The impacts of COVID-19 crisis on spillovers between the oil and stock markets: Evidence from the largest oil importers and exporters

Abstract

This study examines the multiscale spillovers and nonlinear causalities between the crude oil futures market and the stock markets of the United States (US), Canada, China, Russia, and Venezuela before and during the COVID-19 pandemic. Using the wavelet coherency method, we find strong co-movement between the oil futures market and these five stock markets, particularly from March 2020 to May 2020 (initial period of the COVID-19 outbreak) at high frequency. Furthermore, we find positive co-movements at low frequency during the overall COVID-19 period. This finding suggests that the bearish trend of stock markets is associated with a downward movement in oil prices. Using the wavelet-based Granger causality approach, we find that the oil and stock indices have less co-movement on a smaller scale but greater movement on a larger scale across all periods. As an exception, the Russian market is significantly influenced by oil prices, even on a small scale, before the COVID-19 period, but not after the beginning of the pandemic. We also find effects in the opposite direction—the Canadian and U.S. markets influence oil prices on a small scale during the COVID-19 period, an effect that is not visible for the U.S. market in the pre-COVID-19 sample. The results also show a significant bidirectional causality from oil to stock markets and vice versa during Russian-Saudi oil price war at high scale. Furthermore, we find that investors should hold more oil futures than stock shares in their portfolios for all periods. This evidence confirms that oil instruments are important for hedging during normal periods and act as safe-haven assets during crisis periods. We observe that the U.S. and Canadian stock markets were more affected by oil price shocks than were other countries.

JEL Classification: G14

Keywords: oil; stock markets; spillovers; frequency; COVID-19

1. Introduction

The ongoing COVID-19 pandemic poses unprecedented challenges to the global economy. The strict lockdowns, social distancing and travel restrictions imposed by many governments—enacted for the purpose of stemming the tide of the disease—are expected to cause a deep global recession. Efforts to contain the spread of the disease have also disrupted global supply chains, reducing aggregate demand (Vidya and Prabheesh, 2020). As a result, there has been a sharp decline in oil consumption and a consequent reduction in crude oil prices in the international market during the first four months of 2020. The situation has been further exacerbated by a price war between Saudi Arabia and Russia, both of which increased their supply just as consumption started falling dramatically. Subsequently, oil prices reached their lowest levels in 17 years, dropping to below $37 a barrel in April 2020 (Cohen, 2020). Fig. A1 plots the monthly West Texas Intermediate (WTI) crude oil prices and COVID-19 deaths and shows an inverse relationship. The monthly WTI oil price is $57.52 per barrel in January 2020 and the number of deaths is 889. In April 2020, the monthly oil price decreases to $16.55 per barrel and the number of deaths increases to 2.8 million. The twin shocks of oil price wars and a pandemic, coupled with the sophistication of today's financial markets, have had a considerable impact on share prices, on a magnitude that is unprecedented (Baker et al., 2020). The United States (U.S.) stock market observed three of its 15 worst trading days during the early lockdown period in March 2020, with the circuit-breaker mechanism being activated four times within 10 days. To put this in context, previously, the breaker was triggered only once—in 1997 (since the inception of this mechanism in 1987). Contrastingly, one of the top ten surges in the market also took place during this period (Wagner, 2020).

The Dow Jones Industrial Average (DJIA) and the S&P500—major stock indices in the US—dropped by 33% and 29%, respectively, between December 31, 2019 and March 20, 2020. The stock market crash, however, was not limited to the US; there were shocks to

European and Asian stock markets as well. The United Kingdom's (UK) main index, the FTSE, plunged more than 10% on March 12, 2020—its most pronounced decline since 1987—while the stock market in Japan dropped by more than 20% from its highest position recorded in December 2019. To counteract these declines, central banks and authorities have implemented sweeping policy measures. Despite the tumult, the major stock indices have rebounded with economic and oil price recoveries during the second half of 2020.

Oil has been the world's most traded commodity since 2000, and significantly influences the global economy. Apart from its impact on corporate incomes, crude oil prices also affect macroeconomic conditions through their influence on monetary policy instruments, inflation, and other economic activities. From a theoretical perspective, the value of a company's stock is equal to the discounted sum of future cash flows, which has an important bearing on the business cycle. Hence, oil price shocks are reflected in stock markets through both their short- and long-term impacts on national economies and corporate incomes (Hamilton, 1983; Badeeb and Lean, 2018). With the increasing importance of crude oil in the world economy, academics have paid greater attention to spillovers between the oil and stock markets, documenting significant spillovers (e.g., Arouri et al., 2011; Bastianin and Manera, 2018; Ewing and Malik, 2016; Guesmi and Fattoum, 2014; Xiao et al., 2018).

The impacts of oil price shocks on stock market returns and volatility are heterogeneous and depend on whether the country is an oil-importing or oil-exporting economy (Park and Ratti, 2008). The rise (fall) in oil prices decreases (increases) the trade balance in oil-importing (exporting) countries due to the inelastic feature of oil prices (Golub, 1983). An increase in oil prices generates higher income for oil-exporting countries due to the low price elasticity of crude oil demand (Bjørnland, 2009). In contrast, the oil price rise augments the production cost and inflation rate and interest rate in oil-importing economies (Jung and Park, 2011). Besides, the duration, direction, and size of stock market responsiveness to oil price shocks rely on whether the country is a net importer or exporter in the world oil market (Wang et al., 2013). Jiang and Yoon (2020) show a time-frequency dependence between oil price returns and stock market returns of oil-importing and oil-exporting economies. They argue that stock prices are more affected by oil prices in oil-exporting economies than in oil-importing economies. Boldanov et al. (2016) show heterogeneous patters in the evolving conditional correlations between oil-importing and oil-exporting countries. Given this heterogeneity, the overall impact of oil price to stock market is based on the country's net position in oil market (Wang et al., 2013; Filis et al., 2011).

The economic effects of COVID-19 are often compared to those of the global financial crisis (GFC) of 2008. However, these effects are not the result of the bursting of an asset price bubble. On the contrary, markets crashed despite the presence of sound fundamentals, as market capitalizations slumped owing to nationwide lockdowns and the closure of most manufacturing and service businesses, which also coincided with the oil price shock. The decline also resulted from the increased interconnectedness and spillover effects between the oil and stock markets in the post-GFC era. Du and He (2015) suggest that the co-movements of the oil and stock markets have intensified after the GFC and have remained strong in some economies. The recent dual shocks created by COVID-19 and the oil price wars constitute sources of systematic risk. However, only a few studies have examined the spillovers between the oil and the stock markets during the COVID-19 pandemic.

Additionally, the financialization of commodity markets has caused oil futures to become hedging instruments against stock market risk. However, the increasing co-movement between the oil and stock markets implies that investors can make only limited gains from portfolio diversification. Thus, modeling the spillovers among markets is crucial to guide hedging strategies and asset allocations.

Accordingly, using a time-frequency-based approach, this study investigates the interconnectedness and lead–lag interplay between West Texas Intermediate (WTI) crude oil prices and the stock market indices of the largest oil importers and exporters, both before and during the initial spread of COVID-19. This study also estimates optimal portfolio weights and hedging effectiveness (HE) for the investigated stock indices and oil prices during the COVID-19 pandemic. The main objective of this research is, thus, to identify differences in the pattern of the oil–stock nexus across the two sample periods (before and during the COVID-19 pandemic) and provide a clear picture of the complex, dynamic, and multiscale co-movements of oil prices and stocks at the onset of this pandemic-induced crisis. Hence, this study examines the multiscale relationships between the oil market and the stock markets of major oil-dependent countries and explores the extent to which the COVID-19 crisis has affected spillovers between the oil and stock markets.

This study contributes to the existing literature in three ways. First, it complements our growing understanding of the co-movement between oil prices and stock markets in the presence of specific and uncertain shocks—that is, the COVID-19 pandemic. Previous research has highlighted the high degree of sensitivity between oil prices and stock market returns in connection to specific events such as the GFC (Albulescu et al., 2019; Bouri, 2015; Roubaud and Arouri, 2018). Therefore, we divided our analysis into two blocs encompassing the pre-COVID-19 period and the COVID-19 period itself, to examine trends in the oil–stock co-movement. For the analysis, we used data for the stock indices of the largest oil importers and exporters across both the short and intermediate terms.

Second, the study conducts a time-dependence analysis of the co-movements between stock markets and oil prices, owing to the heterogeneity of market participants. Short-term movements of the indices are more relevant for active investors such as large investment banks, rather than for passive investors, who are more interested in the long-term performance of their portfolios, such as commercial banks, insurance companies, and individuals. As a result, investors from different groups have diverse risk characteristics. The varying nature of stock returns over time requires the inclusion of time-varying features (Lehkonen and Heimonen, 2014). The wavelet-based multi-time scale analysis methodology allows the simultaneous assessment of the strength of co-movements across different frequencies, as well as the magnitude of this strength over time. Hence, in this study, we employ wavelet methods—specifically, continuous wavelet transformation (CWT) and wavelet coherence (WTC). The wavelet coherence and cross-wavelet plots enable the assessment of the time-varying co-movement among the investigated variables. We further check the robustness of the findings using Granger causality analysis.

Finally, we extend our findings regarding the co-movement structure by including portfolio analysis. In particular, we evaluate the added value of crude oil to an equity portfolio of stock indices by quantifying their optimal weights. We also explore the effectiveness of WTI crude oil as a potential hedging instrument for equity investors in oil-based stock markets by estimating the hedging effectiveness of a risk-minimizing portfolio during the COVID-19 crisis.

Our results from wavelet analysis show strong co-movement during COVID-19's initial spread, indicating that a negative oil price movement is associated with a bearish trend in stock markets in the US, China, Russia, and Canada. This co-movement is limited on a smaller scale, but assumes significance on a larger scale. A robustness check using Granger causality provides evidence for a bidirectional relationship between oil prices and stock markets. More specifically, the U.S. and Canadian markets have a larger impact on oil prices. The results reveal a bidirectional causality from oil to stock markets and vice versa during Russian-Saudi oil price war at high scale (64 trading days). The findings from the portfolio analysis suggest a higher weight allocation for oil commodities, relative to stocks, regardless of market conditions. We also document the superiority of the oil futures market, instead of the spot market, as a potential asset for cross-hedging. These findings highlight the time- and frequency-varying features of co-movements, providing rich information for investors and policymakers alike in preparing for future shocks or, indeed, future pandemics, if they arise.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature; section 3 discusses the methodology used to obtain the empirical results; section describes the data and descriptive statistics; section 5 discusses the empirical results; and, finally, section 6 concludes.

