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In search of time-varying jumps during the turmoil periods: Evidence from crude oil futures markets

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ABSTRACT

Prior literature demonstrates that energy prices are characterized by time-varying jumps. However, earlier studies do not investigate if the intensity of such jumps appears to be higher amid periods of extreme volatility in comparison to normal periods. Employing the GARCH-jump model, this study examines whether jumps occurring in energy prices are an indicator of market crashes. To serve this purpose, we consider several downturns in oil markets spanning over the last few years. Our empirical analyses reveal that the conditional expected number of jumps in WTI and Brent oil futures prices increases significantly amid the depression periods, which is, however, not the case when the market functions normally. We, therefore, conclude that such clusters of jumps may contain predictive information for oil market crashes and thus provide early signals of future downturns. The findings further show that crude oil volatility, the US equity VIX, and economic policy uncertainty play a significant role in explaining the time-dependent jumps during the turmoil periods. The findings of our research could be useful for investors participating in global crude oil markets and for policymakers watching out for the impact of energy prices on the economy.

1. Introduction

Oil is considered one of the most important production inputs in an economy (Vo, 2011). In the US, for instance, nearly 8% of the GDP comes from oil. Hence, a rise in energy prices may exert a substantial impact on GDP growth by increasing production costs (Vo, 2009). Significant variations in crude oil prices are, therefore, a matter of serious concern for policymakers. In addition, being a strategic commodity, crude oil also plays a key role in global financial markets. In fact, earlier studies (e.g., Shi and Variam, 2017; Ji et al., 2018) show that energy market uncertainty impacts investment decisions as oil is often used to hedge portfolio risk.

Against this backdrop, market participants closely follow energy price variability and its forecasts (Manickavasagam et al., 2020). However, acquiring such knowledge seems to be a complex task given that energy markets tend to behave differently under diverse market conditions (i.e., bearish, normal, and bullish states). Choi and Hammoudeh (2010), for example, show that oil prices experience an increment amid periods of low volatility, while Gronwald (2012) claims that political violence, natural calamities, and terrorist activities could cause substantial drops in energy prices. In addition, high correlations between energy and important financial markets (e.g., stock, gold, and exchange rate) could also lead to a significant increase or decrease in global energy prices (Liu et al., 2013; Tiwari et al., 2020). Hence investors are required to have accurate estimates of energy price volatility to precisely assess the market risk.

In addition to time-varying volatility, jumps in energy prices, which could occur as a consequence of recessions, terrorist activities, or pandemics, represent an important element of risk as well. According to Bollerslev et al. (2008) and Eraker et al. (2003), jumps in financial time series signify a major source of non-diversifiable risk that needs to be modeled precisely. Besides, employing appropriate methods for capturing time-varying jumps occurring in energy prices is essential given that such jumps may result in specification errors in conventional

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estimation methods.[1] Moreover, as jumps in asset prices are occasional events, the existence of large price swings in a specific sample period could have a significant effect on the volatility prediction (Chiang and Chen, 2019). It is, therefore, important to adopt a sophisticated econometric approach that can simultaneously capture both jumps and time-varying volatility of crude oil prices.

Given the importance of detecting time-varying jumps in energy prices, a growing number of studies have considered employing the GARCH-jump process to simultaneously model the jumps and volatility in international energy markets. Notable contributions include Zhang and Chen (2011), Gronwald (2012), Zhang and Chen (2014), Zhang and Qu (2015), Zhang and Tu (2016), Zhang et al. (2018a), Zhang et al. (2018b), Dutta et al. (2018), Liu et al. (2020), and Dutta et al. (2020).

Among these articles, Zhang and Chen (2011), Gronwald (2012), Zhang and Chen (2014), Zhang and Qu (2015), Zhang and Tu (2016), Zhang et al. (2018a), Zhang et al. (2018b) and Liu et al. (2020) provide empirical evidence that crude oil prices are characterized by time-dependent jumps, while Dutta et al. (2018) find similar jumps in the US ethanol prices. Besides, Dutta et al. (2020) show that jumps also exist in the crude oil volatility index (hereafter, OVX) and they do evolve over time. All these studies confirm the presence of extreme price movements in international energy markets and hence the empirical distributions of energy prices seem to have thick tails.[2] It is worth mentioning that jumps in oil prices have significant implications for other markets as well. Zhang and Qu (2015) and Zhang and Tu (2016), for example, show that the information on time-varying jumps in oil prices could predict changes in the price levels of Chinese agriculture and metal indexes, respectively. Overall, these articles argue that taking such jumps into account would play a crucial role in making proper investment decisions.

Our study extends the current literature in two major ways. First, while previous studies have focused on the significance of modeling jump dynamics in energy markets, they do not investigate whether the presence of such jumps in energy prices provides early signals of market crashes. This paper examines whether time-varying jumps, which could occur in energy prices due to unusual news events, have predictive content for downturns in international energy markets. Earlier studies argue that future market downturns could be realized in a series of jumps during a short interval of time. Maheu and McCurdy (2004), for instance, claim that the probability that jumps would occur in financial time series increases right before the market crash. In addition, Bates (1991) demonstrates that when the expected number of jumps in option prices escalates, crash fears among market participants seem to be increasing. Chan and Maheu (2002) also argue that the intensity of jumps is sensitive to economic states, which rise during periods of extreme volatility. In sum, all these studies document that systematic behavior in jumps is usually observed before the market downturns. To the best of our knowledge, we are the first to examine whether time-varying jumps in oil prices are an indicator of market conditions.

Second, unlike prior literature, we attempt to identify the determinants of oil price jumps during the turmoil periods given the existence of such jumps in global energy markets. Since jumps in crude oil prices represent a large fraction of market volatility, which is usually difficult to explain, detecting the key determinants of such price movements could provide new information on how oil market risk can be hedged. To achieve our goal, we explore the role of different uncertainty measures including crude oil price volatility (i.e., OVX), the US equity market implied volatility (hereafter, VIX), and economic policy uncertainty (hereafter, EPU) indexes. A growing body of literature finds evidence that variations in oil prices react significantly to a range of uncertainty indicators (Haugom et al., 2014; Antonakakis et al., 2014; Bekiros et al., 2015; Aloui et al., 2016; Antonakakis et al., 2017; Miao et al., 2017; Wei et al., 2017; Gkillas et al., 2018; Demirer et al., 2018; Brandt and Gao, 2019; Liu et al., 2019; Dutta et al., 2020).[3] Our objective is to assess whether these uncertainty measures have predictive information for time-varying jumps in crude oil futures.[4] This makes an important extension to existing literature given that predicting such jumps has important implications to both investors and policymakers.

The key takeaway from our empirical analysis is that crude oil futures market dynamics are significantly influenced by the extreme price movements and that the conditional expected number of jumps in oil futures prices increases significantly amid the depression periods, which is, however, not the case when the market functions normally. Hence, it can be inferred that such clusters of jumps may contain predictive contents for oil market crashes, providing early signals of future downturns. Testing for the gradual information diffusion hypothesis, we also provide statistical evidence that time-varying jumps occurring in the global crude oil market can forecast its price changes during the ongoing COVID-19 pandemic periods. Our results further show that the information content of crude oil volatility, the US equity VIX, economic policy uncertainty, and financial stress indexes can successfully explain the time-dependent jumps during the stress periods.

Notably, our findings are novel given that while the expected number of jumps in global crude oil markets tend to increase around the financial and health crisis periods, jump intensities during the pandemic are higher than those during the 2008 economic downturns. These results indicate that the likelihood of jumps may vary amid periods of financial and health crises. Hence, jumps occurring in crude oil markets may be heterogeneous with respect to the type of crisis. We also observe that oil prices may contain predictive content that the GARCH-jump process could exploit in forecasting future market downturns. While traditional GARCH and stochastic volatility (SV) models can successfully explain smooth persistent changes in volatility, they fail to capture these large discrete changes occurring in asset returns. Thus the GARCH or SV volatility component of the conditional variance may become less important in describing the total volatility while jumps become more important just before a crash.

The rest of the paper is structured as follows: The next section describes the data, while Section 3 presents the methodological framework. Our empirical results are discussed in Section 4. Lastly, Section 5 includes concluding remarks.

2. Data

We collect daily observations on WTI and Brent oil futures prices from the Thomson Reuters DataStream database. In addition, the

[1] As Li et al. (2016) mention 'Jump risks are not only important for investors who may demand a large premium to carry these risks, but also vital for policy makers who must make decisions in real time during times of jump-inducing chaotic conditions in financial markets.'

[2] Dutta (2018a) argues that jumps in time series data can lead to serious distortion of model specifications, parameter estimation, and volatility forecasting. Given that time-varying jumps represent an important element of an asset's risk, detecting such jumps is crucial for increasing the accuracy of model prediction.

[3] Haugom et al. (2014) show that the realized volatility of oil prices is significantly affected by the changes in the levels of crude oil volatility (OVX). Dutta et al. (2020) also document that the conditional volatility of WTI oil prices is sensitive to OVX shocks. In addition, Antonakakis et al. (2014) argue that economic policy uncertainty has substantial impacts on global crude oil markets given that uncertainties in economic policy decisions lead to a reduction in firms' investments, which would cause a negative effect on energy prices. Moreover, Liu et al. (2019) claim that increasing geopolitical risk could exert impacts on oil prices by affecting the oil supply policy of OPEC countries. Overall, trading decisions as well as market sentiments may react significantly to these uncertainty indicators, which could cause oil prices to upsurge or decline.

[4] The geopolitical risk index has not been used due to lack of daily data during the COVID-19 pandemic period.

Table 1
Descriptive statistics and unit root tests.

