# Crude oil and stock markets in the COVID-19 crisis: evidence from oil exporters and importers

Reinhold Heinlein[a,*], Gabriella D. Legrenzi[b,c,d], Scott M. R. Mahadeo[e]

[a] *Bristol Business School, University of the West of England, BS16 1QY, United Kingdom*
[b] *Keele Business School, University of Keele, ST5 5AA, United Kingdom*
[c] *CESifo Research Network*
[d] *Rimini Centre for Economic Analysis*
[e] *Portsmouth Business School, University of Portsmouth, PO1 3DE, United Kingdom*

**Abstract**

Financial assets tend to immediately react to the developments of a global crisis. We investigate how the relationship between crude oil and stock market returns for a heterogeneous selection of oil exporters and importers has been affected in the onset of the COVID-19 pandemic. Using a contagion test based on local Gaussian correlation with high frequency intraday data, we provide evidence of significantly higher correlations between oil and stock markets returns during the COVID-19 outbreak for all countries in our sample. The results also show that stock markets of commodity exporters in different groups of countries have stronger correlations with oil returns than their importing counterparts. Our results are robust to different crisis dating and consistent across different segments of the assets return distributions. These findings indicate a more limited role of oil in portfolio diversification during the global health crisis, which has implications for the hedging strategies of investors in the stock markets of oil exporting and importing countries alike.

*Keywords*: contagion; intraday data; local correlation; oil; stock markets

*JEL classification*: C58; G01; G15

## 1. Introduction

The consequences of the COVID-19 pandemic on the world economy have been forecasted to be *much worse* than the 2008/2009 Global Financial Crisis (GFC) (IMF, April 2020), resulting in

*Declarations of interest: none. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Corresponding author's e-mail: Reinhold.Heinlein@uwe.ac.uk. We would like to thank seminar participants at University of Portsmouth and UWE Bristol, the audience at the 7$^{th}$ RCEA time series workshop, as well as the editor and an anonymous referee.

*a crisis like no other* (IMF, June 2020). As well documented by Baker et al. (2020), no previous infectious disease outbreak (including the Spanish Flu) has ever affected the stock market as forcefully as the COVID-19 pandemic.

Considering the crude oil market, although episodes of oil price fluctuations have occurred since the commercialisation of oil (Mohaddes and Pesaran, 2017), 2020 has proven to be another extraordinary year for crude oil. Given that the last global crisis, i.e. the GFC, accentuated the financialisation of commodity markets (Creti et al., 2013), it is important to begin unravelling the implications that the current global health crisis can have for the nexus between oil and stock markets. In this paper, we use a contagion test based on local Gaussian correlation with high frequency data to evaluate the interaction between oil and stock returns in commodity exporting and importing countries surrounding the initial period of the ongoing global pandemic. A contemporaneous perspective provided by contagion analysis in financial markets is particularly useful in obtaining an early understanding of the ongoing COVID-19 debacle, since a *health* crisis is unlike a *financial* crisis and leading macroeconomic indicators are expected to be helpful in understanding the ramifications of the novel coronavirus crisis retrospectively.

Shortly into the new year, equity indices around the world dipped for a stint as the markets absorbed information about the geopolitical tensions in the wake of the assassination of the Iranian general, Qasem Soleimani, in Iraq. At the same time, prices in the crude oil market experienced an uptick likely as a hedging strategy for equities and due to perceived oil supply disruptions in the OPEC market. The oil price buoyancy quickly abated as the coronavirus proliferated around the world. Transportation, which is almost 60% of global crude oil demand, dramatically plummeted in the first quarter of 2020 alone (IEA, April 2020). For hydrocarbon assets, sector level data of world stock markets show that oil, gas, and coal firms lead the negative returns, which are approximately 50% lower than prices at the start of 2020, driven primarily by a plummet in oil prices and depressed global consumption (Fernandes, 2020). Yet another remarkable event is historically low benchmark crude oil prices as a result of a storage scarcity related to the physical delivery of the hard commodity: the Brent fell below \$20 per barrel against an average of \$64 in 2019; and the WTI dropped into negative territory for the first time in history at -\$37.63 per barrel on 2020/04/20[1].

Crude oil is a globally influential commodity because it is the major source of primary energy, followed by other hydrocarbons resources like coal and natural gas[2]. Furthermore, as natural gas contracts are indexed to crude oil prices, the latter is able to also reflect information about the natural gas market (Zhang and Broadstock, 2020). However, the existence, sign, and nature of the dependence structure between the crude oil and stock markets is less straightforward (see, e.g., Reboredo and Rivera-Castro (2014), Wen et al. (2012), Avdulaj and Barunik (2015), Baker et al. (2020) and references therein), pointing to a complex relationship between oil and stocks, as oil prices impact not only on firms' future cash flows but also on their discount factors, given the influence of oil prices on inflation, and, consequently, on monetary policy and interest rates.

Oil and stock market returns might present a negative correlation: increases in oil prices are reflected in increases in production costs and therefore linked to decreasing stock returns.

On the other hand, crude oil prices might reflect market expectations regarding future macroeconomic variables, such as aggregate demand, implying a positive correlation between oil and stock returns. In fact, because macroeconomic data is usually available at relatively low frequencies, it is possible for policymakers to proxy the oil-macroeconomy relationship with the oil-stock market interaction by using the stock market as a high frequency barometer for macroeconomic activity (Ding et al., 2017; Mohaddes and Pesaran, 2017). This is a plausible assumption given that stock markets absorb all available information, including the developments in the crude oil market (Bjørnland, 2009).