2. Literature Review

Numerous studies have investigated the relationship between the oil and stock markets. Sadorsky (1999) using the vector autoregressive (VAR) model finds a causal relationship between oil price and oil price volatility on the one hand and stock returns on the other. The study further documents that this relationship implies that oil prices can be used to forecast stock price futures. Similarly, Jones and Kaul (1996) provide evidence for stock price reaction in the US and Canada due to influence of oil price shocks. In contrast, Huang et al. (1996) using VAR model, find no such relationship between oil price and S&P 500 index.

Following these pioneering studies, many studies investigated the co-movement between oil price and stock markets. Arouri et al. (2012) employ a vector autoregressive-generalized autoregressive conditional heteroskedasticity (VAR-GARCH) model, finding significant co-movement between oil prices and sector stock returns using a sample of oil and sector stock prices in Europe for the period January 1998 to December 2009. Mensi et al. (2013), also employing the VAR-GARCH model, find significant volatility transmission between the U.S. stock and commodity markets (crude oil, food, gold, and beverages). Their findings also suggest that commodity assets provide diversification benefits to stock portfolios.

Wang et al. (2013) use a structural VAR model and reveal that the dynamics between oil and stock markets depend on whether the country is a net oil importer or exporter. Arouri and Rault (2012) analyze the relationship between oil and stock prices in oil exporting countries of Gulf Cooperation Council (GCC), demonstrating a positive association.

A more recent body of literature evaluates the co-movement between oil prices and stock markets at the multiscale level using wavelet analysis (Jammazi and Reboredo, 2016; Cai et al., 2017; Lin et al., 2019). Cai et al. (2017) use wavelet analysis and find significant co-movement between oil prices and East Asian stock markets in the long run. Using the wavelet approach, Huang et al. (2016) argue that the relationship between the Chinese stock market and crude oil and gold prices varies across both the time and frequency domains, simultaneously. The results show high degrees of co-movement between the combination of oil and gold prices and the Chinese stock market at medium- and high-frequency bands. They also find bidirectional Granger causalities for the oil–Chinese-stock-market nexus, in both scales 1 and 2 and scales 6 and 7.

In the case of previous instances of financial turmoil, extensive research has been conducted on the interconnectedness, contagion, and spillover effects between the oil and financial markets. Several authors support the contagion hypothesis and find an increase in co-movement between the commodity and stock markets following the GFC (e.g., Mensi et al., 2018; Awartani and Maghyereh, 2013; Zhang and Hamori, 2021). Mensi et al. (2018), using wavelet and VAR-based wavelet methods, examine the relationship between crude oil; gold; and the stock markets of Brazil, Russia, India, China, and South Africa (the BRICS countries). The study finds evidence of significant co-movements at low frequencies, with this interconnectedness intensifying after the GFC. Likewise, Zhang and Hamori (2021) analyze the oil–stock nexus in the context of Germany, Japan, and the US. They find both short-term return spillovers and long-term volatility spillovers between the oil and stock markets, which were more pronounced during the GFC. Awartani and Maghyereh (2013) and Wen et al. (2018) also show a similar strengthening of co-movement between oil prices and equities in the GCC countries in the post-GFC era.

In light of the global extent of COVID-19's impact, a new stream of literature on the dynamics and interactions between financial markets and oil prices has emerged. Sharif et al. (2020) examine the co-movements between commodities, equities, and economic policy uncertainty during the COVID-19 pandemic in the US. Using the coherence wavelet and wavelet-based Granger causality methods, the study finds a significant impact of COVID-19 and oil price shocks on stock market volatility at the low-frequency bands. The influence of COVID-19's spread is significantly greater on U.S. geopolitical risk and economic uncertainty than on its stock market. Mensi et al. (2021a) find a similar increase relating to short-term spillovers between oil futures and the Middle East and North Africa (MENA) stock markets (especially in relation to oil-exporting countries) during the COVID-19 outbreak. The study also provides evidence of strong co-movements between oil futures and stock markets at intermediate and low frequencies. Mensi et al. (2021b) report significant long-term co-movements between the five emerging stock markets of the BRICS economies and the oil and natural gas markets. The results suggest that natural gas, as opposed to oil, provides higher portfolio diversification benefits for equity investors in these countries. Abuzayed (2021) uses a dynamic conditional correlation generalized autoregressive heteroskedastic (DCC-GARCH) model and reports a larger effect of the oil shock on GCC stock market returns during COVID-19 compared to normal periods.

Zu et al. (2021) use a GARCHSK-Mixed copula-CoVaR-Network method to examine the spillovers between the stock markets of the US and China and that for crude oil during the COVID-19 pandemic. Consistent with previous findings, their study documents greater oil–stock risk spillovers during the COVID-19 pandemic compared to normal times. The significant risk spillovers stem from the U.S. and Chinese stock markets' reaction to changes in oil prices. Moreover, the bidirectional spillovers between the Chinese stock market and oil prices increased during the COVID-19 pandemic. Cui et al. (2021) employ the wavelet coherence and BK frequency connectedness methods to analyze the risk connectedness of oil and stock markets. They find significant total risk spillovers in the long run, with the magnitude of the risk increasing after major international crises such as the GFC, oil price collapses, and the COVID-19 pandemic. In addition, their findings suggest that risk spillovers in the stock markets are directed to Russia and the oil markets of the US, European Union (EU), and Canada. The study also provides evidence for the heterogeneity and time-varying nature of risk spillovers. More recently, Cui et al. (2021) examine the time-frequency relationships between oil and stock markets in oil-importing and oil-exporting countries using wavelet approach as well as both time domain spillover index of Diebold and Yilmaz (2012) and time-frequency spillover index of Baruník and Krehlík. (2018). The authors show strong co-movements in the long-term scales. The lead-lag structure between oil and stock markets is time varying. Besides, the risk spillovers are higher in the long term than in both short- and intermediate-terms. The intensity of spillovers is more pronounced during financial, oil and COVID-19 crises.

Overall, limited studies have investigated the time-frequency co-movements, lead-lag, relationships and frequency causality analysis between oil price returns and stock markets of both oil-importing and oil-exporting countries. In addition, previous studies based on wavelet analysis have conducted using a single type of wavelet approach. Extending this analysis, we fill this gap by examining the effects of the COVID-19 pandemic on the oil–stock nexus using data from the largest oil-importing (U.S and China) and oil-exporting (Russia, Canada, Venezuela) countries by applying two types of wavelet transforms together (continuous wavelet transformation and wavelet coherence). Thus, by revisiting the oil and stock market dynamics, we derive useful insights into the shift in contagion and spillover effects prior to and during the COVID-19 crisis period, contributing to this large and important research area. More interestingly, we examine the multiscale bidirectional causality from oil to stock markets and vice versa before and during the pandemic crisis. Interestingly, we further investigate the frequency causality between markets under investigation during the Russia-Saudi Arabia oil price war. Finally, we explore the hedging ability of oil asset by analyzing the hedging effectiveness and quantifying the optimal weights of an oil–stock portfolio and the optimal hedge ratios before and during the pandemic periods.

Table 1. Summary of the relevant empirical literature

Authors	Data period	Sample	Empirical Methods	Main conclusion
Abuzayed et al. (2021)	Daily data from January 2, 2020 to May 28, 20202.	Stock price indices for GCC member countries, namely Saudi Arabia, the UAE, Kuwait, Qatar, Oman, and Bahrain.	VaR and bivariate DCC-GARCH	All GCC stock markets received greater oil systemic risk in Phase 2 of COVID-19.
Ashfaq et al. (2020)	Daily data from September 1, 2009 to August 31, 2018.	Oil-exporting countries (United Arab Emirates, Iraq, and Saudi Arabia) and oil-importing countries (Japan, China, India, and South Korea).	VAR-DCC-GARCH model	Conditional volatility and shocks inevitability are more dependent on its own market rather than the volatility spillover
Cui et al. (2021)	Daily closing prices from May 1, 2004 to October 23, 2020.	WTI and stock market in the oil-exporting countries (Canada, Russia, Saudi Arabia, the UAE, Oman, and Qatar) and oil-importing countries (China, the US, India, Japan, South Korea, and the EU)	Wavelet coherence and spillover index of DY12 and BK18	The risk connectedness between oil and stock markets intensified during GFC and COVID-19. The lead-lag relationships are mixed.
Feng et al. (2017)	January 4, 2000, to July 30, 2016	Stock index from G7 realized volatility	Autoregressive model (AR)	The strength of the predictive evidence is substantial during the relatively high and low level of the stock market, while is substantially higher for recessions vis-á-vis expansions. Oil VRP can also contain additional information for predicting a series of macroeconomic variables, which serves as an available explanation for its forecasting ability.
Jammazi et al. (2016)	Daily data from 4 January 2000 to 29 June 2015	USD (US dollars) for Brent crude oil and the MSCI stock index	Wavelet and Copula Analysis	Oil-stock return dependence, before 15 September 2008, was weak for finer time scales but increased considerably as the time scale lengthened. After this date, dependence increased significantly for all time scales, providing evidence of contagion and interdependence.