Index →	WTI futures	Brent futures	OVX	VIX	US EPU	UK EPU
Mean	−0.0137	−0.0132	37.94	19.94	115.54	320.57
Standard deviation	3.2496	2.8726	19.40	9.90	82.67	203.04
Skewness	−2.4565	−2.6031	4.42	2.41	2.69	2.42
Kurtosis	99.55	103.34	38.37	10.65	13.88	17.20
Jarque-Bera test	1286793***	1397077***	183,325.8***	11,307.41***	20,187.62***	45,044.46
ADF test	−11.69***	−12.93***	−4.76***	−4.47***	−5.80***	−5.40***
PP test	−63.48***	−58.51***	−3.55***	−5.28***	−34.55***	−55.70***
DF-GLS test	−6.63***	−8.57***	−3.97***	−3.66***	−4.92***	−5.37***
NPZa	−15.61***	−40.37***	−38.97***	−28.11***	−45.40***	−43.13***

Notes: This table includes the descriptive statistics and results of unit root tests for different indexes. Returns are considered for the oil markets, while OVX, VIX and EPU data appear at levels. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively.

Table 2
Results of the LP unit root test for WTI and Brent futures returns.

Markets ↓	TB1	TB2	Number of lags	Test statistic
WTI futures	21.08.2009	16.02.2010	6	−8.91***
Brent futures	07.11.2008	05.05.2009	5	−13.75***

Notes: The critical values for the LP test are - 7.19, −6.62 and − 6.37 at the 1%, 5% and 10% levels, respectively. TB1 and TB2 refer to break dates. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively.

information on VIX and OVX indexes is retrieved from the website of the Chicago Board Options Exchange (CBOE). Finally, the EPU data are taken from *www.policyuncertainty.com*.[5] Our sample period ranges from 10.5.2007 to 30.6.2020. The starting period of our sample depends on the availability of OVX data. It is worth mentioning that the chosen period encompasses three important events of oil market depressions including the 2008 global financial crisis, the 2014 oil market downturn, and the ongoing COVID-19 pandemic.

Table 1 reports the descriptive statistics and unit root test results for different oil return and uncertainty indexes. Given that the GARCH-jump approach requires stationary data, we use log returns for oil market indexes. Of these two crude oil markets, WTI appears to be more volatile than Brent. Besides, both indexes exhibit negative skewness and seem leptokurtic. Among the uncertainty indexes, which are considered at levels, the UK EPU has a higher mean and standard deviation than the rest. Moreover, employing the Jarque-Bera test, we also note that none of these indexes satisfies the normality assumption. Finally, the results of different unit root tests - augmented Dickey-Fuller (ADF), Phillips–Perron (PP), DF-GLS, and Ng-Perron (NP) - show that all these indexes appear to be stationary.

Next, Table 2 reports the results of the Lumsdaine and Papel (1997) unit root test with two structural breaks. This test is conducted mainly for WTI and Brent indexes as we intend to test for time-varying jumps in these markets. These findings suggest that for both oil markets, breaks occur during the global financial crisis period. We further note that each return index appears to be stationary.

Fig. 1 demonstrates the futures prices of WTI and Brent markets. Both indexes exhibit a similar pattern. For instance, each market experiences a substantial drop amid the 2008 global financial crisis, 2014 oil market recession, and COVID-19 pandemic periods. Notably, the fall in oil futures prices during the ongoing COVID-19 crisis period is higher than that observed during 2008 as well as 2014 downturns.

3. Methodology

3.1. The GARCH-jump process

The GARCH-jump model, developed by Chan and Maheu (2002), is widely employed in recent finance and economics literature (Xiao and Zhou, 2018; Zhang et al., 2018a, 2018b; Zhou et al., 2019; Chiang and Chen, 2019; Gronwald, 2019; Dutta et al., 2020). The immense popularity of this model emanates from the fact that it can successfully capture the time-varying jumps, which occur in asset prices due to some unexpected major events. Jumps represent a risk, which could emerge as a vital factor impacting the investors' portfolio allocation (Zhou et al., 2019). Hence capturing time-varying jumps plays a significant role in portfolio risk analyses.

Following Chan and Maheu (2002), we consider the following form for the GARCH-jump specification[6]:

$$R_t = \pi + \mu R_{t-1} + \epsilon_t \tag{1}$$

where R_t refers to the log return of an oil index at time t, and ϵ_t denotes the innovation which is split into the following parts:

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t} \tag{2}$$

where ϵ_{1t} is assumed to follow the GARCH (1,1) process as follows:

$$\epsilon_{1t} = \sqrt{h_t} z_t,\ z_t \sim NID(0,1)$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1} \tag{3}$$

In addition, ϵ_{2t} refers to a jump innovation taking the following form:

$$\epsilon_{2t} = \sum_{l=1}^{n_t} J_{tl} - \theta \lambda_t \tag{4}$$

where J_{tl} refers to the jump size having a mean θ and a variance d^2, $\sum_{l=1}^{n_t} J_{tl}$ represents the jump factor, and n_t denotes the number of jumps at time t, which follows a Poisson distribution defined as:

$$P(n_t = j | I_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^j}{j!}, j = 0, 1, 2, \dots \tag{5}$$

with an autoregressive conditional jump intensity (ARJI) given as:

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1} \tag{6}$$

In Eq. (6), λ_t represents the time-varying conditional jump intensity parameter, λ_0 indicates the constant jump intensity, and ξ_{t-1} is the intensity residual. These parameters satisfy the following constraints: $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$, and $\gamma > 0$.

Now, let us define the log-likelihood as:

[5] We consider the daily observations for the US and UK EPU indexes. The US EPU data are used when predicting the jumps in WTI index, while the UK EPU data are considered for predicting the jumps in Brent index.

[6] The AR(1) process is chosen based on the AIC and BIC values.

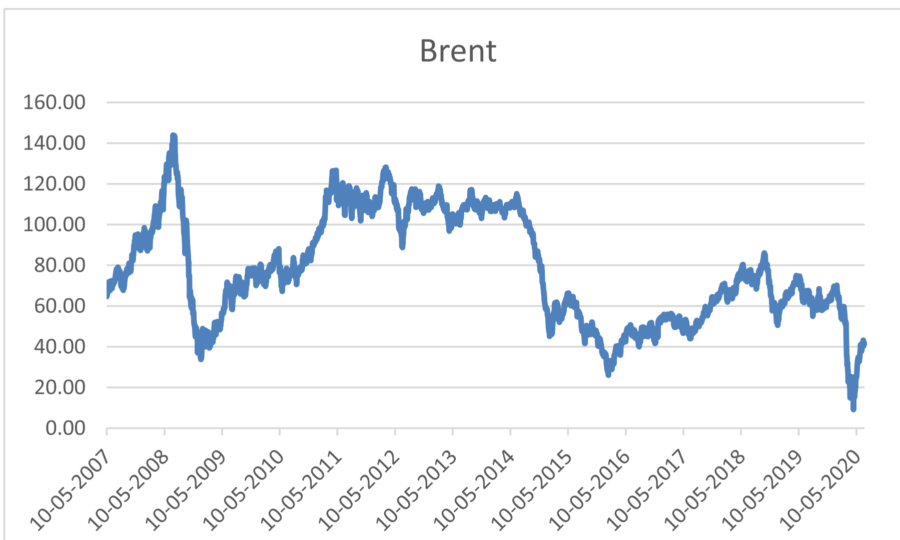


Fig. 1. WTI and Brent futures price indexes.

$$L(\Theta) = \sum_{t=1}^{T} logf(R_t|I_{t-1}\,;\Theta)$$

where $\Theta = (\pi, \mu, \omega, \alpha, \beta, \theta, d, \lambda_0, \rho, \gamma)$ and $I_{t-1}$is the information set.

We then employ the maximum likelihood estimation technique for obtaining these estimates.

3.2. Determinants of jumps

In this section, we examine whether different uncertainty indicators play any key role in explaining the time-varying jumps in oil prices. As mentioned earlier, we aim to use EPU, OVX, and VIX indexes as the uncertainty measures. Aloui et al. (2016), for instance, argue that variations in the EPU index may detect the supply-side, aggregate-demand, and oil-specific demand shocks, which lead to significant changes in oil prices. Hence, an upturn (downturn) in EPU would exert a negative (positive) impact on the economy, which in turn results in decreasing (increasing) demand and supply of crude oil, triggering oil price volatility. Balcilar et al. (2016) also hold similar arguments when testing the impact of EPU on oil price volatility. Besides, Wei et al. (2017) claim that increasing EPU can lead to serious divergence in the expectations of oil consumers, producers, and speculators simultaneously, impacting the demand, supply, or speculation stock for crude oil. Nevertheless, there is no consensus that EPU has emerged as the main determinant of crude oil volatility. Other uncertainty indicators such as the crude oil volatility index (i.e., OVX) and VIX, which are often considered as measures of financial uncertainty, may also drive oil price volatility (Liu et al.,

Table 3
Estimates of GARCH-jump models.

Coefficient	WTI (Full)	Brent (Full)	WTI (2008 Crisis)	Brent (2008 Crisis)	WTI (COVID-19)	Brent (COVID-19)
π	0.0771**	0.0844***	0.0930	0.0511	0.3681***	0.4085
	(0.0369)	(0.0322)	(0.1513)	(0.0590)	(0.0509)	(0.6986)
μ	−0.0273	0.0277	−0.0572	0.0543***	−0.0653	−0.0936
	(0.0181)	(0.0176)	(0.0632)	(0.0207)	(0.0558)	(0.1959)
ω	0.0557***	0.0443***	0.0464	0.0697*	0.0079***	0.0619
	(0.0170)	(0.0130)	(0.0824)	(0.0362)	(0.0015)	(0.1755)
α	0.0562***	0.0612***	0.0620***	0.0464***	0.0062***	0.0307
	(0.0121)	(0.0089)	(0.0219)	(0.0051)	(0.0001)	(0.0390)
β	0.9127***	0.8999***	0.9245***	0.9253***	0.9827***	0.8751***
	(0.0180)	(0.0148)	(0.0322)	(0.0061)	(0.0009)	(0.0428)
θ	−1.1412***	−0.4654**	0.1850	−0.1994	−1.6252***	−1.2328
	(0.3648)	(0.1867)	(1.1660)	(1.1503)	(0.2290)	(3.9432)
d^2	3.7099***	2.6065***	−3.6233***	5.7786***	−3.2363***	2.4409***
	(0.6354)	(0.3124)	(0.9259)	(0.4952)	(0.3573)	(0.7031)
λ_0	0.0049	0.0016	0.0268	0.0421***	0.0001***	0.0068
	(0.0040)	(0.0011)	(0.0298)	(0.0128)	(0.00002)	(0.0066)
ρ	0.9638***	0.9945***	0.8107***	0.5863**	1.0272***	0.9919***
	(0.0288)	(0.0038)	(0.1600)	(0.1075)	(0.0028)	(0.0494)
γ	0.2684	0.1164***	2.2009***	0.0957**	0.1862***	0.2226***
	(0.2057)	(0.0421)	(0.4292)	(0.0441)	(0.0132)	(0.0749)
Log-likelihood	−7134.47	−6929.60	−990.85	−901.73	−235.02	−232.35

Notes: This table shows the estimates of GARCH-jump models (see Eqs. (1)–(6)) for full period, 2008 financial crisis period and COVID-19 pandemic period. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. Standard errors are in parentheses.