Moreover, the net oil exporting/importing status of different countries seems to matter, with increasing evidence in favour of a country-specific nature of such a linkage (see, e.g., Wang et al., 2013).

Given the above, ascertaining the nature of the association between crude oil and stock markets is particularly important, as the presence of an oil-stock market contagion will matter for investors, portfolio managers and policymakers.

A negative (positive) correlation between oil and the stock markets during crisis periods will

[1]Bloomberg news 2020/04/22

[2]See U.S. Energy Information Administration international data, available at www.eia.gov/international/data/.

enhance (decrease) the perceived benefits of using oil as an hedging tool for stocks within diversified portfolios.

It will also have important implications for policy-makers, who will need to closely monitor the evolution of the oil-stock market nexus during crises in order to design appropriate stabilisation policies, given the macroeconomic links above discussed.

Given our discussion, it is not surprising that crude oil has prominently featured in the developing economic literature on the COVID-19 pandemic.

In particular, more recent studies have been aimed at ascertaining the impact of COVID-19 on oil prices (see, e.g. Narayan (2020) and references therein), the link between oil and other commodities and/or financial assets such as bitcoin (see, e.g. Goodell and Goutte (2021), Gharib et al. (2021), Gkillas et al. (2020) and references therein) and the connectedness of oil with geopolitical risk and policy uncertainty (see, e.g. Sharif et al. (2020) and references therein).

Within the (narrower) subject matter of the oil-stock market nexus at the time of the COVID-19 pandemic, a few studies have focussed on the spillover index of Diebold and Yılmaz (2014) (see, e.g. Mensi et al. (2021) documenting a connectedness between the WTI oil futures and ten disaggregated Chinese stock indices). Further research (e.g. Vo and Hung (2021), Amar et al. (2021), Wu et al. (2020) and references therein) has associated the time-domain analysis of the spillover index with wavelet/frequency-based techniques, generally documenting positive spillovers between crude oil and selected stock markets.

Other researchers have adopted dynamic correlation approaches (e.g. Corbet et al. (2020) on oil prices and selected US energy stocks, Kinateder et al. (2021) on different assets classes, including oil, and Sakurai and Kurosaki (2020) on oil-US stock market).

Panel techniques have also been used, to circumvent the small sample issue associated with lower frequency data on the fist wave of the pandemic (see, e.g. Salisu et al. (2020)).

Our contribution differs from the above cited works in methodology, data, application, and findings. In particular, we focus on correlation and contagion rather than causation, and we use high frequency intraday data (at 5 minute intervals) to tackle the small sample issue in analysing the changing relationship between crude oil and stock markets in the wake of the COVID-19 pandemic. This is of particular relevance as contagion, defined as an increase in cross-market linkages in the wake of a shock to one market (Forbes and Rigobon, 2002), is appropriately detected using a high frequency approach, as it can appear and vanish very quickly (Reboredo et al., 2014).

Moreover, our focus on a time series analysis of a sample of three oil exporting and three oil importing countries across G7 (Canada and Japan), BRICS (Russia and China), and Scandinavian (Norway and Sweden) countries allows us to determine whether the nature of the oil-stock market relationship is context specific in the current crisis, as the previous literature seems to suggest. In particular, the heterogeneous composition of the countries in our sample provides comparative insights for the relationship between crude oil and the stock markets of exporters and importers in advanced, emerging, and small economies during the COVID-19 pandemic.

Our empirical analysis is based on the local Gaussian correlation introduced by Tjøstheim and Hufthammer (2013) and the contagion testing in Støve et al. (2014), which allows us to examine the nexus between the crude oil and stock market at different segments of the assets return distributions. Using this non-parametric, local approach of measuring dependence structures is optimal when dealing with heavy tailed distributions and in nonlinear situations.

Considering previous studies applying the local Gaussian methodology to contagion testing, Bampinas and Panagiotidis (2017) provide evidence of flight-to-quality from stocks to crude oil during different financial crises; Nguyen et al. (2020) finds contagion between energy commodities and the US stock market. To the best of our knowledge, we are the first to apply this type of analysis to the ongoing global pandemic and to high frequency data in general. Further, as we focus on the instantaneous linkages between the oil and stock markets, our research will be particularly relevant for policymakers and investors, allowing a prompt detection of contagion to inform portfolio diversification and risk management strategies.

The rest of the paper is organised as follows: Section 2 presents the methodology, detailing the pre-filtering process of the intraday data, the local Gaussian correlation approach, and the specification of a contagion test based on this procedure. Next, Section 3 describes all data used for the analysis. We present and interpret our empirical findings in Section 4, and conclude in Section 5.

# 2. Methodology

## 2.1. Pre-filtering of the intraday data

Forbes and Rigobon (2002), among others, show that the increased volatility of asset returns during crisis periods leads to spurious contagion detection. As such, we pre-filter the series before computing the local Gaussian correlations. For this purpose, we apply the multiplicative component GARCH model of Engle and Sokalska (2012), which builds on Andersen and Bollerslev (1997). The conditional variance is a multiplicative product of daily, diurnal, and stochastic intraday volatility. Intraday returns, with subscript $t$ for days and $i$ for intraday observations called bins, are described by the following process:

$$r_{t,i} = \sqrt{h_t s_i q_{t,i}} \varepsilon_{t,i} \quad \text{and} \quad \varepsilon_{t,i} \sim N(0,1), \tag{1}$$

where

$h_t$ is the daily variance component,

$s_i$ is the diurnal (calendar) variance pattern,

$q_{t,i}$ is the intraday variance component, with $E(q_{t,i}) = 1$, and

$\varepsilon_{t,i}$ is an error term.