Jun Zhang et al. (2019)	Daily data from January 4, 2000, to December 31, 2014	S&P 500 index in the United States, FTSE 100 index in the UK, Nikkei 225 index, MSCI global index	Expectile-based VaR (EVaR) based on CAR-ARCHE model	Past positive and negative returns of WTI, S&P 500, FTSE100, Nikkei 225, and MSCI have significant negative effects on their current EVaRs in most cases
Li et al. (2018)	Daily data from Jan. 4, 2000, to Jun.30, 2017	Daily Brent crude oil spot price and Shanghai Stock Exchange Composite Index (SSEC)	Variational mode decomposition (VMD) method, conditional VaR (CoVaR) and delta CoVaR (ΔCoVaR)	The recent financial crisis enhances the dependence between the crude oil market and China stock market.
Lin et al. (2021)	The period from January 25, 2002, to October 11, 2019	Weekly prices of the international stock index (Chinese Shanghai stock index, S&P 500 index, and Stoxx European 600 index) and weekly prices of the global crude oil market (WTI, Brent, and Dubai).	Markov regime-switching vector autoregression model (MS-VAR)	There are linear risk spillovers running from the US stock markets to the WTI oil market in the short term
Mensi et al. (2021a)	Daily closing prices from January 2, 2003, to October 5, 2020.	Daily closing prices of Brent oil futures and 12 MENA stock markets.	Wavelet coherence, Portfolio hedging, and optimization, Spillover index of DY12 and BK18	The frequency of spillovers between crude oil futures and stock markets. The lead-lag relationships between crude oil and stock markets are mixed and time-varying.
Mensi et al. (2021b)	Daily closing spot prices from January 1, 1999 to February 28, 2018	Daily returns for crude oil, natural gas, and the BRICS stock markets	Cross or squared wavelet coherence approach, Partial wavelet coherency (PWC), Multiple wavelet coherency (MWC)	Co-movements between oil price and stock market returns at the lower scale or in the long-term.
Mensi et al. (2021c)	January 4, 2005 to May 15, 2020	The 10 sub-indices of the CSI 300 sector index. Gold futures and WTI crude oil futures.	Generalized VAR (GVAR),	Time-varying asymmetry spillovers among commodity and the ten sectors

Mensi et al. (2017)	June 4, 1998 to May 6, 2016	WTI crude oil, Dow Jones Pacific Stock Index and TSX-Toronto Stock Exchange 300,	The marginal distribution model, Copula approach, VMD method	The oil market is riskier than the stock markets in both bearish and bullish market conditions.
Sarwar et al. (2020)	The daily, weekly, and monthly frequency, over the period July 1, 1997, to December 31, 2015	Pakistani, Shanghai Bombay stock market data	Bivariate BEKK-GARCH model	Oil price volatility has negative spillover effects due to the past shocks as expected
Wen et al. (2019)	January 4, 2000, and ends on August 31, 2018	Daily spot price data of West Texas Intermediate (WTI) and the US stock data	VAR for VaR approach	The strong persistence in VaRs of the S&P 500 index and oil prices. The risk spillover effect between these two markets is asymmetric.
Xu et al. (2019)	January 4, 2007, to April 28, 2016	Data from the Light Sweet Crude Oil (WTI) futures contract with a maturity of one-month trade on the NYMEX to represent the Crude Oil market as WTI futures traded on the NYMEX, the S&P 500 index, and the Shanghai Stock Exchange Composite Index (SSEC)4 to represent the stock markets in the US and China.	AG-DCC model	The volatility spillovers between the oil and stock markets are time-varying, and the interdependence between the oil and stock markets strengthened during the financial crisis.
Zhu et al. (2021)	The daily data from December 31, 2019, to February 9, 2021	The US and Chinese stock markets	GARCHSK-Mixed Copula-CoVaR-Network method	There are significant risk spillovers from the stock markets to the oil markets and oil markets receive high-risk spillovers from second board markets.

3. Methodology

While plenty of researcher try to examine both linear and non-linear causal relationship between oil and stock market sometimes, they fail to address the heterogeneity across oil market participants or the dynamics of factors determining oil prices. Therefore, we use wavelet-based granger causality technique as it accommodates important feature of the oil and stock series, such as, the time-varying lead-lag relation between oil and stock markets originating from varying horizons. The time-scale multiresolution analysis is used to decompose raw series into different scales (Karuppiah and Los, 2005; Mensi et al., 2016). Following Qiao et al. (2020), this study considers scale S1 (short term) with the time horizons of 2–4 days, scale D2 (medium term) corresponds with the time horizons of 4–8 days and scale D3 (long term) represents the horizons of 8–16 days. Apart from original data with daily frequency, we consider three other terms to capture how causality works in different scales.

3.1. Continuous wavelet transformation

Wavelet transformation decomposes a time series localized across both frequency and time. Continuous wavelet transformation (CWT) is defined as

$$(W_s, f)(t) = \int f(t)\psi_{s,\tau}(t)\, dt \tag{1}$$

The mother wavelet is expressed as:

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{2}$$

where s and τ are the scale and translation parameters that determine the stretch and control the frequency of the wavelets. The graph can simultaneously provide information on time and frequency using this function. The parameters are real values and change continuously; hence the name—continuous wavelet transformation.

The basic wavelet function $\psi(t)$ must fulfill a few conditions: zero mean, $\int_{-\infty}^{\infty} \psi(t)\, dt = 0$; squares integrated to unity $\int_{-\infty}^{\infty} \psi^2(t) dt = 1$; and admissibility, which refers to obtaining the inverse from the CWT by the basic wavelet ψ; that is, $C_\psi = \int_{-\infty}^{\infty} \frac{\hat{\psi}|(\omega)|^2}{|\omega|} d\omega$, $0 < C_\psi < \infty$, where $\hat{\psi}$ is the Fourier transform of $\psi(t)$.

The admissibility condition that permits the reform of a time series from its continuous wavelet transform $W_x(\tau, s)$ is reached via the following equations:

$$x(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} \frac{1}{\sqrt{s}} \psi\left(\frac{t-\tau}{s}\right) W_x(\tau, s) d\tau \right] \frac{d_s}{s^2} \tag{3}$$

$$W_x(s, \tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{4}$$

The complex conjugate is denoted by * in Eq. (4). For a time-series $x(t), t = 1, \cdots, N$, we have:

$$W_x(\tau, s) = \frac{1}{\sqrt{s}} \sum_{t-1}^{n} x(t) \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{5}$$

By varying the wavelet scale, s, and translating along with the localized time, τ, a clearer picture can be obtained by presenting both the amplitude of any features versus the scale (Torrence and Compo, 1998). The Morlet wavelet is a commonly used mother wavelet that may be a good choice for decomposing financial time series.

$$\psi(t) = \pi^{-1/4} e^{-1\omega_0 t} e^{-t^2/2} \tag{6}$$

where ω_0 is the frequency, and t signifies time without dimension. Hence, the related Fourier transformation is given by:

$$\hat{\psi}(t) = \pi^{1/4} \sqrt{2e}^{-\frac{1}{2}} (\omega - \omega_0)^2 \tag{7}$$

3.2 Wavelet coherence and cross wavelet

In the case of two related time series, one can deduce wavelet coherency to identify the time and frequency bands. Wavelet coherency is defined by smoothing both time and scale (Liu, 1994). Given two time series $x(t)$ and $y(t)$, the cross-wavelet spectrum and wavelet coherence can be defined as

$$W_{xy}(\tau, s) = W_x(\tau, s)\overline{W_y(\tau, s)} \tag{8}$$

$$R^2(\tau, s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau,s)\right)\right|^2}{S\left(s^{-1}W_y(\tau,s)\right)^2 S\left(s^{-1}W_x(\tau,s)\right)^2} \tag{9}$$

where S is the smoothing operator of frequency and time. $W_x(\tau, s)$ and $\overline{W_y(\tau, s)}$ are the wavelet transformations of the two time series, where $W_{xy}(\tau, s)$ represents the strength of correlation between the time series.

To identify the lag–lead relationship as a function of frequency, the wavelet coherency phase difference is defined as:

$$\varphi_{x,y} = tan^{-1}\left(\frac{Im\left\{S\left(s^{-1}W_{xy}(\tau,s)\right)\right\}}{Re\left\{S\left(s^{-1}W_{xy}(\tau,s)\right)\right\}}\right) \tag{10}$$

where Im and Re are the imaginary and real operators of the smoothed cross-wavelet transformation, respectively.

3.3 Portfolio design

We construct portfolios covering oil prices and five important oil-dependent indices from around the world, intended to minimize unsystematic risk without changing the potential of the expected returns. Kroner and Ng (1998) demonstrate that at time t, the optimal portfolio is

$$W_t^{oil} = \frac{h_t^{stock\ index} - h_t^{oil.stock\ index}}{h_t^{stock\ index} - 2h_t^{oil.stock\ index} + h_t^{oil}}, \text{ with } \begin{cases} 0 & W_t^{oil} < 0 \\ W_t^{oil} & 0 \leq W_t^{oil} \leq 1 \\ 1 & W_t^{oil} > 1 \end{cases} \tag{11}$$

where $h_t^{stock\ index}$, h_t^{oil}, and $h_t^{oil.stock\ index}$ indicate the conditional volatility of oil and stock indices, conditional volatility of the WTI oil price, and conditional covariance between the oil price and stock indices at time t, respectively. In this study, we calculate the optimal weight of stock indices as $(1 - W_t^{oil})$. For each oil–stock index pair, the estimations for computing W_t^{oil} are obtained through the DCC-GARCH model.

We also use the risk-minimizing hedge ratios (see Kroner and Sultan, 1993) by considering a portfolio of oil and stock indices. To minimize the risk of a portfolio with a $1 long position in any oil commodity, the investor should short $\$\beta$ in each stock market. The risk-minimizing hedge ratio is defined as:

$$\beta_t = \frac{h_t^{oil.stock\ index}}{h_t^{oil}}, \tag{12}$$

We compute the hedging effectiveness using Ku et al.'s (2007) formula:

$$HE = 1 - \frac{Var_{Hedged}}{Var_{Unhedged}}, \tag{13}$$

where Var_{Hedged} and $Var_{Unhedged}$ denote the variance of the hedged and unhedged portfolios, respectively.

