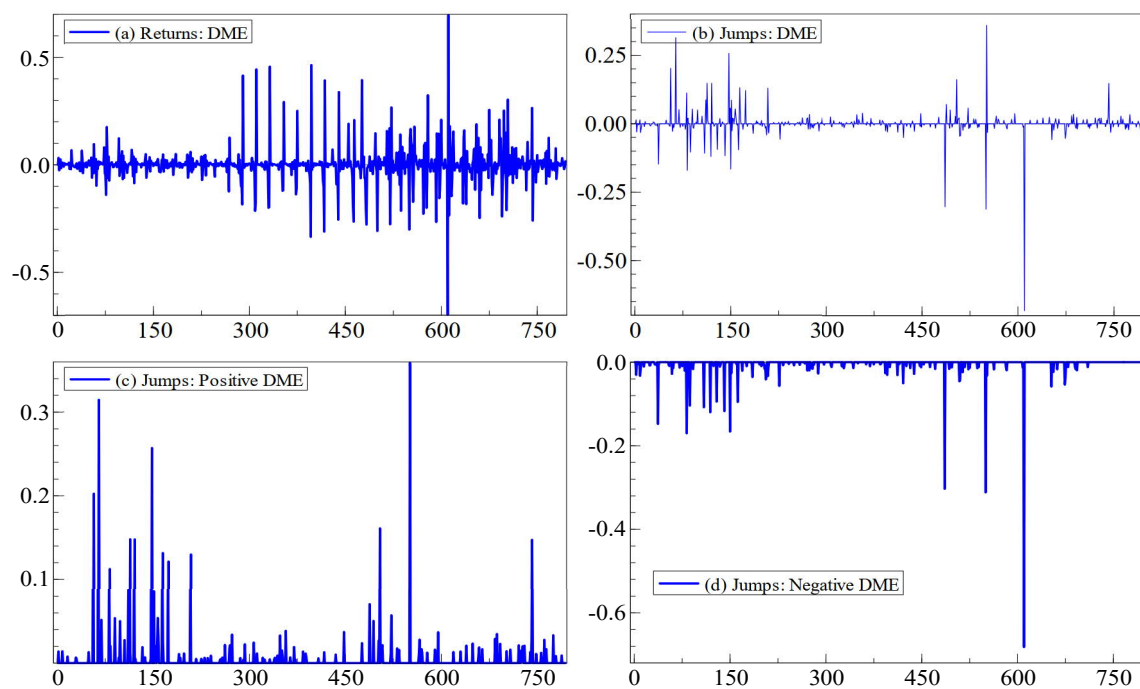
Figure A1: Intraday Jumps and Bi-power Variations in WTI



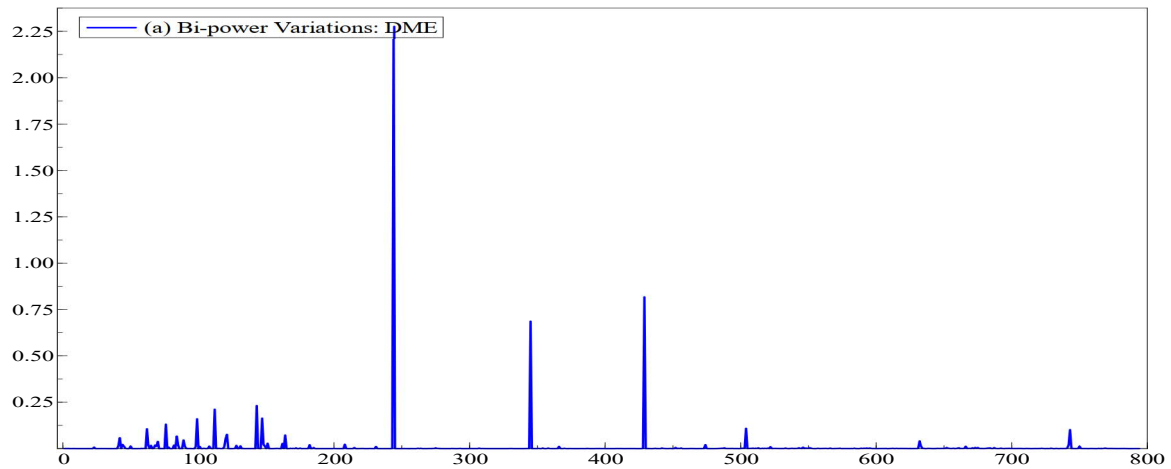
Notes: The figures (a-d) illustrate the intraday jumps in WTI (West Texas Intermediate) returns, positive jumps and negative jumps in oil returns and Bi-power variation, respectively.