For the daily variance component, $h_t$, we use a predicted conditional variance from a GARCH model working with a longer sample of daily data. After deflating with the daily variance component, the diurnal component, $s_i$, is computed as a sample average of the variance of each bin $i$. After normalizing the returns by daily and diurnal volatility components, the remaining intraday volatility, $q_{t,i}$, is modelled as a GARCH(p,q) process with a t-distribution for the innovations.

## 2.2. Local Gaussian correlation

Local Gaussian correlation has been introduced by Tjøstheim and Hufthammer (2013). The bivariate density $f$ for two return series is usually not Gaussian. The unknown density can be approximated locally with a family of Gaussian distributions. At each point $(x, y)$, the density

$f(x, y)$ is approximated by a Gaussian density:

$$\phi_{x,y} = \phi(u, v, \mu_1(x, y), \mu_2(x, y), \sigma_1(x, y), \sigma_2(x, y), \rho(x, y))$$
$$= \frac{1}{2\pi\sigma_1(x, y)\sigma_2(x, y)\sqrt{1-\rho(x, y)^2}} exp\Bigg\{ - \frac{1}{2(1-\rho(x, y)^2)} \times \Bigg[ \left(\frac{u-\mu_1(x, y)}{\sigma_1(x, y)}\right)^2 + \left(\frac{v-\mu_2(x, y)}{\sigma_2(x, y)}\right)^2$$
$$- 2\rho(x, y)\left(\frac{u-\mu_1(x, y)}{\sigma_1(x, y)}\right)\left(\frac{v-\mu_2(x, y)}{\sigma_2(x, y)}\right)\Bigg]\Bigg\} \tag{2}$$

The parameters $\mu, \sigma$ and $\rho$ depend on $(x, y)$. The approximation $\phi_{x,y}$ is close to $f$ in a neighbourhood of $(x, y)$. The dependence structure of the pair of random variables is described by the correlation $\rho$. By having a local approximation of the bivariate density, and hence an estimate of a local correlation, the approach is capable of detecting and quantifying nonlinear dependence structures. The Gaussian densities $\phi_{x,y}$ are fitted to $f$ in the neighbourhood of $(x, y)$ with the method of local likelihood (see Tjøstheim and Hufthammer, 2013).

### 2.3. Contagion testing

Our energy contagion test follows Støve et al. (2014). Let $Y_t$, $t = 1, ..., T$ be the oil price returns and $X_t$, $t = 1, ..., T$ the stock market returns in a country. We filter the data for dependence and volatility effects as described in Section 2.1 and denote the standardised returns as $d_t = (X'_t, Y'_t)$. The data are split up in a stable non-crisis period (NC) and in a turmoil period (C). Contagion is present if the local correlation function for the turmoil period is significantly above the local correlation function for the stable period. The null and alternative hypothesis are:

$$H_0 : \rho_{NC}(x_i, y_i) = \rho_C(x_i, y_i) \quad \text{for} \quad i = 1, ..., n \quad \text{(no contagion)}$$
$$H_1 : \sum_{i=1}^{n}(\rho_C(x_i, y_i) - \rho_{NC}(x_i, y_i)) > 0 \quad \text{(contagion)}$$

The correlation is computed on a grid $(x_i, y_i)$ for $i = 1, ..., n$, which we choose to be a diagonal grid, where $x_i = y_i$. A bootstrap is performed, whereby observations $(d_1, ..., d_T)$ are drawn randomly with replacement. The resample $(d_1^*, ..., d_T^*)$ is divided into the time periods NC and C and the local correlations on the grid are calculated. A test statistic is computed as follows:

$$D_1^* = \frac{1}{n} \sum_{i=1}^{n} [\hat{\rho}_C^*(x_i, x_i) - \hat{\rho}_{NC}^*(x_i, x_i)] w(x_i, x_i), \tag{3}$$

where $w_i$ is a weight function to concentrate on the region where data points are available.

# 3. Data

We use intraday data, at a 5 minutes frequency, from 2019/10/08 to 2020/04/16 for a sample of oil importers (Japan, China and Sweden) and exporters (Canada, Russia and Norway). In line with the existing literature, we adopt a split between crisis/non-crisis sample of 1:2.5. The tickers for the national stock markets are: Canada (SPTSX60), Japan (NKY), Russia (IMOEX), China (SHCOMP), Norway (OSEAX) and Sweden (OMX). The oil price is Brent (CO1), as it is the benchmark for two thirds of the global oil supply. Using a 5 minute sampling frequency allows to capture the instantaneous links between oil and stock markets, which can be missed at a lower frequency, given the high liquidity of all markets in our sample. We transform the price data into US Dollar, compute return series by taking first difference of the log prices and remove overnight returns as customary. Figure 1 shows our series during the identified calm and turbulent phases, and the descriptive statistics of the return series are reported in Table 1[3]. Overall, the series are well behaved.

We filter according to the multiplicative component GARCH model of Engle and Sokalska (2012)[4]. To estimate the daily volatility, we use data of daily frequency for a sample of 10 years. All the GARCH coefficients are statistically significant and the models are stable, see the coefficients of the intraday GARCH models in Table 2. For some series autoregressive terms have been

[3]The different number of observations are due to different trading hours per day and different bank holidays.
[4]We use the R package ‘rugarch’, see Ghalanos (2020).