2013). We, therefore, use the information content of EPU, OVX, and VIX indexes to predict oil price jumps. To serve this purpose, we estimate the following regression model:

$$\lambda_t = \varphi_0 + \varphi_1 \lambda_{t-1} + \varphi_2 U_{t-1} + \varepsilon_t \tag{7}$$

In the above equation, U refers to a vector of uncertainty indexes. Altogether, we run three different sets of regressions (full and subsamples) to examine the role of VIX, OVX, and EPU indexes in explaining the intensities of jumps occurring in oil futures prices If the value of $\varphi_1$is significantly different from zero for a particular uncertainty index, we conclude that the uncertainty measure under investigation may contain predictive information for the time-varying jumps in international energy markets.

4. Empirical results

4.1. Results of the GARCH-jump process

4.1.1. Full period analyses

The findings of the autoregressive conditional jump intensity process are shown in Table 3. Estimates for both full and subsamples (crisis periods) are given in this table. The results of our full period analyses suggest that the GARCH coefficients (α, β) are strongly significant, which provides evidence of volatility clustering in crude oil futures markets.[7] We further observe that the parameter λ_0 is insignificant for both WTI and Brent indexes, while ρ, γ appear to be significant in most of the cases. This finding implies the time-variability in the jump intensity and demonstrates large abrupt price variations. Taking Brent crude as an example, the parameter ρ being 0.9945 suggests that the time-varying jump intensity is persistent (Chan and Maheu, 2002). Besides, the γ coefficient, assessing the sensitivity of λ_t to a lagged shock ξ_{t-1}, is 0.1164, implying that an increment in ξ_{t-1} would lead to a diminished impact (0.1164) on the next period's jump intensity. Moreover, all the jump intensity parameters (λ_0, ρ, γ) assume positive values, which would justify the choice of ARJI specification when detecting time-dependent jumps in the Brent market. In addition, the significance of ρ and γ confirms the fact that λ_t, the jump intensity, is influenced by both lagged jump intensity (λ_{t-1}) and lagged intensity residuals (ξ_{t-1}). The high value of ρ also indicates a high degree of persistence in λ_t. For the US oil market, we report similar findings as well, although the parameter γ is found to be insignificant meaning that λ_t is influenced by its lagged values only.

On the whole, we find evidence that global oil price indexes experience time-varying jumps implying that these markets are characterized by unexpected price variations.[8] Our findings are in line with Zhang and Chen (2011), Gronwald (2012), Zhang and Chen (2014), Zhang and Qu (2015), Zhang and Tu (2016), Zhang et al. (2018a), Zhang et al. (2018b) and Liu et al. (2020).

We now focus on the plots (Fig. 2 and Fig. 3) depicting the jump intensities of WTI and Brent oil prices for the whole sample period. Fig. 2 exhibits the predictive information of jump intensity (λ_t) in forecasting a jump in the WTI index. It is evident from this graph that the first jump was anticipated during September 2008 (i.e., when Lehman Brothers filed a bankruptcy). We then observe an upsurge in the intensity parameter amid the 2014 oil price downturn. However, the conditional expected number of jumps appears to be less than one during this period suggesting that jumps are not much apparent, although global oil markets saw a downturn as a consequence of oversupply of crude oil. Next, we detect a cluster of jumps during the ongoing COVID-19 pandemic era. The jump intensity parameter starts to increase in March 2020 and

[7] The quantity, $\alpha + \beta$, also suggests a high degree of volatility persistence in S&P 500 index.

[8] Outliers are often observed in oil price indexes (Charles and Darne, 2014). Identifying outliers, which occur due to wars, natural disasters, political conflicts, is crucial given that the presence of such outliers can lead to model misspecifications, poor forecasts and invalid inferences. We, therefore, examine the presence of outliers in the WTI and Brent markets. In doing so, we employ the process proposed by Ané et al. (2008). Dutta (2018b) also advocates this approach while finding outliers in metal markets. Using this procedure, discussed in Appendix A, we find a number of outliers in global crude oil prices. After correcting for these outliers, we re-estimate the GARCH-jump model and find that jumps still exist implying that the presence of outliers does not have any significant influence on our earlier results. These results are presented in the appendix (see Table A1). It is also worth mentioning that when estimating the GARCH-jump process after correcting for outliers, we assume that ϵ_{1t} follows the EGARCH process instead of the GARCH (1,1) process as shown in Eq. (3). Dutta et al. (2020) also assume the same as the EGARCH model captures asymmetry in crude oil price indexes.

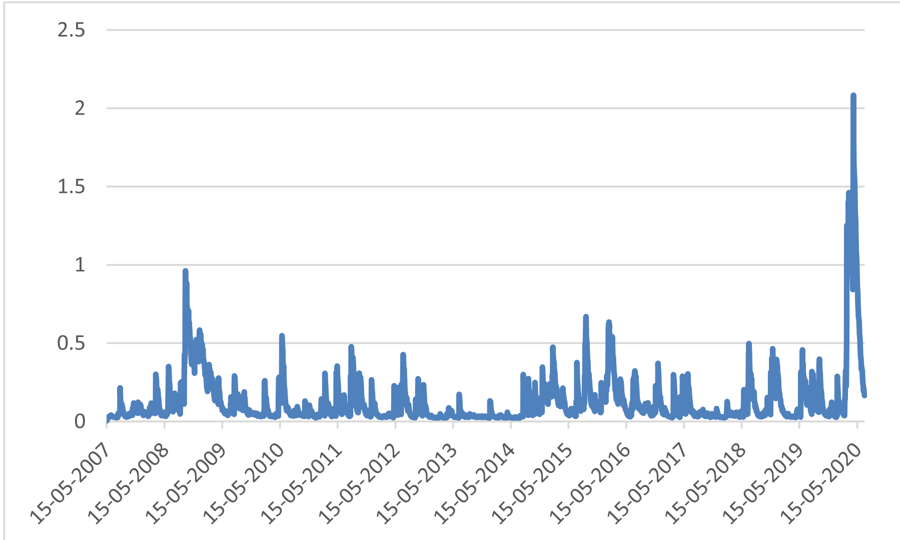


Fig. 2. Jump intensity for WTI index (Full period).

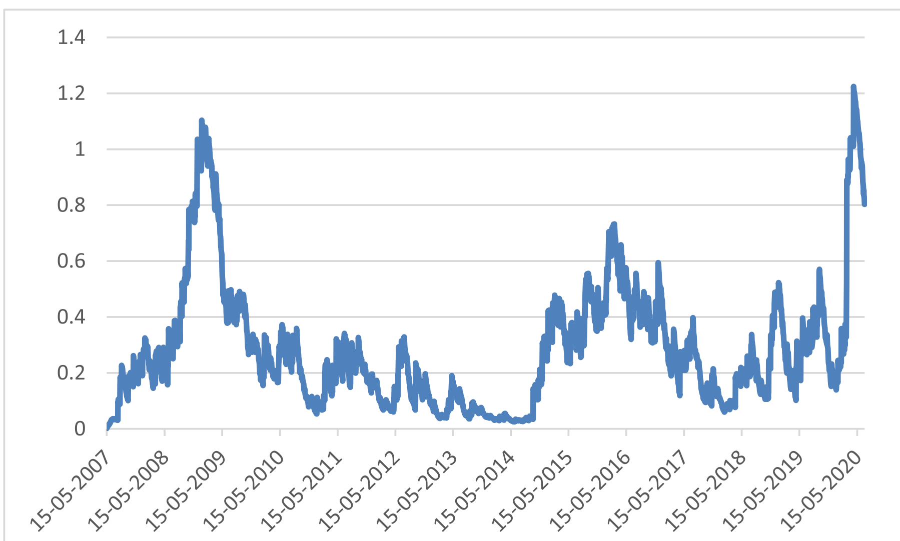


Fig. 3. Jump intensity for Brent index (Full period).

right before the Black Monday I (i.e., 9 March 2020), we expect a jump in the WTI oil price index. The intensity parameter continues to increase until May 2020. It is evident that the expected number of jumps is much higher during the COVID-19 period compared to the 2008 global financial crisis era. These findings indicate that the impact of COVID-19 on international oil markets seems unprecedented.