Figure A2: Intraday jumps and bi-power variations in DME returns

Panel A: Jumps in DME returns

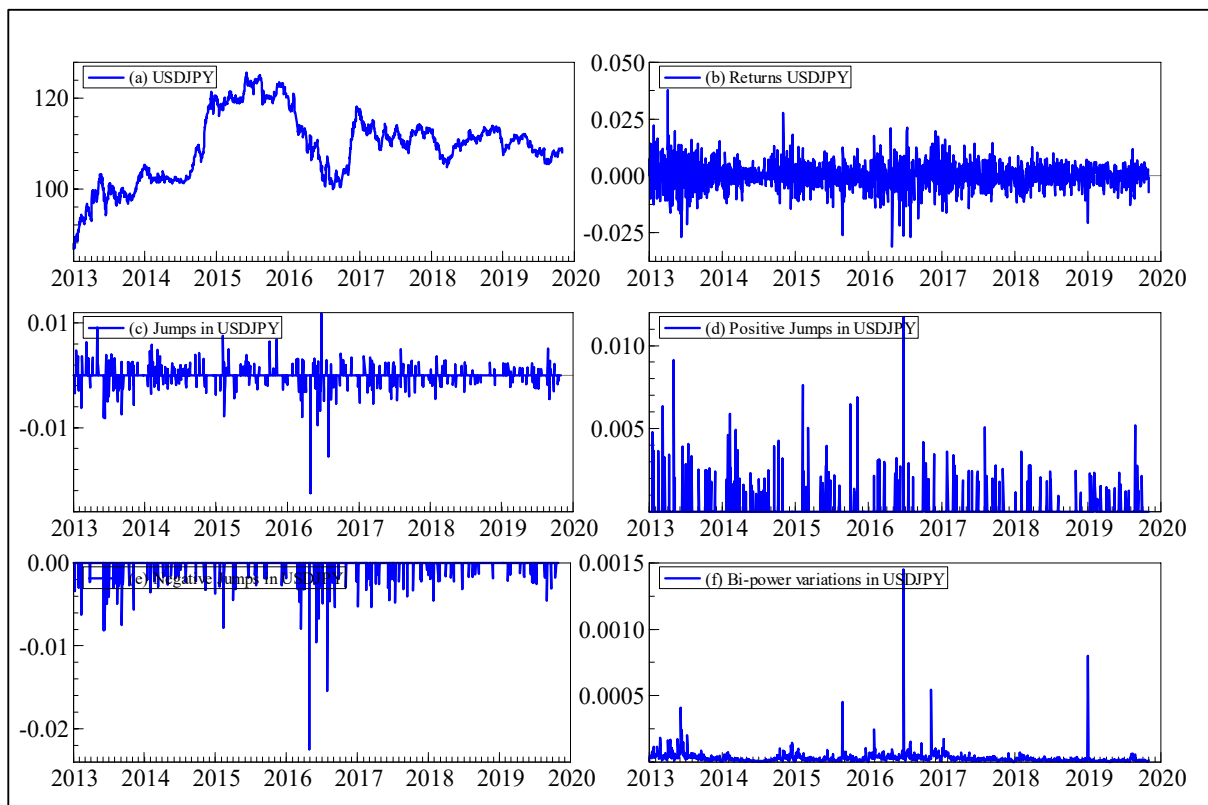


Panel B: Bi-power variations in DME returns



Notes: In panel A, the figures (a-d) illustrate the daily returns of DME Oman Crude Oil Energy futures trade at DME (Dubai Mercantile Exchange), corresponding intraday jumps in oil returns, and positive jumps and negative jumps in oil returns, respectively. Panel B shows the intraday Bi-power variation of DME returns.

**Figure A3: Intraday jumps and bi-power variations in USDJPY returns**



Notes: USDJPY is the exchange rates of the Japanese Yen against the US dollar (a). The figures (b-e) illustrate the daily returns of USDJPY, corresponding intraday jumps in USDJPY returns, and positive jumps and negative jumps in USDJPY returns, respectively. (f) shows the Bi-power variation of USDJPY returns.



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