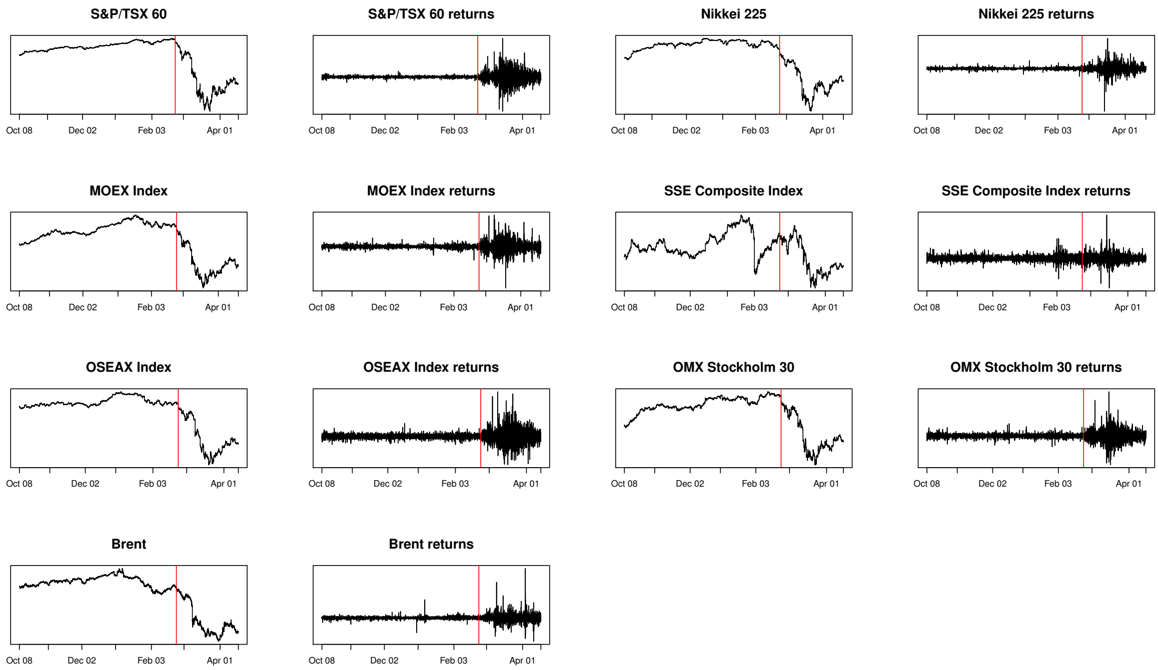


Figure 1: Price indices and return series, 2019/10/08 to 2020/04/16. The beginning of the crisis period, 2020/02/23, is shown with a vertical red line.

added to the mean equation to avoid autocorrelation issues. Using Ljung-Box tests, we report no autocorrelation in the standardised residuals and some indication of remaining heteroscedasticity for Japan and Norway only.

The oil and stock market returns, filtered with the procedures described above, are then used to compute the local correlations.[5] We use a version of the local Gaussian approach where the data is transformed to marginal standard normality, so the correlation is computed locally, while the local means and local standard deviations are fixed to 0 and 1 respectively.[6] We compute the correlations along a grid between percentile 0.01 and 0.99 with 100 grid points. In the contagion tests, we perform 1000 replications in the bootstrap procedure.

The turbulent period for our contagion tests begins on 2020/02/23, *Fever Sunday*, which coincides with the so-called "feverish" price movements in stock markets around the world on the heels of the first wave of lockdowns outside of China (see, e.g., Ramelli and Wagner, 2020). We

[5]We perform the computation of local correlation and contagion tests using the R package 'lg', see Otneim (2019).
[6]The method used for bandwidth selection is an approximate "plugin" procedure.

Table 1: Descriptive statistics of the return series. Overnight returns removed.