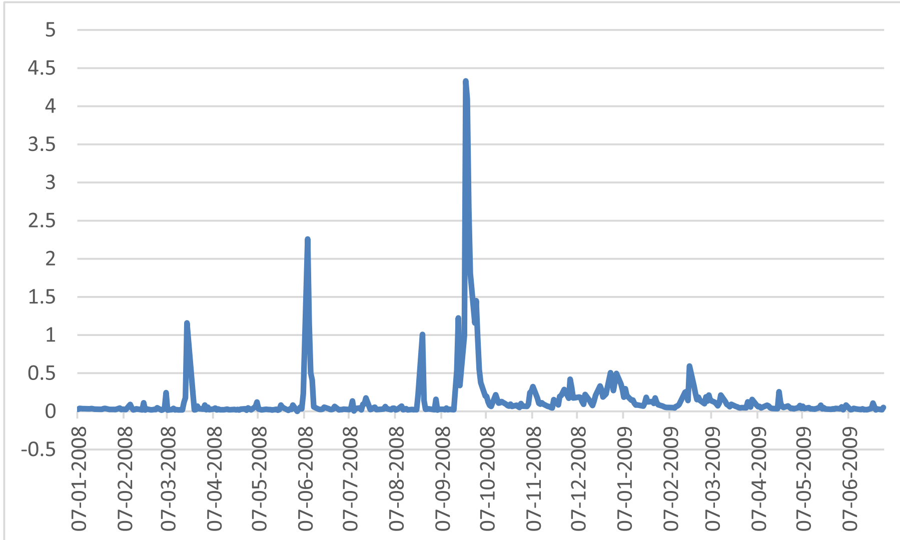
Moving to Fig. 3, we find a similar pattern for the Brent market. The main difference is that over the COVID-19 period the intensity of jumps in Brent prices is lower than that in WTI prices. One explanation of this is that Brent is a better representative of global oil markets than WTI. WTI pertains to the US production of crude oil and the US market is more sensitive to shocks than the global oil market. Therefore, the expected number of jumps appears to be higher for the WTI oil index compared to the Brent index. In sum, jumps are frequently observed during the turmoil periods, while energy markets function normally throughout the low volatility regimes.

4.1.2. Subsample analyses

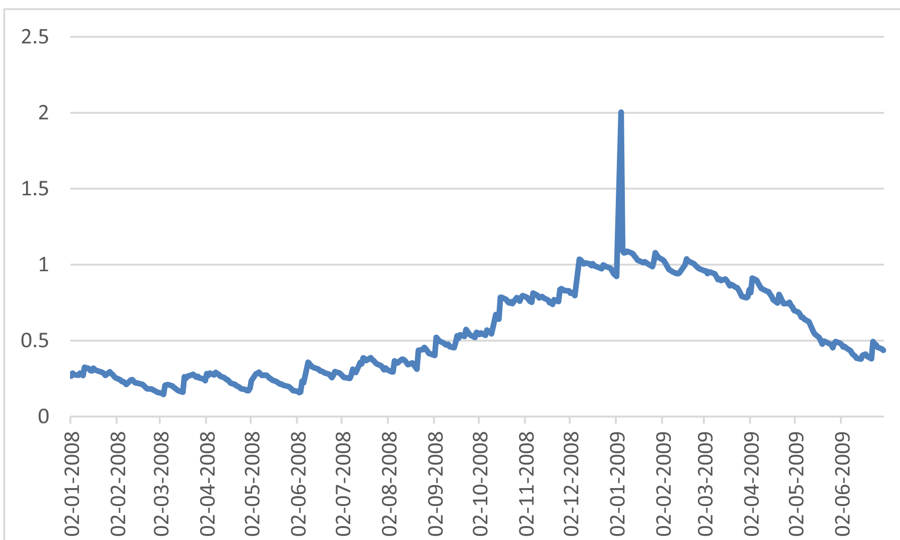
This section includes the discussion of subsample analyses. Two different subsamples related to crisis periods are considered. The 2008 crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 sample spans from 1.1.2020 to 30.6.2020. Table 3 shows the estimates of GARCH-jump models for both subsamples under investigation. One interesting finding stemming from this analysis is that for the WTI index, the γ parameter is now significant for both subsamples, which was not the case when analyzing the full period sample. This outcome indicates that current intensity residuals have a significant effect on future jump intensity during periods of high uncertainty. For the Brent market, on the other hand, both ρ and γ appear to be significant in each case. Overall, the estimates suggest the presence of time-varying jumps in oil prices amid the turmoil periods.

Next, Fig. 4 and Fig. 5 exhibit the jump intensities for the subsamples. During the great recession era, the expected number of jumps increased for both WTI and Brent markets when the Lehman Brothers filed bankruptcy in September 2008. However, for the WTI index, we detect a series of jumps even in March 2008 and in June 2008. Fig. 5 also shows a cluster of jumps for global crude oil futures markets amid the ongoing COVID-19 pandemic phase.

We now more closely scrutinize the jump intensities for crude futures markets following the inception of novel coronavirus disease. Fig. 6



(a)



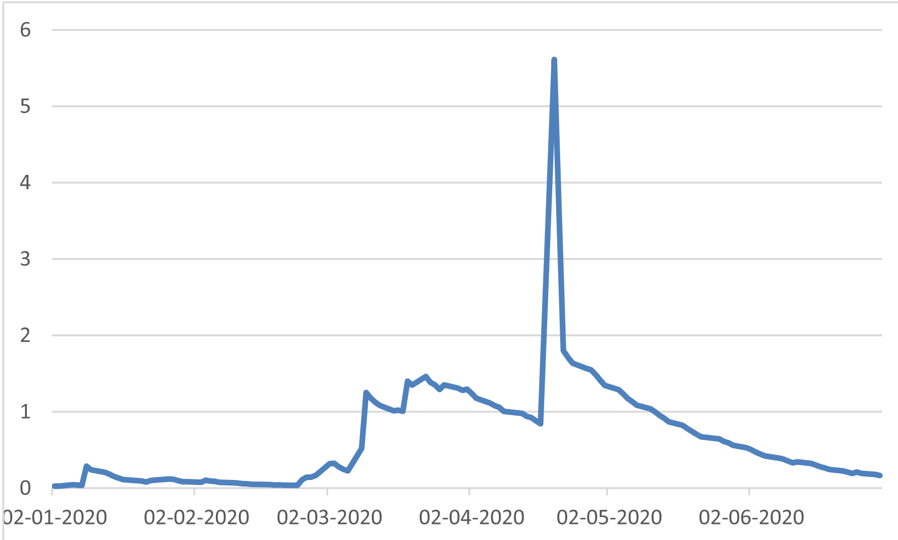
(b)

Fig. 4. Jump intensity for WTI (a) and Brent (b) indexes (2008 crisis period).

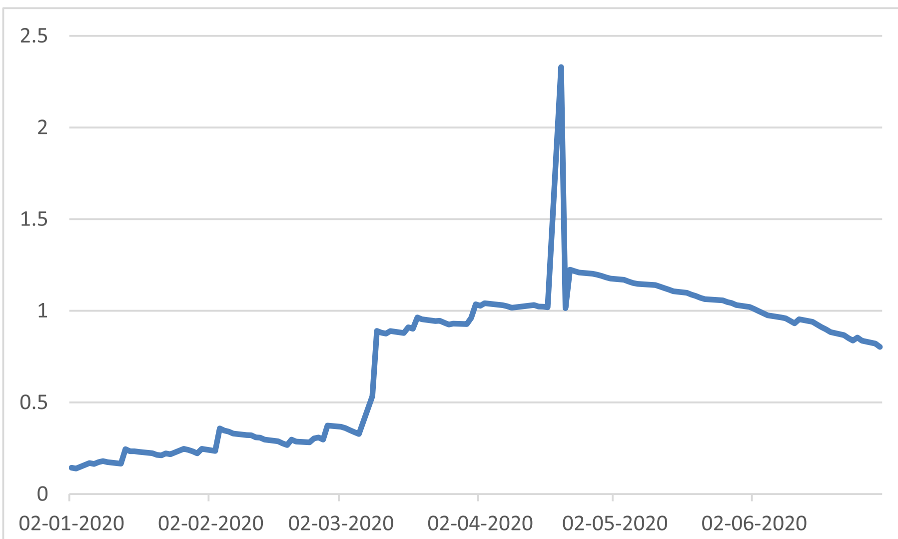
displays the jump intensities for both WTI and Brent indexes during the period from 01.04.2020 to 20.04.2020. We choose this period to detect the presence of jumps right before the oil market crash on 20th April.[9] Hence, our objective is to verify whether there are clusters of jumps before the crash. Doing so will allow us to detect these clusters and examine if they help predict the market crash. Remarkably, this plot shows that for the Brent market at least one jump is expected on each day indicating the existence of a cluster of jumps before this historical downturn. Looking at the jump intensities for the WTI index, plotted in the same figure, we find that at least five jumps were anticipated on the day of the market crash. This finding is in line with Chan and Maheu (2002) suggesting the significance of jumps which usually occur just before major drops in asset prices.

Note that while the phenomenon of jump intensity is well-investigated in the mainstream financial literature (Chan and Maheu, 2002; Kim and Mei, 2001; Rangel, 2011), examinations of jump behavior in the commodity markets are limited (Zhang and Tu, 2016; Zhang et al., 2018a, 2018b). Crude oil is a widely traded commodity with financial characteristics. Thus, understanding the jump behavior in the crude oil market becomes imperative given that the jump dynamics in any market are intensified around the phases of economic downturns (Maheu and McCurdy, 2004). Our sample period covers two important periodical segments of economic downturns: the period of the global financial crisis (GFC, 2007–08) and the COVID-19 pandemic. While the event of 2007–08 is essentially a financial crisis, the COVID-19 is a form of a health crisis. A contagious disease like COVID-19 is likely to have a higher impact on the economy than the financial crises, in general, and on the oil prices, in particular. The curfews and travel restrictions contribute to the sluggish demand for oil. Similarly, the logistics

[9] On 20th April 2020, WTI futures price becomes negative, taking the value around -$37 per barrel. This is the first time in history when oil prices turn negative.



(a)



(b)

Fig. 5. Jump intensity for WTI (a) and Brent (b) indexes (COVID-19 phase).