4. Data and summary statistics

4.1 Data and summary statistics

We use the daily closing spot prices of WTI crude oil futures and stock indices of five important oil-dependent countries. These are the S&P 500 index for the US, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela. The sample period spans from January 1, 2019 to March 31, 2021. Data are obtained from Datastream. We divided the sample period into two subperiods. The breakpoint for splitting the sample was March 11, 2020, when the World Health Organization (WHO) announced COVID-19 as a global pandemic.[1] Fig. 1 shows the major events related to COVID-19, as determined by the WHO. Among these major dates, we consider March 11, 2020 as our breaking point given that the WHO stated on this day that the rapidly spreading coronavirus outbreak was indeed a pandemic and that the virus would likely spread to all countries. This breakpoint is adopted by Ali et al. (2020) and Corbet et al. (2020). Fig. 2 shows the return dynamics of the five indices with the oil index. The vertical red line on the Y-axis indicates the date when the WHO declared COVID-19 a pandemic (March 11, 2020). The graph clearly shows that all returns are highly volatile both just before and after the red line. Volatility gradually reduced and returned to a relatively normal state after approximately 1.5 months.

[1] https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020

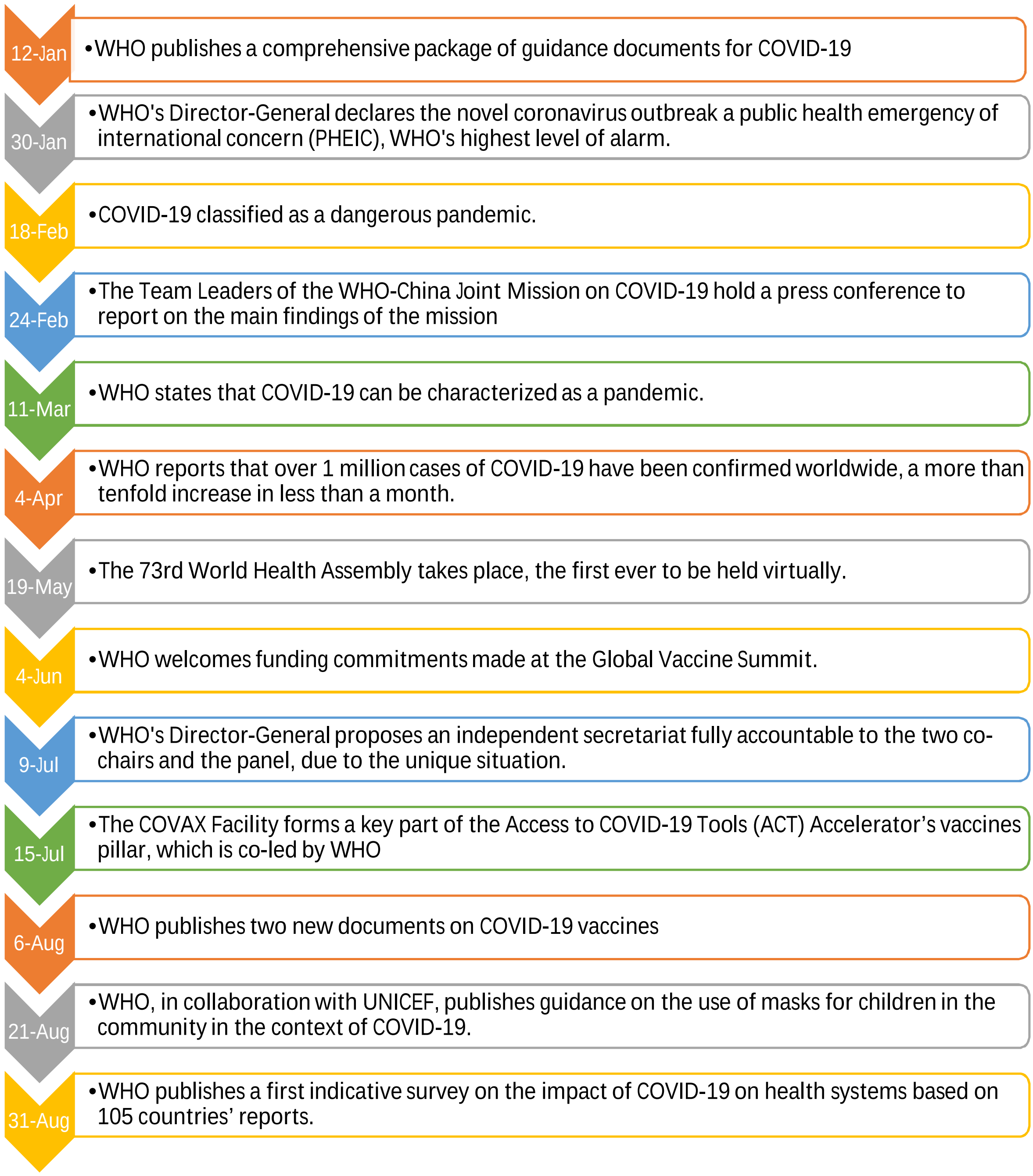


Fig. 1. COVID-19 global events during the first eight months of the pandemic

Note: Timeline Information Source: World Health Organization (WHO)

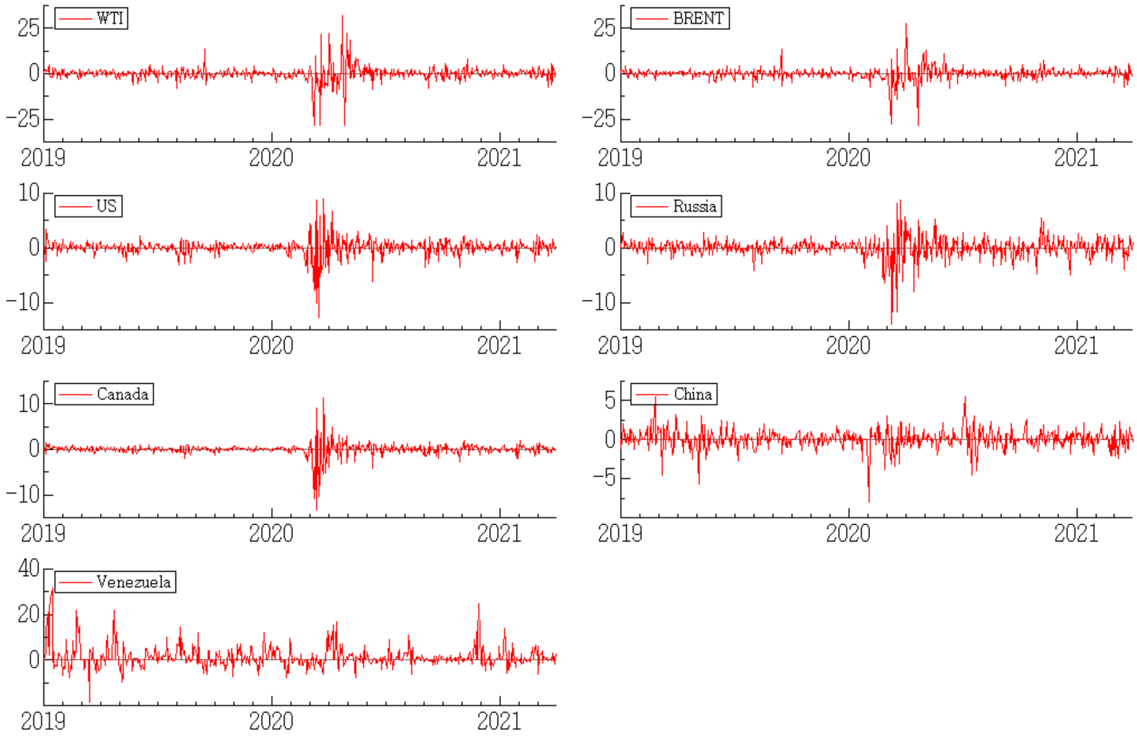


Fig. 2. Dynamic of oil and stock market returns

Note: The vertical red line indicates the date when WHO declared the COVID-19 outbreak as a pandemic (March 11, 2020).

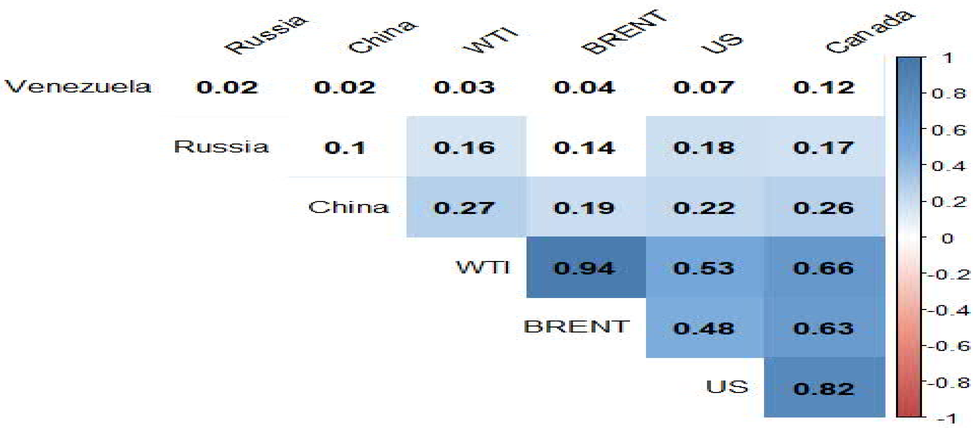
4.2 Summary statistics

Table 2 presents the summary statistics of the return series of the oil and stock markets before and during the COVID-19 crisis. The mean return of oil price is negative in the pre-COVID-19 period, but positive during the spread of the pandemic. The oil market return's standard deviation is slightly higher than in the COVID-19 period. By contrast, all market indices generate a positive average return in both the pre-and COVID-19 periods. The mean return is higher during the pandemic crisis for all stock markets with the exception of Venezuela. More interestingly, we observe that all return series are asymmetric and leptokurtic, as indicated by the skewness and kurtosis tests and as confirmed by the Jarque-Bera test. According to ADF, PP and KPSS test, we show that all return series are stationary. The correlations between oil and US stock markets is negative before the pandemic and shifts to positive during the COVID-19 crisis.