| Country | Asset market | Obs | Min | Max | Range | Std Dev | Skew | Kurt |
|---|---|---|---|---|---|---|---|---|
| *Full sample* | | | | | | | | |
| Canada | S&P/TSX 60 | 10247 | -0.02 | 0.02 | 0.05 | 0.0017 | 0.30 | 23.88 |
| Japan | Nikkei 225 | 7747 | -0.03 | 0.02 | 0.05 | 0.0015 | -0.83 | 45.95 |
| Russia | MOEX Index | 13493 | -0.03 | 0.02 | 0.05 | 0.0018 | 0.28 | 23.53 |
| China | SSE Composite Index | 6355 | -0.01 | 0.02 | 0.03 | 0.0012 | 0.50 | 14.20 |
| Norway | OSEAX Index | 11525 | -0.01 | 0.02 | 0.04 | 0.0017 | 0.65 | 18.56 |
| Sweden | OMX Stockholm 30 | 13260 | -0.02 | 0.03 | 0.04 | 0.0016 | 0.27 | 20.25 |
| | Brent | 34505 | -0.04 | 0.09 | 0.13 | 0.0025 | 2.81 | 113.06 |
| *Stable period* | | | | | | | | |
| Canada | S&P/TSX 60 | 7292 | -0.00 | 0.00 | 0.01 | 0.0004 | -0.15 | 5.09 |
| Japan | Nikkei 225 | 5490 | -0.01 | 0.01 | 0.01 | 0.0005 | -0.06 | 9.51 |
| Russia | MOEX Index | 9682 | -0.01 | 0.01 | 0.02 | 0.0008 | -0.14 | 7.99 |
| China | SSE Composite Index | 4508 | -0.01 | 0.01 | 0.02 | 0.0009 | 0.32 | 6.60 |
| Norway | OSEAX Index | 8361 | -0.00 | 0.01 | 0.01 | 0.0008 | 0.06 | 2.92 |
| Sweden | OMX Stockholm 30 | 9486 | -0.01 | 0.01 | 0.01 | 0.0007 | 0.06 | 5.85 |
| | Brent | 24735 | -0.03 | 0.03 | 0.06 | 0.0011 | 0.54 | 63.8 |
| *Crisis period* | | | | | | | | |
| Canada | S&P/TSX 60 | 2955 | -0.02 | 0.02 | 0.05 | 0.0030 | 0.18 | 5.45 |
| Japan | Nikkei 225 | 2257 | -0.03 | 0.02 | 0.05 | 0.0026 | -0.52 | 14.34 |
| Russia | MOEX Index | 3811 | -0.03 | 0.02 | 0.05 | 0.0032 | 0.21 | 6.66 |
| China | SSE Composite Index | 1847 | -0.01 | 0.02 | 0.03 | 0.0016 | 0.53 | 10.23 |
| Norway | OSEAX Index | 3164 | -0.01 | 0.02 | 0.04 | 0.0031 | 0.47 | 5.03 |
| Sweden | OMX Stockholm 30 | 3774 | -0.02 | 0.03 | 0.04 | 0.0027 | 0.23 | 6.15 |
| | Brent | 9770 | -0.04 | 0.09 | 0.13 | 0.0043 | 1.85 | 40.11 |

note that, even for crises already completed, there is no consensus with respect to their dating (Fry-McKibbin et al., 2014). This is further complicated in our analysis by the lack of a single catalyst event, as the oil market experienced several momentous events occurring within our window of analysis, such as: (i) the forecasted slump in oil demand (IEA 2020/02/15), (ii) the lack of OPEC/OPEC+ agreement on the implementation of Vienna's (2020/03/05) supply cuts, and (iii) Saudi Arabia's announcement of price discounts (2020/03/08). At the same time, COVID-19, which is to be declared a global pandemic on 2020/03/11, counted for 79,331 confirmed cases on 2020/02/24[7] with the first lockdowns in Europe announced on 2020/02/21 in the Lombard municipalities in Italy. For these reasons, we carry out robustness tests on our analysis around other key

[7] WHO situation report 35/2020.

Table 2: Intraday GARCH model coefficients and Ljung-Box test results

| | S&P/TSX 60 | Nikkei 225 | MOEX | SSE Comp | OSEAX | OMX 30 | Brent |
|---|---|---|---|---|---|---|---|
| $AR(1)$ | $-0.022^{*}$ | | | $0.089^{**}$ | $-0.066^{**}$ | | $-0.050^{**}$ |
| $AR(2)$ | | | | | $-0.025^{**}$ | | $-0.015^{**}$ |
| $\alpha$ | $0.073^{**}$ | $0.122^{**}$ | $0.060^{**}$ | $0.053^{**}$ | $0.055^{**}$ | $0.079^{**}$ | $0.097^{**}$ |
| $\beta_1$ | $0.917^{**}$ | $0.618^{**}$ | $0.929^{**}$ | $0.931^{**}$ | $0.542^{**}$ | $0.605^{**}$ | $0.514^{**}$ |
| $\beta_2$ | | $0.254^{*}$ | | | $0.388^{**}$ | $0.303^{**}$ | $0.375^{**}$ |
| *Q-Stat(10) res* | 7.512 | 5.694 | 14.97 | 14.37 | 9.047 | 3.038 | 24.54 |
| p value | 0.584 | 0.840 | 0.133 | 0.110 | 0.338 | 0.981 | $0.002^{**}$ |
| *Q-Stat(100) res* | 91.48 | 94.90 | 115.98 | 126.59 | 96.90 | 91.51 | 98.80 |
| p value | 0.692 | 0.625 | 0.131 | 0.032 | 0.513 | 0.716 | 0.458 |
| *Q-Stat(10)* $res^2$ | 17.66 | 19.68 | 5.438 | 12.14 | 43.20 | 18.47 | 29.17 |
| p value | $0.024^{*}$ | $0.006^{**}$ | 0.710 | 0.145 | $0.000^{**}$ | $0.010^{*}$ | $0.000^{**}$ |
| *Q-Stat(100)* $res^2$ | 120.74 | 132.76 | 100.38 | 96.38 | 165.77 | 116.30 | 108.43 |
| p value | 0.059 | $0.009^{**}$ | 0.414 | 0.527 | $0.000^{**}$ | 0.088 | 0.201 |

$^{**}$ significant at 1% level, $^{*}$ significant at 5% level.

dates suggested in the crude oil market, as this can well influence the nexus between the oil and stock markets. For instance, Mahadeo et al. (2019) propose the concept of energy contagion to describe the strengthening of correlations between oil and financial markets in crisis periods in the crude oil market. We also make note of our sensitivity findings in the subsequent section.