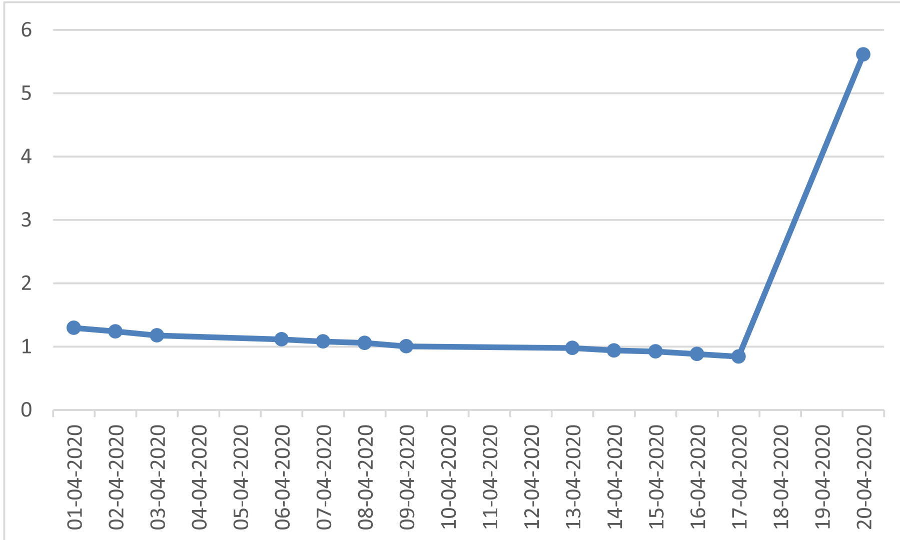
industry is constrained due to border closures, hence less transportation and consumption of oil. Besides, COVID-19 has also led to job-losses or pay-cuts exposing the individuals to lower disposable incomes. Consequently, the consumption propensity of the public at large is curbed. The demand for the luxury items is expected to fall. For instance, the automotive sector in India is hit severely because of lower demand for vehicles.[10] A current lower demand for vehicles would also have impacts on future demand for oil. The plot for oil jump intensity in Fig. 5 also comply with our arguments. We can observe higher spikes during the COVID-19 sub-period. Thus, it is indeed relevant to reconcile the similarities or differences in the response of oil prices during the periods of financial and health crises.

It is also worth mentioning that the process governing the arrival of jumps may be heterogeneous with respect to the type of crisis. As evidenced by our findings, the likelihood of jumps may vary amid periods of financial and health crises. Given that the prediction of extreme volatility plays a crucial role in risk management, identification of jump dynamics in different crisis periods has important implications for oil market participants.

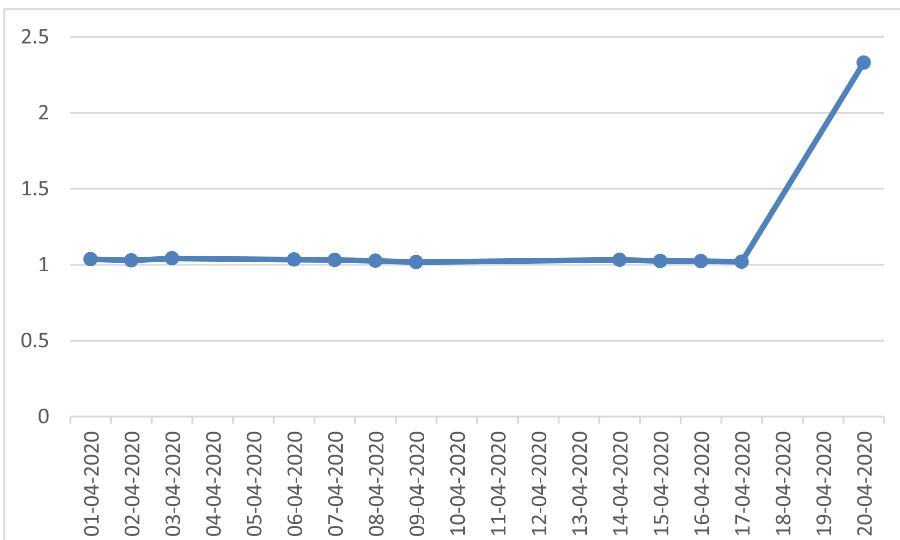
4.2. Summary statistics of jump intensities

Table 4 reports the summary statistics of the jump intensities for both WTI and Brent futures markets. In order to facilitate comparison, these statistics are computed for the full period (Panel-A), 2008 crisis period (Panel-B), and COVID-19 pandemic period (Panel-C). We find that for each of the oil markets, the mean intensity is higher amid the volatile

[10] Chhibber, B. and Gupta, N., "The Indian Automotive industry: from resilience to resurgence?", McKinsey & Company, available at: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-indian-automotive-industry-from-resilience-to-resurgence#, accessed August 11, 2021, 18:57 h, IST.



(a)



(b)

Fig. 6. Jump intensity for WTI (a) and Brent (b) indexes (1.4.2020–20.4.2020).

periods (2008 financial crisis and COVID-19 pandemic) when compared to the full period. In addition, the mean intensity increases significantly during the ongoing COVID-19 pandemic time indicating that before the fall in global crude oil markets due to the novel coronavirus, the conditional expected number of jumps in different energy markets tends to increase. Overall, our results reveal that the information on time-varying jumps could be used in predicting future market downturns. Therefore, we conclude that these jumps in crude oil futures prices may provide early signals of market crashes (e.g., 2008 global financial crisis or COVID-19 pandemic). Our results also imply that global pandemics have a higher likelihood of causing energy market crashes than economic crises. Increasing temperatures and the number of extreme weather events due to climate change lead to environmental and social conditions ripe for pandemics. Hence, this implication may become even more important.

4.3. *Determinants of time-varying jumps*

Tables 5 and 6 display the estimates of Eq. (7). These findings will verify if OVX, VIX, and EPU indexes contain predictive information for future time-varying jumps occurring in international crude oil prices. Table 5 shows the results for the WTI index, while Table 6 exhibits the findings for the Brent market. These results are based on the analyses of the full period, 2008 crisis period and the ongoing COVID-19 pandemic period demonstrated in Panels A, B, and C, respectively.

The findings, reported in Table 5, reveal that both OVX and EPU appear to have predictive contents for the intensity of jumps in the WTI index when the estimates of Panel A are taken into account. The impact of the VIX index, on the other hand, is insignificant. It is also worth mentioning that jump intensity is influenced by its past values as well. We further notice that among the uncertainty indicators, crude oil volatility has a higher impact than the rest as evidenced by the magnitude of the corresponding coefficients. Hence, for the full period sample,

Table 4
Summary statistics of jump intensities.

	Mean	Std. Dev.	Maximum	Minimum
Panel A: Full sample				
WTI	0.1280	0.1813	2.0832	0.0049
Brent	0.2860	0.2262	1.2243	0.0016
Panel B: 2008 crisis				
WTI	0.1498	0.3991	4.3314	0.0000
Brent	0.5417	0.2928	2.0037	0.1454
Panel C: COVID-19				
WTI	0.6456	0.6824	5.6128	0.0259
Brent	0.7247	0.3734	2.3298	0.1392

Notes: This table reports the summary statistics of the jump intensities for both WTI and Brent futures markets. The statistics are computed for full period (Panel-A), 2008 crisis period (Panel-B) and COVID-19 pandemic period (Panel-C).

Table 5
Determinants of jumps in WTI futures prices.

	Estimate	Standard error	*p*-value
Panel A: Full sample			
Constant	−0.0716 ***	0.0053	0.00
λ_{t-1}	0.5955***	0.0161	0.00
OVX	0.0026***	0.0002	0.00
VIX	0.00001	0.0002	0.97
US EPU	0.0002***	0.00003	0.00
F-statistic	2345.75***		
R^2 (%)	74.02		
D-W statistic	2.38		
VIF	2.94		
Panel B: Financial crisis			
Constant	−0.0102	0.0079	0.19
λ_{t-1}	0.9461***	0.0175	0.00
OVX	0.00025	0.00023	0.28
VIX	0.00002	0.00003	0.93
US EPU	0.00004	0.0003	0.12
F-statistic	1992.66***		
R^2 (%)	95.54		
D-W statistic	1.73		
VIF	3.09		
Panel C: COVID-19 crisis			
Constant	−0.2253**	0.0957	0.02
λ_{t-1}	0.1459	0.1139	0.20
OVX	0.0032	0.0020	0.11
VIX	0.0033	0.0038	0.38
US EPU	0.0012***	0.0003	0.00
F-statistic	41.40***		
R^2 (%)	58.18		
D-W statistic	2.09		
VIF	4.01		

Notes: This table shows the estimates of Eq. (7) for WTI futures market. The results are provided for full period, 2008 financial crisis period and COVID-19 pandemic period. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. VIF refers to variance inflation factor and D—W stands for Durbin-Watson.

OVX seems to be the most influential determinant of oil price jumps. These findings are not unexpected given that OVX is a forward-looking measure of crude oil volatility and hence it represents markets' consensus on the expected future uncertainty (Maghyereh et al., 2016).

The results further indicate that none of these uncertainty measures can predict future jumps in WTI futures prices during the global financial crisis era given that all the associated coefficients are insignificant.

Table 6
Determinants of jumps in Brent futures prices.

	Estimate	Standard error	p-value
Panel A: Full sample			
Constant	−0.0066 ***	0.0021	0.00
λ_{t-1}	0.9403***	0.0060	0.00
OVX	0.0004***	0.0001	0.00
VIX	0.0005***	0.0001	0.00
UK EPU	0.000002	0.000004	0.52
F-statistic	19,998.64***		
R^2 (%)	96.05		
D-W statistic	2.77		
VIF	2.49		
Panel B: Financial crisis			
Constant	−0.0525***	0.0163	0.00
λ_{t-1}	0.8121***	0.0263	0.00
OVX	0.0027***	0.0005	0.00
VIX	0.0001	0.0005	0.71
UK EPU	0.00001	0.00003	0.62
F-statistic	1479.12***		
R^2 (%)	94.08		
D-W statistic	2.67		
VIF	3.94		
Panel C: COVID-19 crisis			
Constant	0.0499	0.0354	0.16
λ_{t-1}	0.16262***	0.0851	0.00
OVX	−0.0004	0.0005	0.32
VIX	0.0027**	0.0013	0.04
UK EPU	0.0003***	0.0001	0.00
F-statistic	154.01***		
R^2 (%)	83.92		
D-W statistic	2.78		
VIF	4.22		

Notes: This table shows the estimates of Eq. (7) for Brent futures market. The results are provided for full period, 2008 financial crisis period and COVID-19 pandemic period. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. VIF refers to variance inflation factor and D—W stands for Durbin-Watson.

Table 7
Testing for gradual information diffusion hypothesis for the COVID-19 subsample.