Table 2. Summary statistics of price returns of oil and stock markets

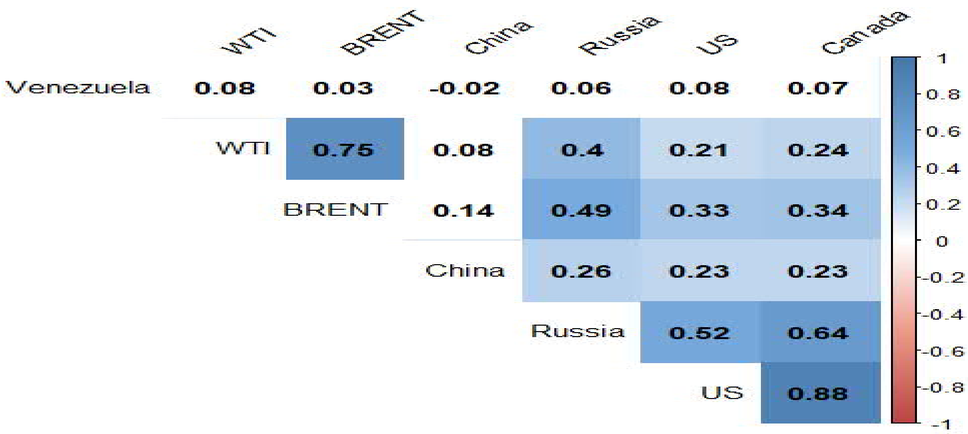
Panel A: Before COVID-19 (1 January 2019 to 11 March 2020)							
	WTI	BRENT	US	Russia	China	Canada	Venezuela
Mean	-0.1025	-0.1306	0.0286	0.0051	0.0558	-0.0011	1.3352
Minimum	-28.22	-27.57	-7.901	-13.94	-8.039	-10.83	-18.27
Maximum	13.69	13.63	4.821	4.100	5.449	3.012	31.74
Standard Deviation	2.746	2.619	1.117	1.421	1.211	0.884	5.209
Kurtosis	36.55	40.12	12.04	31.03	9.011	73.34	7.744
Skewness	-3.211	-3.527	-1.479	-3.760	-1.116	-6.450	1.879
Jarque Bera	17908.***	21575.***	1998.3***	13254.***	1120.6 ***	72090.***	963.4***
ADF	-17.52***	-17.67***	-11.18***	-16.30***	-18.19***	-3.222**	-10.56***
PP	-17.63***	-17.68***	-20.71***	-16.60***	-18.22***	-17.74***	-10.79***
KPSS	0.642*	0.655*	0.486*	0.744**	0.202	0.779**	0.429**

Correlation



Panel B: During COVID-19 (12 March 2020 to 31 March 2021)							
	WTI	BRENT	US	Russia	China	Canada	Venezuela
Mean	0.4312	0.2087	0.1349	0.1117	0.0538	0.0983	1.208
Minimum	-28.18	-27.97	-12.76	-11.68	-4.602	-13.17	-7.859
Maximum	31.96	27.41	8.968	8.825	5.554	11.29	24.83
Standard Deviation	5.318	4.126	1.933	2.229	1.133	1.864	3.802
Kurtosis	15.72	18.01	15.55	9.492	5.967	22.39	10.59
Skewness	0.603	-0.040	-0.956	-0.840	-0.005	-1.164	2.076
Jarque Bera	1871.6***	2584.2***	1848.8***	516.07***	100.8***	4374.3***	858.7***
ADF	-11.77***	15.26***	-27.02***	-19.81***	-15.84***	-27.44***	-11.30**
PP	-15.39***	15.25***	-29.87***	-19.82***	-15.85***	-28.80***	-11.90**
KPSS	0.118	0.058	0.036	0.041	0.074	0.028	0.066

Correlation



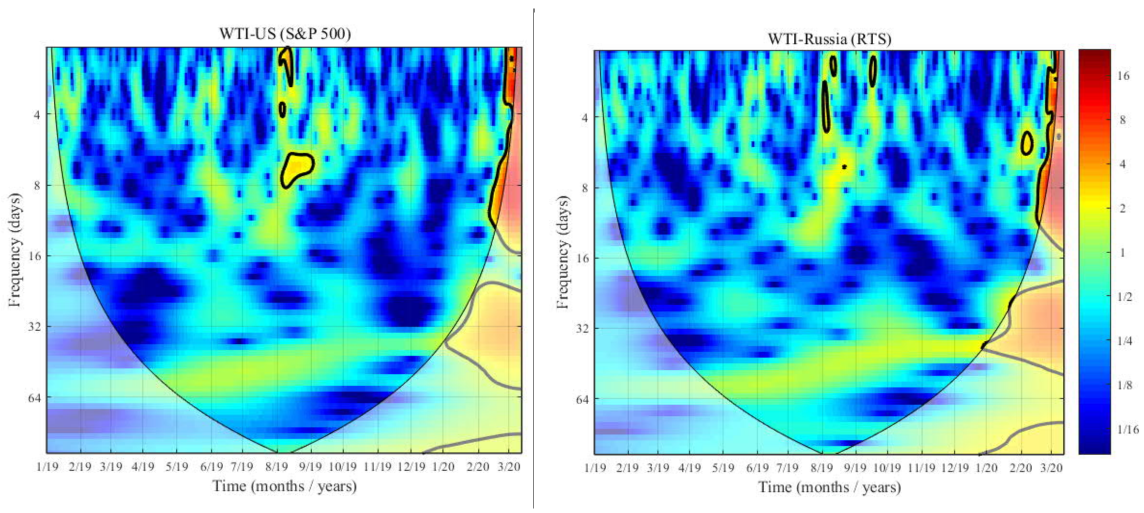
Note: This table shows the descriptive statistics of the WTI oil price returns and five major oil-based stock indices. We use the S&P 500 index for the US market, the S&P/TSX Composite index for the Canadian market, the SSE Composite Index for the Chinese market, the RTS Index for the Russian Market, and the Índice Bursátil de Capitalización (IBC) for the Venezuelan Market. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels.

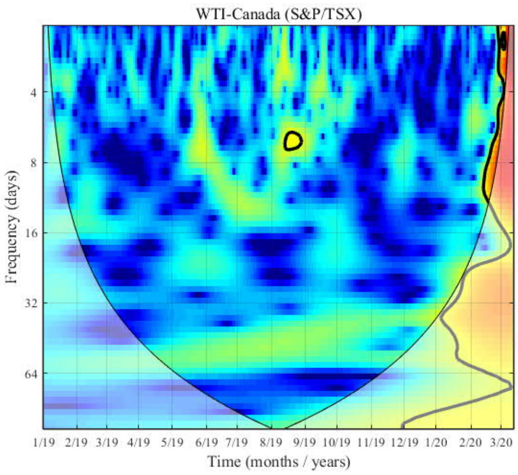
5. Empirical Results

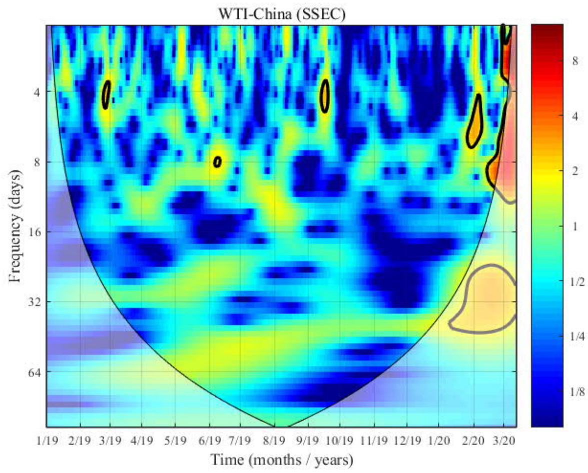
5.1. Multiscale analysis between crude oil and stock markets

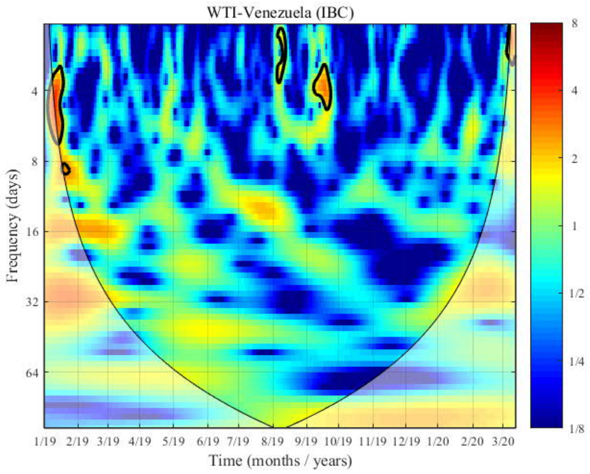
Figs. 3 and 4 plot the magnitude and direction of multiscale co-movements between oil prices and different stock index price returns using cross-wavelet transformation before and during COVID-19 crisis. In Fig. 3, except in the Venezuelan market, we observe moderate co-movement in the low-frequency band (32 to 64 days) and a high level of co-movement in the high-frequency band (4 to 16 days) between oil prices and stock returns before the pandemic. Most of the arrows are directed to the right, meaning that both oil prices and stock indices move in the same direction. This result exhibits reductions in diversification benefits. However, for the Venezuelan market, all frequency bands have strong co-movements between the oil price and stock index. In the U.S., Russian, and Chinese markets, there are a few arrows appearing in the low-frequency band. By contrast, Fig. 4 specifies the magnitude and direction of multiscale co-movements between oil prices and different stock indices during the pandemic period. We observe that the U.S. and Canadian markets have a similar pattern of co-movement with oil price, and that both countries have a few dark islands with a rightward-directed arrow from March 2020 to June 2020, mainly in the low-frequency band. More importantly, we show that oil prices lead the US and Canadian stock returns at high and medium frequencies. However, for Russia, these islands appear from March 2020 to June 2020 and in November 2020. In the Chinese market, a dark-red spot with an arrow appears in the period from June 2020 to July 2020 at high and medium frequencies. Moreover, oil and stock market variables are in phase, indicating positive relationships. Overall, the during-COVID-19 periods have fewer co-movements in the low-frequency band than in the high-frequency band. This higher strength in the co-movements at high frequencies implies a higher return over the short-run horizon. In a similar study, Salisu et al. (2020) find unidirectional causality between oil and stock returns before the announcement of the pandemic and a bidirectional link after the announcement. They indicate that, although the COVID-19 pandemic and oil shocks may produce only a short-term economic impact, they nevertheless could adversely affect the oil price–stock nexus.