# 4. Results and discussion

Table 1 contains summary statistics of the asset returns for the crude oil market and the six stock market indices examined in full sample, as well as in the stable and crisis periods. The standard deviation of returns is a simple measure of market volatility, and volatility is a common proxy for stock market uncertainty (see, e.g., Bloom et al., 2007). Therefore, we observe that markets are more uncertain in the COVID-19 crisis and oil is the most volatile financial asset, both artefacts are as we might expect. For instance, the findings of Xu et al. (2019) suggest that investors are more pessimistic about the oil market in comparison to the stock market. Volatility is also higher in all oil-exporting countries in the crisis compared to the oil-importers.

A typical feature of the distribution of returns in a crisis is a change from negative skewness to positive skewness, which can be partly explained by risk averse agents having a preference for frequent small losses and few large gains versus small gains and few extreme losses in a crisis (see, e.g., Fry et al. (2010) and references therein). This switch to positive skewness is seen in the large oil exporter cases of both Canada and Russia. Another typical feature of asset returns is that crisis (calm) periods are associated with higher (lower) kurtosis values (Fry-McKibbin and Hsiao, 2018). We note that this feature is present in all stock markets with the exceptions of Russia and the crude oil market.

Our results in Table 3 show that the null of no contagion is comfortably rejected for all countries in our sample: during the identified turbulent sample in the source market, the correlations between oil and stock returns become significantly higher, regardless of the oil exporter/importer status. Furthermore, oil exporters tend to exhibit higher oil-stock market correlations than importers, in both the crisis and non-crisis period. This implies a comparatively heightened vulnerability to adverse shocks and a reduction in portfolio diversification benefits for investors holding assets consisting of oil and stocks of these oil-exporting countries. The most pronounced difference in oil-stock market correlations within country groupings are noted between the two emerging BRICS markets in our sample: China, the first country to be affected by the virus, which exhibited the lowest correlation of 0.31 in the COVID-19 crisis; and Russia which exhibited the highest correlation of 0.65 in the pandemic period jumping from 0.36. It is possible to explain the strong contemporaneous relationship between the crude oil and stock market for Russia with the country-specific characteristic that it is the largest oil-exporter in our sample.

Table 3: Correlation and contagion tests

| Country | Asset market | Non-crisis | Crisis | $D_1$ | p value | Contagion |
|---|---|---|---|---|---|---|
| Canada | S&P/TSX 60 | 0.206 | 0.424 | 0.218 | 0.000 | yes |
| Japan | Nikkei 225 | 0.198 | 0.378 | 0.180 | 0.000 | yes |
| Russia | MOEX Index | 0.358 | 0.650 | 0.291 | 0.000 | yes |
| China | SSE Composite Index | 0.205 | 0.306 | 0.101 | 0.006 | yes |
| Norway | OSEAX Index | 0.265 | 0.471 | 0.206 | 0.000 | yes |
| Sweden | OMX Stockholm 30 | 0.193 | 0.401 | 0.208 | 0.000 | yes |

Note: $D_1$ is the difference in the correlations between the crisis and non-crisis periods and the test statistic in the contagion test of Støve et al. (2014), see equation (3).

From Figure 2, the correlations during crisis are higher for all segments of the returns distributions, with the exception of China, and there is no evidence of a non-linear dependence structure: the correlations between oil and stock returns are not systematically higher or lower when the markets experience extreme shocks, within the given calm/crisis regime. In fact, China's lower correlations in pre-COVID-19 period and onset of the pandemic illustrated in Table 3 and Figure 2 suggest that it is in a comparatively better position than other stock markets to withstand oil price fluctuations in the COVID-19 crisis. This finding is consistent with past evidence on the resilience of China to disturbances in the oil market suggested in Broadstock and Filis (2014) but contradicts those of Bai and Koong (2018) who find that the Chinese stock market is relatively responsive to oil market fluctuations.