	Estimate	Standard error	*p*-values
Panel A: WTI			
Constant	−0.1145*	0.0618	0.07
b_0	−3.8471***	0.9776	0.00
b_1	5.0468***	0.5637	0.00
b_2	5.5786***	0.5518	0.00
b_3	6.6312***	0.5693	0.00
b_4	7.4119***	0.6561	0.00
b_5	−1.0871**	0.5093	0.03
b_6	−0.9863*	0.5745	0.08
b_7	−0.3973	0.5677	0.48
b_8	−0.1843	0.5940	0.76
$H_0 : b_0 = b_1$	−8.8939***	2.3699	0.00
Panel B: Brent			
Constant	−0.0892	0.0773	0.25
b_0	4.0688***	1.1565	0.00
b_1	14.4940***	1.3385	0.00
b_2	19.0418***	1.2930	0.00
b_3	4.6366***	1.3453	0.00
b_4	4.3033***	1.2932	0.00
b_5	1.7295	1.1576	0.13
b_6	−1.3940	1.3463	0.30
b_7	0.7468	1.3452	0.58
b_8	−0.0158	1.3386	0.99
$H_0 : b_0 = b_1$	−10.42***	2.0849	0.00

Notes: $H_0 : b_0 = b_1$is the null hypothesis of the Wald test for the difference between the estimates of the effects of jumps at lag 0 and at lag 1. These estimates are obtained for the COVID-19 subsample (1.1.2020 to 30.6.2020). ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively.

Table 8
Testing for gradual information diffusion hypothesis for the COVID-19 subsample (the case of OVX).

	Estimate	Standard error	*p*-values
Panel A: WTI			
Constant	0.3849**	0.1951	0.04
b_0	−4.8141***	0.6876	0.00
b_1	3.7299***	0.7011	0.00
b_2	0.1610	0.7010	0.82
b_3	−0.2794	0.6589	0.67
b_4	−2.4043***	0.5897	0.00
b_5	−0.3307	0.7118	0.64
b_6	−0.0472	0.7019	0.94
b_7	1.4586***	0.4316	0.00
b_8	−1.0328	0.6884	0.13
$H_0 : b_0 = b_1$	−8.5441***	1.0746	0.00
Panel B: Brent			
Constant	0.4108	0.1709	0.02
b_0	−5.7509***	0.6090	0.00
b_1	2.9175***	0.6218	0.00
b_2	0.1838	0.6217	0.76
b_3	0.3716	0.5279	0.49
b_4	−1.1481***	0.6424	0.07
b_5	−0.4348	0.5325	0.44
b_6	−0.8119	0.5111	0.12
b_7	−0.2102	0.6226	0.74
b_8	1.0780*	0.6096	0.07
$H_0 : b_0 = b_1$	−8.6684***	0.9553	0.00

Notes: $H_0 : b_0 = b_1$is the null hypothesis of the Wald test for the difference between the estimates of the effects of jumps at lag 0 and at lag 1. These estimates are obtained for the COVID-19 subsample (1.1.2020 to 30.6.2020). ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively.

Table 9
Determinants of jumps in WTI futures prices (Additional analyses).

	Estimate	Standard error	p-value
Panel A: Full sample			
Constant	0.0005	0.0024	0.81
λ_{t-1}	0.9993***	0.0100	0.00
FS	0.0270***	0.0052	0.00
TED	0.0019	0.0037	0.59
TWEX	−0.0047	0.0048	0.32
F-statistic	2810.05***		
R^2 (%)	78.11		
D-W statistic	2.16		
VIF	3.01		
Panel B: Financial crisis			
Constant	0.0024	0.0043	0.58
λ_{t-1}	0.9641***	0.0159	0.00
FS	0.0173***	0.0033	0.00
TED	0.0040	0.0042	0.33
TWEX	−0.0052	0.0040	0.19
F-statistic	2097.41***		
R^2 (%)	95.86		
D-W statistic	1.81		
VIF	2.97		
Panel C: COVID-19 crisis			
Constant	−0.0117	0.0653	0.86
λ_{t-1}	0.8516***	0.1161	0.00
FS	0.0692**	0.0302	0.02
TED	0.3063**	0.1534	0.04
TWEX	−0.0922	0.0791	0.24
F-statistic	40.66***		
R^2 (%)	58.58		
D-W statistic	1.98		
VIF	3.71		

Notes: This table shows the estimates of Eq. (7) for WTI futures market. The results are provided for full period, 2008 financial crisis period and COVID-19 pandemic period. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. VIF refers to variance inflation factor and D—W stands for Durbin-Watson.

However, for the COVID-19 subsample, the EPU index emerged as a key determinant. This finding could be attributed to the fact that an increase in policy uncertainty could cause an upsurge in oil price volatility given that oil suppliers can stock up as a result of precautionary motives (Wei et al., 2017). In line with our findings, Balcilar et al. (2016) also concur that EPU is a driver of oil price fluctuations and that EPU impacts oil prices positively amid the period of high uncertainty.

Looking at the estimates shown in Table 6, we find evidence that OVX has, in general, better predictive contents than the VIX and EPU indexes. Only for the COVID-19 period, both EPU and the VIX indexes outperform OVX as its coefficient is not significant. These results are somewhat in line with those reported in Table 3. That is, for both WTI and Brent markets, OVX acts as the major determinant of global crude oil market jumps. Hence, OVX, which is considered as the leading indicator of oil market uncertainty, represents the main source of time-varying risk linked to crude oil future prices. We further note that for the Brent market, unlike the WTI index, VIX has predictive power for the jumps for both the full sample and the COVID-19 subsample. The impact of VIX is, however, is insignificant amid the 2008 financial crisis period. It is also observed that the EPU index fails to explain the jumps for the full sample and that the information content of OVX is important for predicting the jumps during the global financial crisis era.

Overall, our results are consistent with those reported in Haugom et al. (2014), Antonakakis et al. (2014), Miao et al. (2017), Wei et al. (2017), Tiwari et al. (2020), and Dutta et al. (2020). These studies also show that crude oil prices are sensitive to different uncertainty indicators. We extend this prior literature in that while the articles cited above are focused on the linkage between uncertainty indexes and

Table 10
Determinants of jumps in Brent futures prices (Additional analyses).

	Estimate	Standard error	p-value
Panel A: Full sample			
Constant	0.0044***	0.0014	0.00
λ_{t-1}	0.9757***	0.0038	0.00
FS	0.0129***	0.0026	0.00
TED	0.0011	0.0018	0.48
TWEX	−0.0014	0.0024	0.55
F-statistic	18,367.94***		
R^2 (%)	95.88		
D-W statistic	2.53		
VIF	1.86		
Panel B: Financial crisis			
Constant	0.0093	0.0106	0.37
λ_{t-1}	0.9636***	0.0139	0.00
FS	0.0070***	0.0014	0.00
TED	0.0081	0.0058	0.16
TWEX	−0.0017	0.0081	0.83
F-statistic	1253.69***		
R^2 (%)	93.26		
D-W statistic	2.84		
VIF	2.56		
Panel C: COVID-19 crisis			
Constant	0.0667**	0.0335	0.04
λ_{t-1}	0.8727***	0.0425	0.00
FS	0.0252**	0.0125	0.04
TED	0.0673***	0.0256	0.00
TWEX	−0.0359	0.0302	0.23
F-statistic	134.53***		
R^2 (%)	82.26		
D-W statistic	2.37		
VIF	3.22		

Notes: This table shows the estimates of Eq. (7) for Brent futures market. The results are provided for full period, 2008 financial crisis period and COVID-19 pandemic period. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. VIF refers to variance inflation factor and D—W stands for Durbin-Watson.

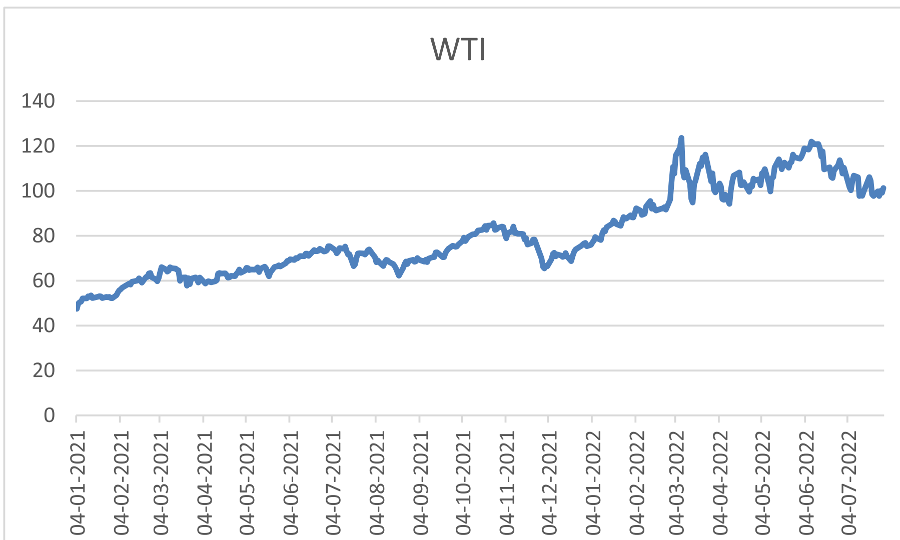
conventional oil price series, ours treats these indicators as determinants of the expected number of jumps occurring in global energy markets. Besides, we also document that crude oil VIX has emerged as the main determinant of oil price jumps when the full period is considered. This finding is somewhat new given that earlier studies find EPU as the main uncertainty indicator explaining oil market volatility (Aloui et al., 2016; Wei et al., 2017). However, for the COVID-19 subsample, EPU appears to be the only significant factor having predictive contents for oil price jumps. In sum, our research could be considered as an important extension given that predicting such jumps has important implications for both investors and policymakers.