Panel A: WTI

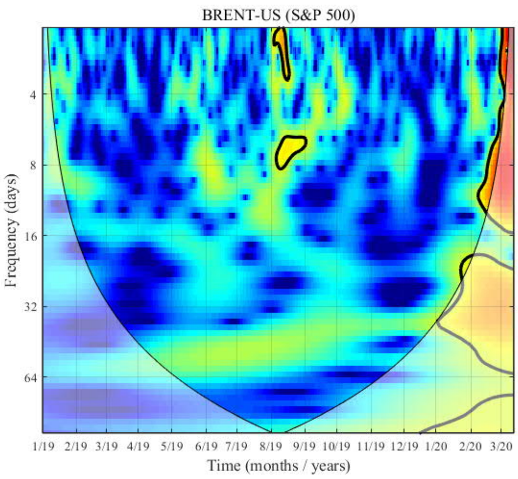


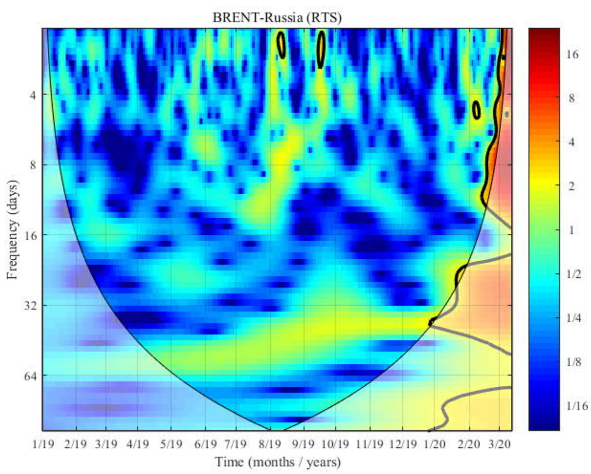






Panel B: BRENT





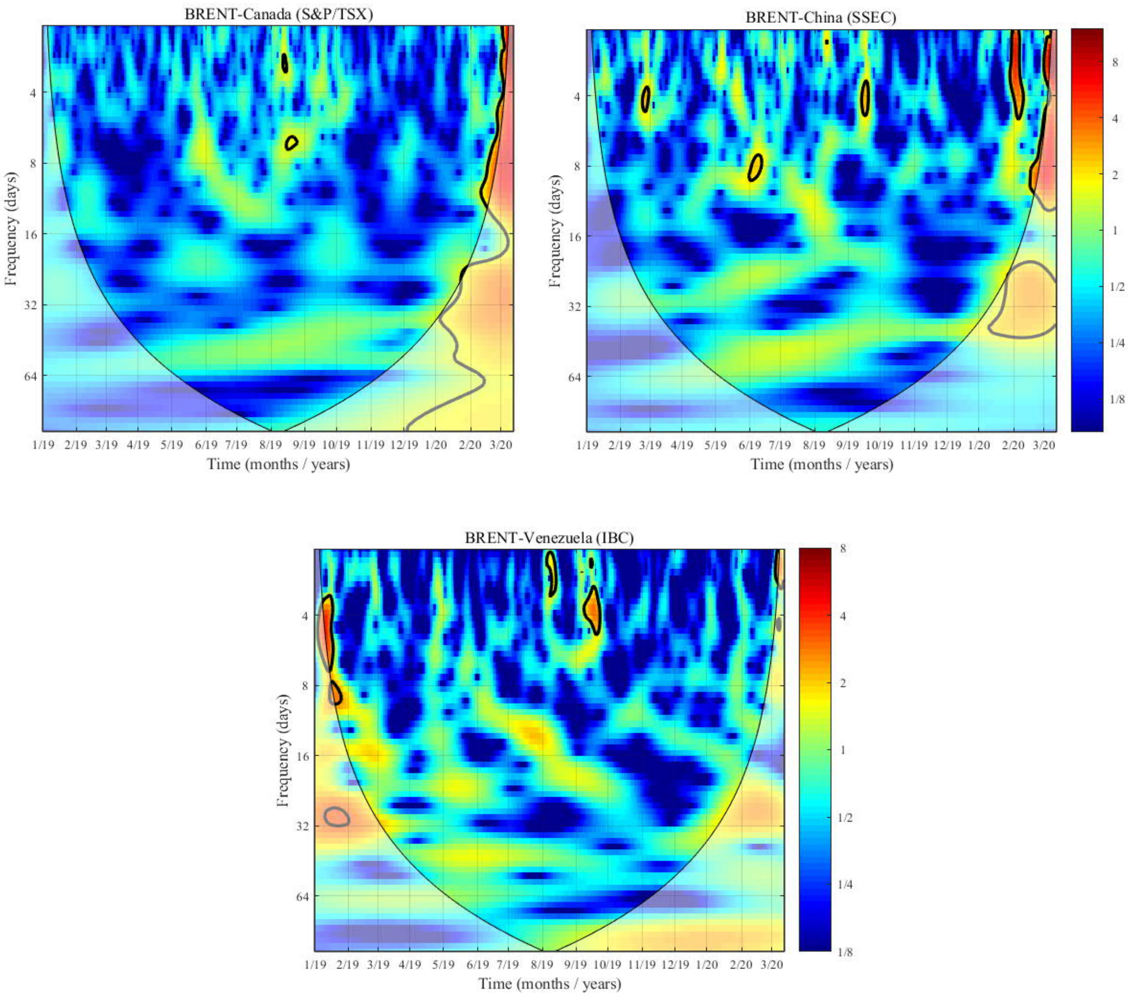
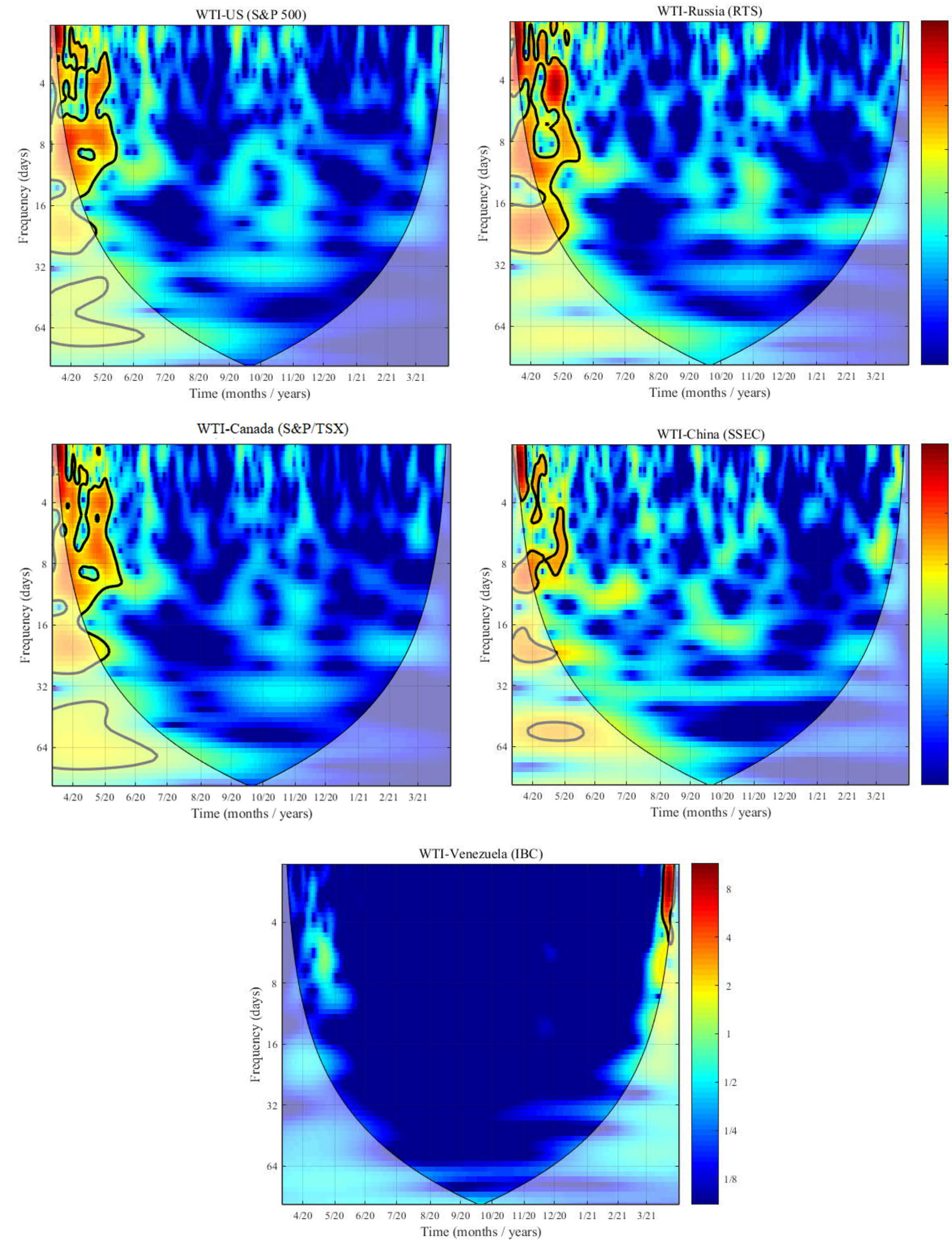


Fig. 3. Cross wavelets between stock and oil price returns in the pre-COVID-19 crisis period (from January 1, 2019 to March 11, 2020)

Note: The figure shows the pre-COVID-19 cross wavelets between stock and oil price returns from January 2019 to March 2020. The arrows highlight the phase difference between oil prices and different stock indices. The rightward-pointing arrows indicate that the variables are in-phase (both variables change in a similar direction), while leftward-pointing arrows indicate that the variables are out-of-phase (oil prices and stock indices move in an inverse direction).