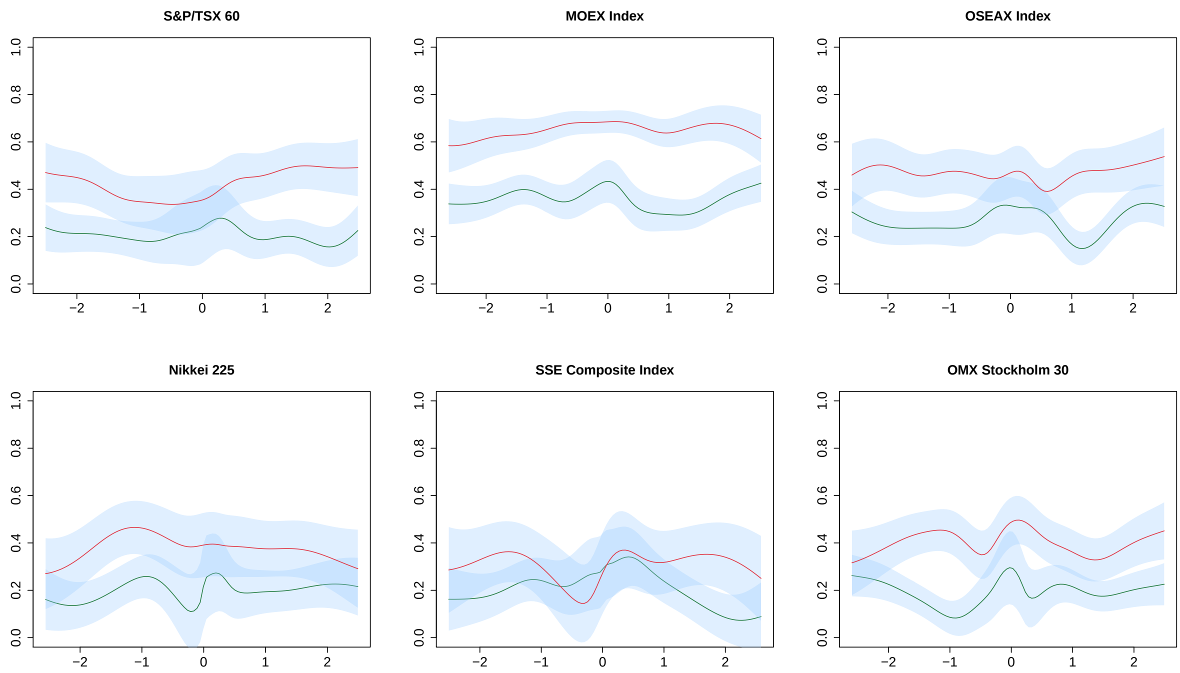


Figure 2: Local Gaussian correlation curves estimated from the equity indices versus Brent in the stable period (green) and crisis period (red), correlations are displayed on the y-axis and standardised residuals on the x-axis, 95% significance bands.

Taken together, our results confirm the importance of the nexus between oil and stock markets, identifying contagion based on high frequency data, with the crude oil and stock markets becoming more interdependent at the time of a crisis. These results are in line those documented in Wen et al. (2012), who find that oil-stock market relationship increased after the collapse of the Lehman

Brothers associated with the 2008/2009 GFC, as well as broadly in line with the emerging COVID-19 literature. The general consistency of our results across the different countries points to oil and stock markets behaving more as “a market of one”.

Finally, we verify the robustness of our results to alternative dating of the crisis, within a +/- 1 week interval of 2020/02/23, surrounding the announcement of the first wave of lockdowns outside of China. A week before and a week after the week commencing 2020/02/23 coincide with aforementioned noteworthy events in the crude oil market: the forecasted slump in oil demand by the IEA on 2020/02/15 and the lack of OPEC/OPEC+ agreements on oil supply cuts on 2020/03/05. Our results from such sensitivity tests yield qualitatively consistent results with those presented.

# 5. Conclusion

We have provided evidence of a significantly higher correlation between crude oil and various stock markets during the onset of the COVID-19 crisis resulting in contagion. The results are robust to different crisis dating, consistent across different groups of oil exporting and importing countries, and different segments of the returns distribution, implying no evidence of non-linear dependence structure between the markets. Overall, our findings confirm the importance of the nexus between crude oil and stock markets in the world economy, even at the high frequency of our analysis.

Our findings have important policy implications for investors, portfolio managers and policy-makers alike, with respect to asset allocation, risk management and macroeconomic stabilisation strategies. In particular, our documented increase in the positive oil-stock market correlation during the crisis period significantly reduces the attractiveness of crude oil in portfolio diversification, with the consequent need for investors and portfolio managers to find alternative hedging tools during crises.

Having documented that oil and stock markets are synchronised, is also important for policy-makers and the design of macroeconomic surveillance policies: crude oil is a fundamental commodity, influencing stock markets of net importers and exporters alike and will need to be closely monitored, given its impact on expected future aggregate demand and inflation.

Given the ongoing nature of the COVID-19 crisis, our results need to be interpreted with some caution, as they document the effects of the first wave of the COVID-19 crisis across the countries in our sample.

Overall, our high frequency analysis has proved insightful for contagion analysis in the very early stages of a new crisis, but larger samples at a lower frequency will be useful in the future to understand the long-run effects and potential structural changes in the oil-stock market relationship of oil exporters and importers in the wake of the COVID-19 pandemic.

Future research on the oil stock-market nexus should take explicitly into account the different waves of the COVID-19 pandemic (and corresponding state-level policy responses), which might require the estimation of different local Gaussian correlation curves associated with the crisis period/s.

*Data availability statement: The data that support the findings of this study are available from Bloomberg. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://bba.bloomberg.net/ with the permission of Bloomberg.*

# References


Amar, A.B., Belaid, F., Youssef, A.B., Chiao, B., Guesmi, K., 2021. The unprecedented reaction of equity and commodity markets to COVID-19. Finance Research Letters 38, 101853.

Andersen, T.G., Bollerslev, T., 1997. Intraday periodicity and volatility persistence in financial markets. Journal of Empirical Finance 4, 115–158.

Avdulaj, K., Barunik, J., 2015. Are benefits from oil–stocks diversification gone? New evidence from a dynamic copula and high frequency data. Energy Economics 51, 31–44.

Bai, S., Koong, K.S., 2018. Oil prices, stock returns, and exchange rates: Empirical evidence from China and the United States. The North American Journal of Economics and Finance 44, 12–33.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. The Review of Asset Pricing Studies 10, 742–758.

Bampinas, G., Panagiotidis, T., 2017. Oil and stock markets before and after financial crises: A local Gaussian correlation approach. Journal of Futures Markets 37, 1179–1204.

Bjørnland, H.C., 2009. Oil price shocks and stock market booms in an oil exporting country. Scottish Journal of Political Economy 56, 232–254.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The review of economic studies 74, 391–415.

Broadstock, D.C., Filis, G., 2014. Oil price shocks and stock market returns: New evidence from the United States and China. Journal of International Financial Markets, Institutions and Money 33, 417–433.

Corbet, S., Goodell, J.W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: New evidence from negative WTI prices during COVID-19. Energy Economics 92, 104978.

Creti, A., Joëts, M., Mignon, V., 2013. On the links between stock and commodity markets' volatility. Energy Economics 37, 16–28.

Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.

Ding, Z., Liu, Z., Zhang, Y., Long, R., 2017. The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. Applied Energy 187, 27–36.

Engle, R.F., Sokalska, M.E., 2012. Forecasting intraday volatility in the US equity market. Multiplicative component GARCH. Journal of Financial Econometrics 10, 54–83.

Fernandes, N., 2020. Economic effects of coronavirus outbreak (COVID-19) on the world economy. Available at SSRN 3557504 .

Forbes, K.J., Rigobon, R., 2002. No contagion, only interdependence: Measuring stock market comovements. The Journal of Finance 57, 2223–2261.

Fry, R., Martin, V.L., Tang, C., 2010. A new class of tests of contagion with applications. Journal of Business & Economic Statistics 28, 423–437.

Fry-McKibbin, R., Hsiao, C.Y.L., 2018. Extremal dependence tests for contagion. Econometric Reviews 37, 626–649.

Fry-McKibbin, R., Hsiao, C.Y.L., Tang, C., 2014. Contagion and global financial crises: lessons from nine crisis episodes. Open Economies Review 25, 521–570.

Ghalanos, A., 2020. Package 'rugarch'. R package version 1.4-2.

Gharib, C., Mefteh-Wali, S., Jabeur, S.B., 2021. The bubble contagion effect of COVID-19 outbreak: Evidence from crude oil and gold markets. Finance research letters 38, 101703.

Gkillas, K., Bouri, E., Gupta, R., Roubaud, D., 2020. Spillovers in higher-order moments of crude oil, gold, and bitcoin. The Quarterly Review of Economics and Finance .

Goodell, J.W., Goutte, S., 2021. Co-movement of COVID-19 and bitcoin: Evidence from wavelet coherence analysis. Finance Research Letters 38, 101625.

IEA, April 2020. Global energy review 2020. International Energy Association (IEA) .

IMF, April 2020. World economic outlook. International Monetary Fund (IMF) .

IMF, June 2020. World economic outlook update. International Monetary Fund (IMF) .

Kinateder, H., Campbell, R., Choudhury, T., 2021. Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. Finance Research Letters , 101951.

Mahadeo, S.M., Heinlein, R., Legrenzi, G.D., 2019. Energy contagion analysis: A new perspective with application to a small petroleum economy. Energy Economics 80, 890–903.

Mensi, W., Al Rababa'a, A.R., Vo, X.V., Kang, S.H., 2021. Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. Energy Economics , 105262.

Mohaddes, K., Pesaran, M.H., 2017. Oil prices and the global economy: Is it different this time around? Energy Economics 65, 315–325.

Narayan, P.K., 2020. Oil price news and COVID-19—is there any connection? Energy Research Letters 1, 13176.

Nguyen, Q.N., Aboura, S., Chevallier, J., Zhang, L., Zhu, B., 2020. Local Gaussian correlations in financial and commodity markets. European Journal of Operational Research .

Otneim, H., 2019. Package 'lg'. R package version 0.4.1.

Ramelli, S., Wagner, A., 2020. What the stock market tells us about the consequences of COVID-19. VoxEU.org eBook: Mitigating the COVID Economic Crisis: Act Fast and Do Whatever , 63.

Reboredo, J.C., Rivera-Castro, M.A., 2014. Wavelet-based evidence of the impact of oil prices on stock returns. International Review of Economics & Finance 29, 145–176.

Reboredo, J.C., Rivera-Castro, M.A., Zebende, G.F., 2014. Oil and US dollar exchange rate dependence: A detrended cross-correlation approach. Energy Economics 42, 132 – 139.

Sakurai, Y., Kurosaki, T., 2020. How has the relationship between oil and the US stock market changed after the Covid-19 crisis? Finance Research Letters 37, 101773.

Salisu, A.A., Ebuh, G.U., Usman, N., 2020. Revisiting oil-stock nexus during COVID-19 pandemic: Some preliminary results. International Review of Economics & Finance 69, 280–294.

Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis 70, 101496.

Støve, B., Tjøstheim, D., Hufthammer, K.O., 2014. Using local Gaussian correlation in a nonlinear re-examination of financial contagion. Journal of Empirical Finance 25, 62–82.

Tjøstheim, D., Hufthammer, K.O., 2013. Local Gaussian correlation: A new measure of dependence. Journal of Econometrics 172, 33–48.

Vo, X.V., Hung, N.T., 2021. Directional spillover effects and time-frequency nexus between oil, gold and stock markets: Evidence from pre and during COVID-19 outbreak. International Review of Financial Analysis , 101730.

Wang, Y., Wu, C., Yang, L., 2013. Oil price shocks and stock market activities: Evidence from oil-importing and oil-exporting countries. Journal of Comparative Economics 41, 1220–1239.

Wen, X., Wei, Y., Huang, D., 2012. Measuring contagion between energy market and stock market during financial crisis: A copula approach. Energy Economics 34, 1435 – 1446.

Wu, K., Zhu, J., Xu, M., Yang, L., 2020. Can crude oil drive the co-movement in the international stock market? Evidence from partial wavelet coherence analysis. The North American Journal of Economics and Finance 53, 101194.

Xu, W., Ma, F., Chen, W., Zhang, B., 2019. Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. Energy Economics 80, 310–320.

Zhang, D., Broadstock, D.C., 2020. Global financial crisis and rising connectedness in the international commodity markets. International Review of Financial Analysis 68, forthcoming.