4.4. Additional tests

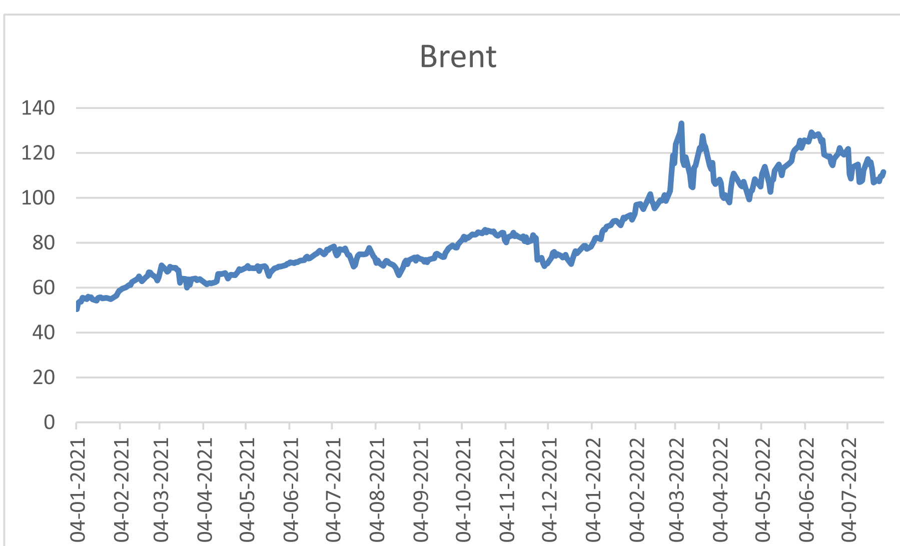
4.4.1. Do jumps predict oil returns?

We now conduct some statistical tests to investigate if the presence of jumps in the crude oil market could be used to predict the oil returns. In doing so, the gradual information diffusion hypothesis is tested where we consider time-varying jump intensities (λ_t) as predictors for oil returns. It is noteworthy that the gradual information diffusion is accepted under two conditions: first, if the impact of lagged jumps on oil returns has a similar or a larger magnitude than the contemporaneous effect of jumps; and second, if the strongest lagged effects appear at higher lags. A number of prior works (Driesprong et al., 2008; Xiao et al., 2019) test for these two conditions when examining the gradual information diffusion hypothesis. In line with these articles, we introduce lags of several trading days between the daily oil returns and lagged jumps. If our results support the gradual information diffusion hypothesis, we can conclude that the relation between crude oil returns and jumps strengthens at higher lags, or investors have difficulty in evaluating the effect of oil market jumps.

Now, To test for the gradual information diffusion hypothesis, we estimate the following regression during the COVID-19 pandemic period (1.1.2020 to 30.6.2020):



(a)



(b)

Fig. 7. WTI and Brent futures prices during Janauary, 2021 to July 2022.

$$R_t = a + \sum_{j=0}^{8} b_j \lambda_{t-j} + e_t \quad (8)$$

where, R_t refers to the log return of an oil index (WTI/Brent) at time t, λ_t denotes the intensity of jumps in oil returns at time t, and e_t denotes the error term.

The estimates of Eq. (8) are shown in Table 7. These results demonstrate that both conditions of the gradual information diffusion hypothesis are satisfied implying that the lagged impacts of jumps are similar to that of the contemporaneous impacts or even higher and that the lagged impacts of λ_t reach its peak and then decline as lag size increases. For example, in the case of the WTI index, the explanatory power of these regressions increases up to a lag of 4 trading days and then rapidly decreases. We document similar findings for the Brent price series as well. Thus when we introduce lags of several trading days between the daily oil returns and lagged jumps, this substantially strengthens the predictability relation. Therefore, we provide evidence that jumps in the crude oil market can predict its returns. A possible explanation for this result is that investors react to information at different points in time, or have difficulty in evaluating the effect of oil market jumps on its returns and act with a delay.

Next, we investigate if jumps in OVX can predict oil market returns. In particular, we first estimate the jump intensity (λ_t) in the crude oil volatility index (i.e., OVX) and then use the information on λ_t to predict the crude oil returns. These results, presented in Table 8, do not support the gradual information diffusion hypothesis as none of the conditions is satisfied. It can be thus concluded that jumps in the traditional oil price index, when compared to that in the oil volatility index, have more predictive contents for the global crude oil returns during this ongoing pandemic. Therefore, the time series of oil prices may alone contain some information that the GARCH-jump process could exploit in forecasting market crashes.

Our findings are novel considering the fact that this is among the initial studies to examine whether time-varying jumps in oil prices are an indicator of market conditions. Testing for the gradual information diffusion hypothesis, we provide empirical evidence that time-varying jumps occurring in the global crude oil market can forecast its price changes during the crisis periods.

It is worth mentioning that while the above analysis reveals that λ_t contains predictive information for oil returns, it does not include the out-of-sample forecast results. Given that a good model should also accurately forecast the series out of the sample, this issue needs to be explored in future works. Note that in order to use jumps to forecast oil returns, it is critical to successfully predict jumps before events like market crashes occur. One way of doing so is finding the ex-ante probability of at least one jump occurring in crude oil returns. In this regard, Chan and Maheu (2002) show that using the GARCH-ARJI process allows us to calculate such probabilities. In particular, Eq. (5) can be used to obtain the ex-ante measure for the jump probability. This exercise is left for future studies.

4.4.2. Additional determinants of time-varying jumps

We now consider three other variables as potential indicators of financial/economic uncertainty, which may have some crucial implications for oil prices. The first variable is the Trade-Weighted Exchange rate (TWEX), which is defined as the weighted average of the foreign exchange value of the US Dollar (USD). This index is created using the broad currencies used and circulated widely by the other countries. The exchange rate plays an essential role in determining the demand for oil, especially by the emerging countries, as oil is priced in USD (Aloui et al., 2012; Basher and Sadorsky, 2006; Das and Kannadhasan, 2020). A negative change in the TWEX index indicates an appreciation of the USD and vice-versa. The second variable is the TED spread (TED). This index is defined as the difference between the interest rates of interbank loans and short-term treasury bills. Previous literature has considered TED as a measure of financial turmoil (Basher et al., 2018; Girardi, 2015). The last index we consider is the Financial Stress Index (FS). FS is the adverse conditions in the financial sector originating from macroeconomic downturns. Studies in the past have shown that FS could be a relevant factor to affect oil prices through the demand channels (Das et al., 2018; Gupta et al., 2019). The data for TWEX and TED are obtained from St. Louis FRED, whereas the data for FS are retrieved from the website of the Office of Financial Research, US Department of the treasury.

To examine whether these indicators (TWEX, TED, and FS) can predict the jumps in crude oil markets, we estimate Eq. (7) using these three measures as the explanatory variables, and the results are reported in Table 9 (WTI) and Table 10 (Brent). These findings show that financial stress appears to be the only significant factor forecasting oil price jumps for both full and subsamples. Our results are consistent with prior literature (Das et al., 2018; Gupta et al., 2019) which also document that FS has emerged as a major determinant of oil demand, exerting substantial effects on oil price variations. We further find that TWEX cannot predict these jumps and this finding could be attributed to the fact that the oil indexes we consider are traded in the US and European markets. For instance, Aloui et al. (2012) argue that although oil prices might be sensitive to TWEX, such impacts are mainly observed in emerging markets. Finally, with regard to TED, we report that it can explain the jumps during the COVID-19 pandemic period only. This result is not unexpected given that TED is considered as an indicator of financial uncertainty. Earlier studies (Basher et al., 2018; Girardi, 2015) also advocate this result.

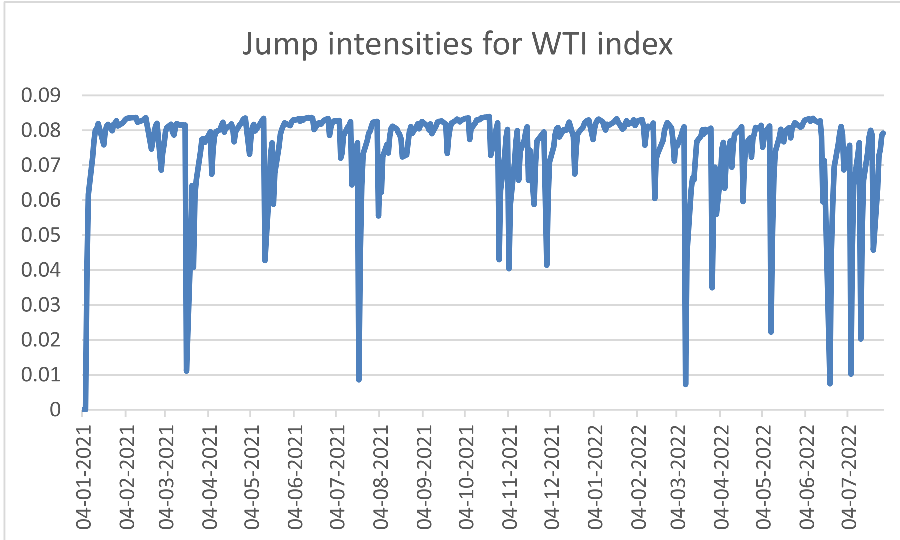
4.4.3. 2021–2022 global energy crisis and time-varying jumps

In this section, we extend our intial sample to examine whether time-varying jumps occur in international crude oil markets during the ongoing global energy crisis. Note that the major sources of this crisis include the 2021–2022 worldwide supply chain crisis, climate abnormality and the Russia–Ukraine war. Of these events, the 2022 Russian invasion of Ukraine and subsequent international sanctions against Russia have caused a significant drop in the supplies of oil, which has lifted the prices of this important commodity (Ahmed et al., 2022). For instance, during early March 2022, Brent oil prices exceed US$120 a barrel, the highest level since June 2014. Similar upsurges are also observed in the WTI market (see Fig. 7). Notably, while we witness large drops in crude oil prices during the 2008 financial crisis and COVID-19

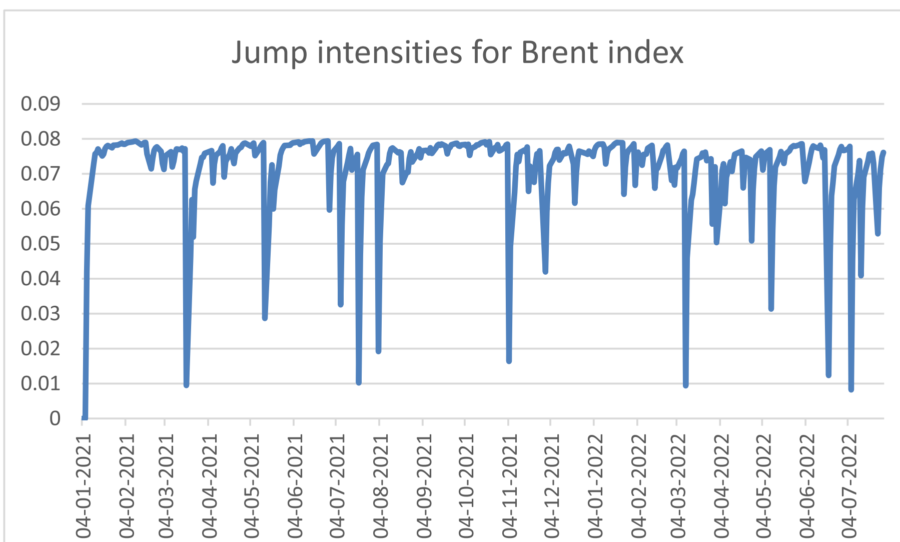
Table 11
Estimates of GARCH-ARJI model during the 2021–2022 energy crisis.