Panel A: WTI



Panel B: BRENT

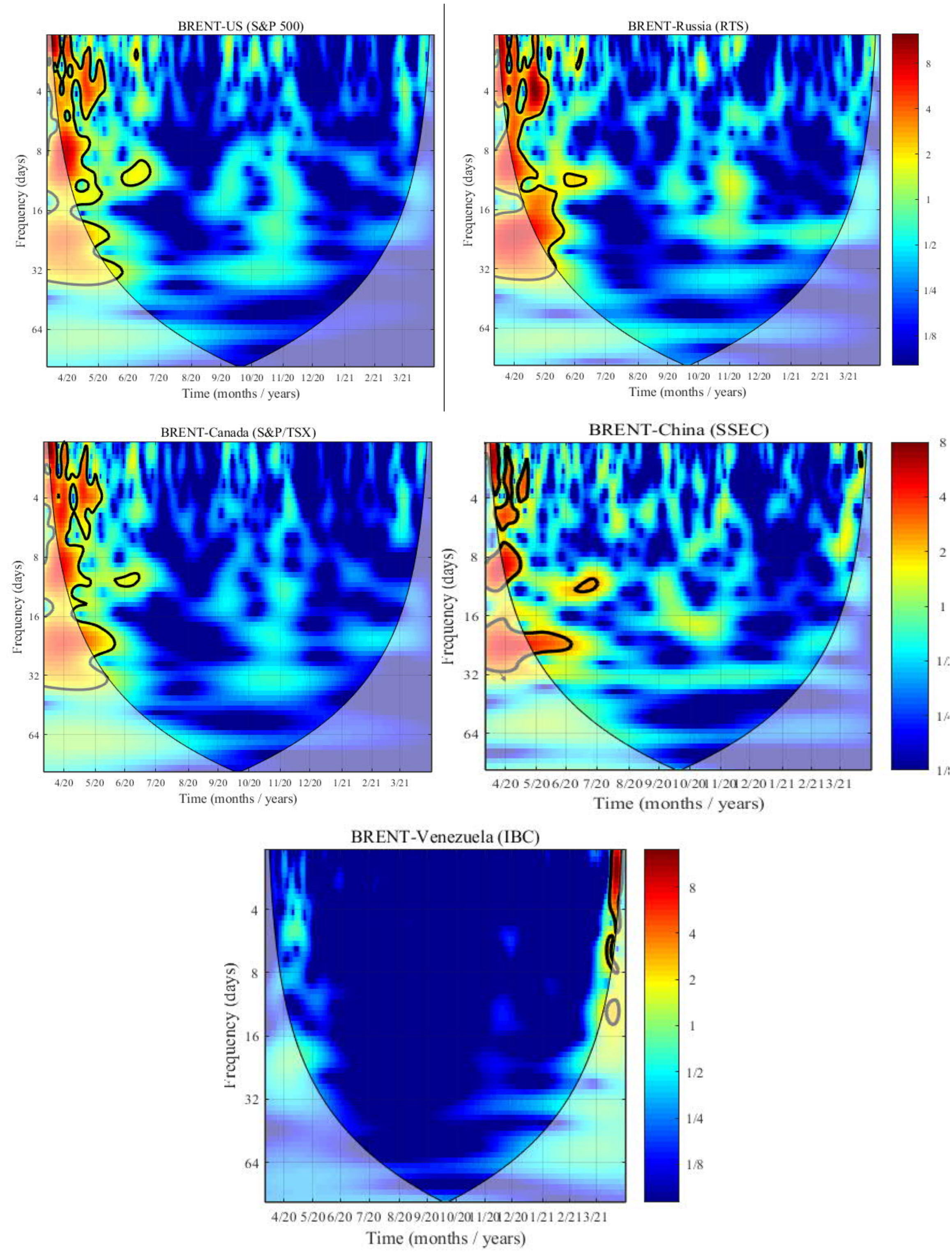


Fig 4. Cross wavelets between stock and oil price returns during the COVID-19 pandemic (from March 12, 2020 to March 31, 2021)

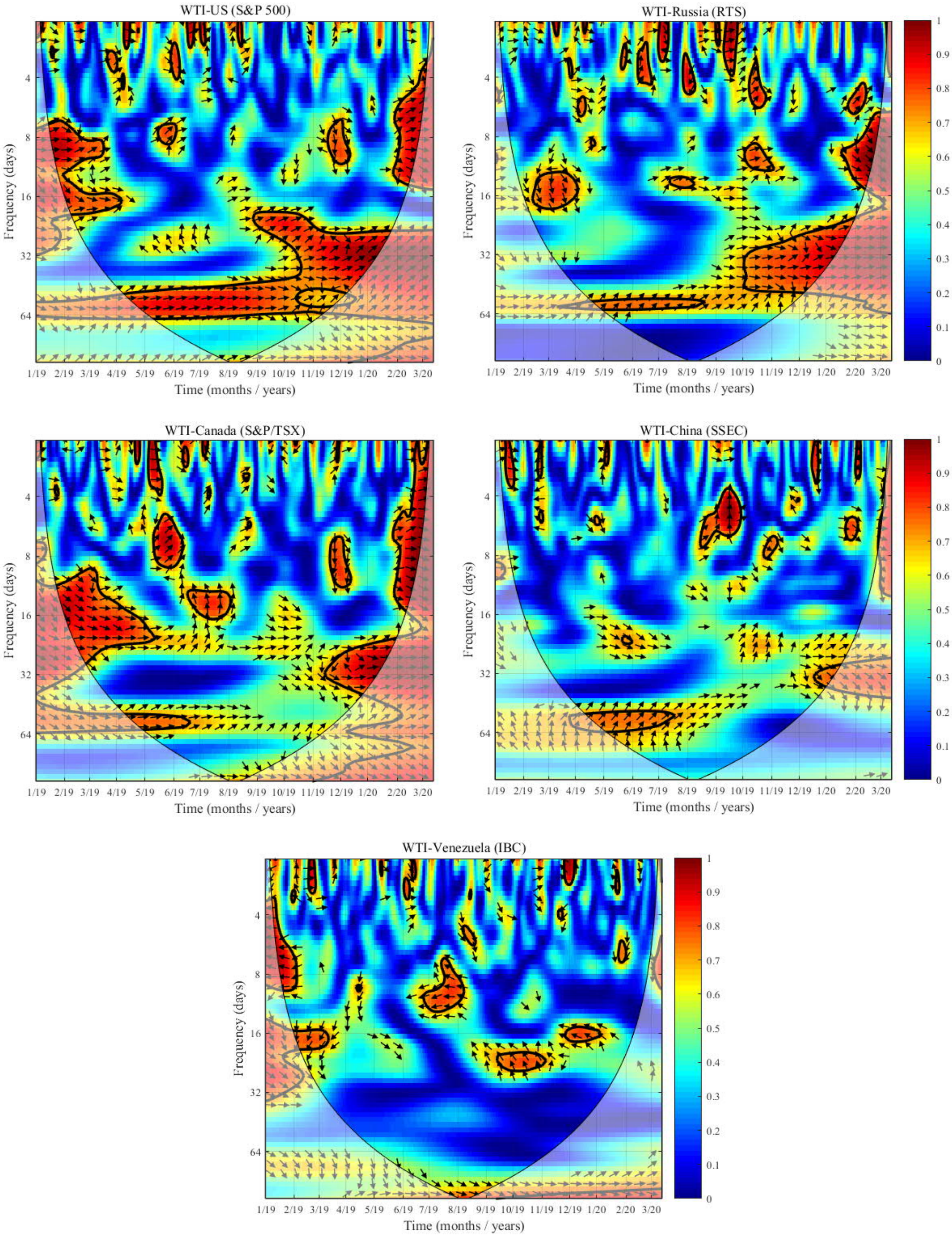
Note: The figure shows the during-COVID-19 cross-wavelets between stock and oil price returns from March 2020 to March 2021. The arrows highlight the phase difference between oil prices and different stock indices. See the note of Fig. 3.

Fig. 5 shows the pre-COVID-19 wavelet coherence between stock performance and oil price returns from January 2019 to March 2020. In the U.S., Russian, Chinese, and Canadian markets, there are few big red islands at the end of the pre-COVID-19 period in the high-frequency band, implying the existence of a high degree of co-movement in these markets. The co-movement is more pronounced at medium scales for Canadian, Russian, and U.S. stock markets from October 2019 to March 2020. However, in the Venezuelan market, the thick red island appears at the beginning of the pre-COVID-19 period. Our results are consistent with the findings of Hung and Vo (2021) who find significant co-movements between WTI oil prices and US stock market pre-COVID-19 crisis at both medium and high scales. The lead-lag relationship results show that oil prices lead the stock market returns with the exception of Chinese market at low frequency (64 days) from January to April 2019. Fig. 6 displays the during-COVID-19 co-movements of oil prices and five different stock markets. There are large red islands in almost all stock markets in the high-frequency band, especially at the beginning of the sample period. The results show positive co-movements between oil price returns and stock markets of Russia and Canada along the sample period. Akhtaruzzamana et al. (2021) indicate that the COVID–19 outbreak appears to have mitigated the oil-price risk exposure of both financial and non-financial industries, and that the oil supply industries have benefited from positive shocks to oil price risk.

The overall results show strong co-movement at different frequencies, especially from March 2020 to May 2020 (the initial period of the outbreak) for the oil–stock return pairs, indicating that the decline in stock markets is associated with a decrease in oil prices. Thus, the significant co-movements for the US, China, Russia, and Canada show that oil is not a suitable asset class in a diversified portfolio, but that oil futures can be a potential asset for cross-hedging during a crisis period. Owing to strong negative public sentiment and panic, the S&P 500 index lost 33.7% of its value between February 19 and March 23, 2020, following a sharp decrease in oil prices. COVID-19 has triggered an unprecedented downturn in oil prices. In early 2020, lockdowns and other restrictions on movement reduced global energy demand by over a quarter. Moreover, the Saudi–Russian price war caused oil prices to reach their lowest levels in over two—becoming less than $20 a barrel in April 2020.