Coefficient	WTI index	Brent index
π	0.0045***	0.0043***
	(0.0005)	(0.0007)
μ	0.0044	−0.0003
	(0.0476)	(0.0458)
ω	0.00003***	0.00002***
	(0.000004)	(0.000002)
α	0.1239***	0.1317***
	(0.0151)	(0.0133)
β	0.7628***	0.7807***
	(0.0114)	(0.0095)
θ	−0.0378***	−0.0380***
	(0.0078)	(0.0098)
d^2	−0.0316***	0.0362***
	(0.0064)	(0.0093)
λ_0	0.0414***	0.0419***
	(0.0104)	(0.0118)
ρ	0.4521***	0.4184***
	(0.1704)	(0.1761)
γ	0.0688	0.0655
	(0.1959)	(0.0745)
Log-likelihood	919.35	946.99

Notes: The sample covers the period from January 2021 to July 2022. ***, ** and * denote statistical significance at 1%, 5% and 10% levels respectively. Standard errors are in parentheses.



(a)



(b)

Fig. 8. Jump intensity for WTI (a) and Brent (b) indexes (1.1.2021–31.7.2022).

pandemic periods, the ongoing energy crisis causes a sharp increase in the WTI and Brent indexes.

Table 11 exhibits the results of the GARCH-ARJI process for the sample period ranging from January 1, 2021 to July 31, 2022. These findings confirm that the jump parameters are mostly significant suggesting the existence of time-varying jumps in both WTI and Brent futures markets amid the phases of global energy crisis. However, Fig. 8 depicitng λ_t reveals that the intensity of such jumps is much lower compared to our previous analyses based on the 2008 financial crisis and COVID-19 pandemic. Therefore, it can be concluded that although jumps represent a common phenomenon in global crude oil prices, their intensity mainly increases during the periods of oil price downturns.

5. Conclusions

A growing body of literature provides empirical evidence that energy prices are characterized by time-varying jumps. However, earlier studies do not investigate if the intensity of such jumps appears to be higher amid periods of high volatility rather than normal periods. This study empirically investigates, employing the GARCH-jump model, whether jumps occurring in energy prices are an indicator of market crashes. To serve this purpose, we consider downturns in oil markets during the 2008 global financial crisis, and the ongoing COVID-19 pandemic.

Our empirical analyses, which are based on WTI and Brent oil futures prices, reveal that the conditional expected number of jumps in energy prices seems to increase significantly right before the depressions, which is, however, not the case when the markets function normally. We thus conclude that such clusters of jumps may contain predictive information for oil market crashes. This empirical work also examines whether different measures of uncertainty play any key role in explaining the time-varying jumps in oil prices. To serve this purpose, we consider the information content of VIX, OVX, and EPU and FS indexes. The results show that all these indicators have adequate power for predicting future jumps in global crude oil markets with the crude oil volatility index outperforming the rest. As an interesting side note, our findings indicate that jump intensities during the pandemic are higher than those during the 2008 crisis. This may prove to be an important implication as the probability of pandemics rise due to climate change.

Our findings seem to be of interest to investors holding assets in the international crude oil markets and to policymakers who closely watch oil prices to design appropriate economic policies. In particular, the results have important implications for risk management and hedging on various oil assets. For instance, the presence of time-varying jumps in oil futures markets indicates that the traditional hedging strategy, which is based on the continuous market price movements, could be indecisive and lead to sudden loss (Kim and Mei, 2001). Hence, there is a need for designing improved hedging strategies which would pay better attention to the incidents of unexpected jumps (Gkillas et al., 2020). In addition, the results offer implications for policymakers as well. They could recommend proper regulations to reduce information asymmetry which may mitigate the potential risks linked to global crude oil futures markets.

Future studies could consider dynamic portfolio allocation in the energy markets with time-varying jump risk (Zhou et al., 2019). Besides, whether exchange rate volatility, geopolitical risk, and financial stress could be utilized to predict oil market jumps could be examined.

CRediT authorship contribution statement

Anupam Dutta: Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Validation, Data curation, Writing – original draft. **Ugur Soytas:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Debojyoti Das:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Visualization, Validation, Data curation, Writing – original draft. **Asit Bhattacharyya:** Conceptualization, Methodology, Investigation, Visualization, Validation, Data curation, Writing – original draft.

Appendix A. Outlier detection method

We follow Ané et al. (2008) in detecting the presence of outliers. Let R_t be the log return for an oil index on day t, which is modeled as:

$$R_t = b_0 + b_1 R_{t-1} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \sigma_{t-1}^2 \tag{2}$$

where $\varepsilon_t = \sigma_t z_t$ with z_t being an i.i.d. process such as $z_t / I_{t-1} \sim IIN(0,1)$; I_{t-1} refers to the filtration of information at time $t-1$.

R_{t+1} is considered an outlier if it does not belong to the following interval:

$$R_{t+1} \in \left[R_{t,t+1} \pm F\left(1 - \frac{\alpha}{2}\right) \sigma_{t,t+1} \right]$$

where, $R_{t,\ t+1}$ is the one-step ahead return forecast given by:

$$R_{t,t+1} = E(R_{t+1}/I_t) = b_0 + b_1 R_t + b_2 R_{t-1}$$

and $\sigma_{t,\ t+1}^2$ denotes the one-step ahead variance forecast defined as:

$$\sigma_{t,t+1}^2 = var(R_{t+1}/I_t) = a_0 + (a_1 + a_2)\sigma_t^2$$

Furthermore, $F\left(1 - \frac{\alpha}{2}\right) = P\left(z_t \le 1 - \alpha/2\right)$ is a fractile of the assumed conditional distribution.

The above detection procedure is rolled-over until the end of the sample period. Notably, the detection procedure is robust to any model mis-specifications (Ané et al., 2008).

Table A1
Estimates of GARCH-jump models after correcting for outliers.

Coefficient	WTI (Full)	Brent (Full)	WTI (2008 Crisis)	Brent (2008 Crisis)	WTI (COVID-19)	Brent (COVID-19)
π	0.0688	0.0569**	0.1157	0.0856	−0.0183*	−0.5294***
	(0.1322)	(0.0288)	(0.1327)	(0.0602)	(0.0098)	(0.0932)
μ	−0.0301	0.0346	−0.0888	0.0309	−0.0768	−0.1128
	(0.0272)	(0.0298)	(0.0741)	(0.0246)	(0.0692)	(0.1768)
ω	0.0578***	0.0536***	0.0761***	0.0598**	0.0061***	0.0428
	(0.0108)	(0.0209)	(0.0147)	(0.0261)	(0.0019)	(0.0518)
α	0.0612***	0.0876***	0.0552***	0.0569**	0.0287***	0.0286***
	(0.0200)	(0.0178)	(0.0171)	(0.0246)	(0.0035)	(0.0029)
β	0.9233***	0.8009***	0.8128***	0.7892***	0.9539***	0.8197***
	(0.0492)	(0.1143)	(0.0400)	(0.0118)	(0.0092)	(0.1728)
θ	−0.7845***	−0.3488***	0.2021	−0.1756	−1.2591***	−0.4681
	(0.2249)	(0.0997)	(0.9871)	(0.8092)	(0.6205)	(1.7001)
d^2	2.9980***	1.9088***	−3.0004***	5.1004***	−2.9031***	2.5421***
	(0.6592)	(0.5439)	(0.9942)	(0.9871)	(0.5486)	(0.8883)

(continued on next page)

Table A1 (*continued*)

Coefficient	WTI (Full)	Brent (Full)	WTI (2008 Crisis)	Brent (2008 Crisis)	WTI (COVID-19)	Brent (COVID-19)
λ_0	0.0032	0.0021	0.0299	0.0059	0.0012	0.0138***
	(0.0058)	(0.0019)	(0.0243)	(0.0073)	(0.0008)	(0.0051)
ρ	0.8972***	0.6459***	0.8379***	0.6105***	0.7865***	0.7519***
	(0.1243)	(0.0102)	(0.1872)	(0.1200)	(0.0155)	(0.0850)
γ	0.1867	0.1499***	0.8345***	0.0837**	0.1671***	0.3693**
	(0.1798)	(0.0326)	(0.1181)	(0.0401)	(0.0377)	(0.1800)
Log-likelihood	−7000.98	−6811.44	−876.09	−858.65	−211.57	−218.79

Notes: This table shows the estimates of GARCH-jump models after correcting for outliers. While estimating this process, it is assumed that the error distribution follows the EGARCH model. The crisis period sample ranges from 1.1.2008 to 30.6.2009, while the COVID-19 period sample spans from 1.1.2020 to 30.6.2020. ***, ** and * indicate statistically significant results at 1%, 5% and 10% levels, respectively. Standard errors are in parentheses.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106275.

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