Once the initial panic subsided and investors developed a better understanding of the pandemic's management, the co-movement returned to a stable state. These results provide deeper insight into how stock markets initially reacted to the oil shock and suggest that the pandemic was not the sole cause for the plummeting of global stock indices. The oil shock was also responsible for increasing uncertainty regarding oil export revenue in countries that are heavily dependent on oil income. Although the magnitude of the effect is not proportionate both within and between countries and regions (Furceri et al., 2020), we see a similar trend in the majority of stock markets. The COVID-19 crisis also affected carbon-intensive industries, such as the fossil fuel industry (Mukanjari and Sterner, 2020), with evidence of investments shifting toward environment-friendly industries, which may (in and of itself) also hamper the short-run profitability of related firms. The pandemic has made the impact of oil price shocks on the economy increasingly intriguing, especially in the major financial markets. Investors like to know how oil price shocks affect stock movements and whether this influence is the same in the short run as in the long run. The present study improves our understanding of the relationship between the COVID-19 crisis and the collapse of oil and stock markets for different time scales.

Panel A: WTI



Panel B: BRENT

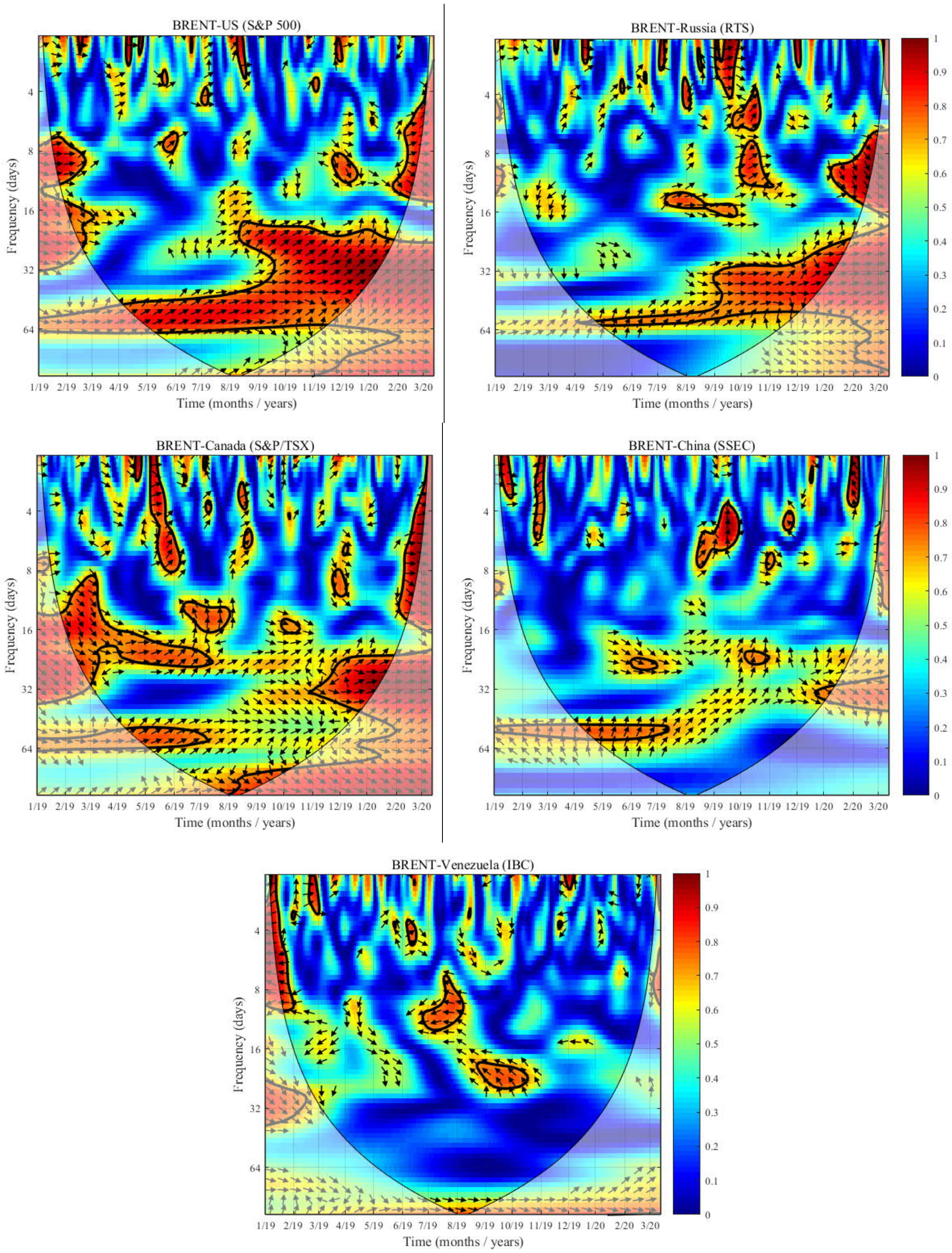
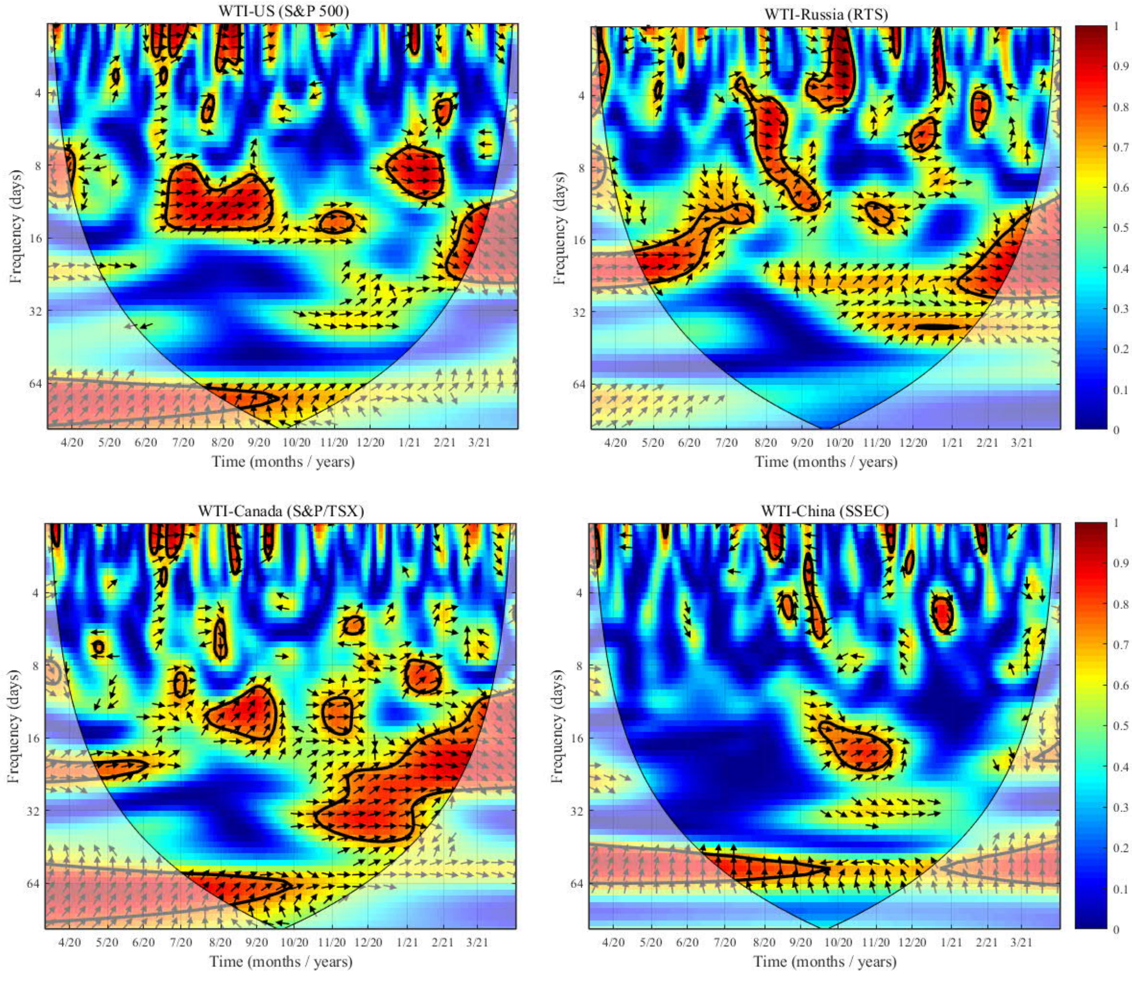


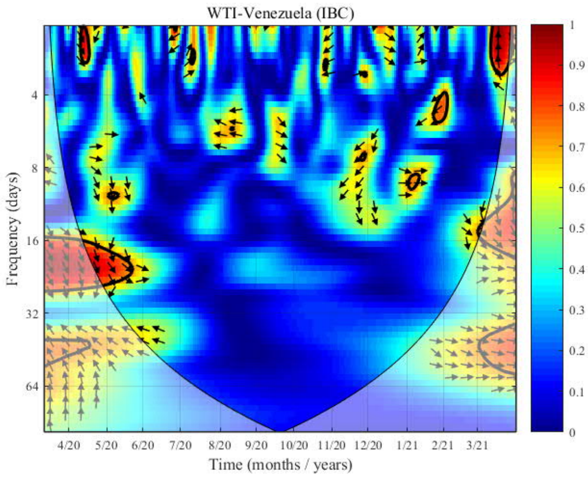
Fig. 5. Wavelet coherence between stock and oil price returns pre-COVID-19 (from January 1, 2019 to March 11, 2020)

Note: The figure shows the wavelet coherence between stock and oil price returns in the pre-COVID-19 period from January 2019 to March 2020. The arrows highlight the phase difference between oil prices and different stock indices. The rightward-pointing arrows indicate that the variables are in-phase (both variables change in a similar direction), while the leftward-pointing arrows indicate that the variables are out-of-phase (oil prices and stock indices move in the inverse direction). The directions of the arrows also indicate leading and lagging relations, which are as follows: (→) ¼ variables are in-phase (i.e., cyclical effect on each other); (←) ¼ variables are out-of-phase (anti-cyclical effect). (↗) or (↙) ¼ first market is leading; (↘) or (↖) ¼ first market is lagging.

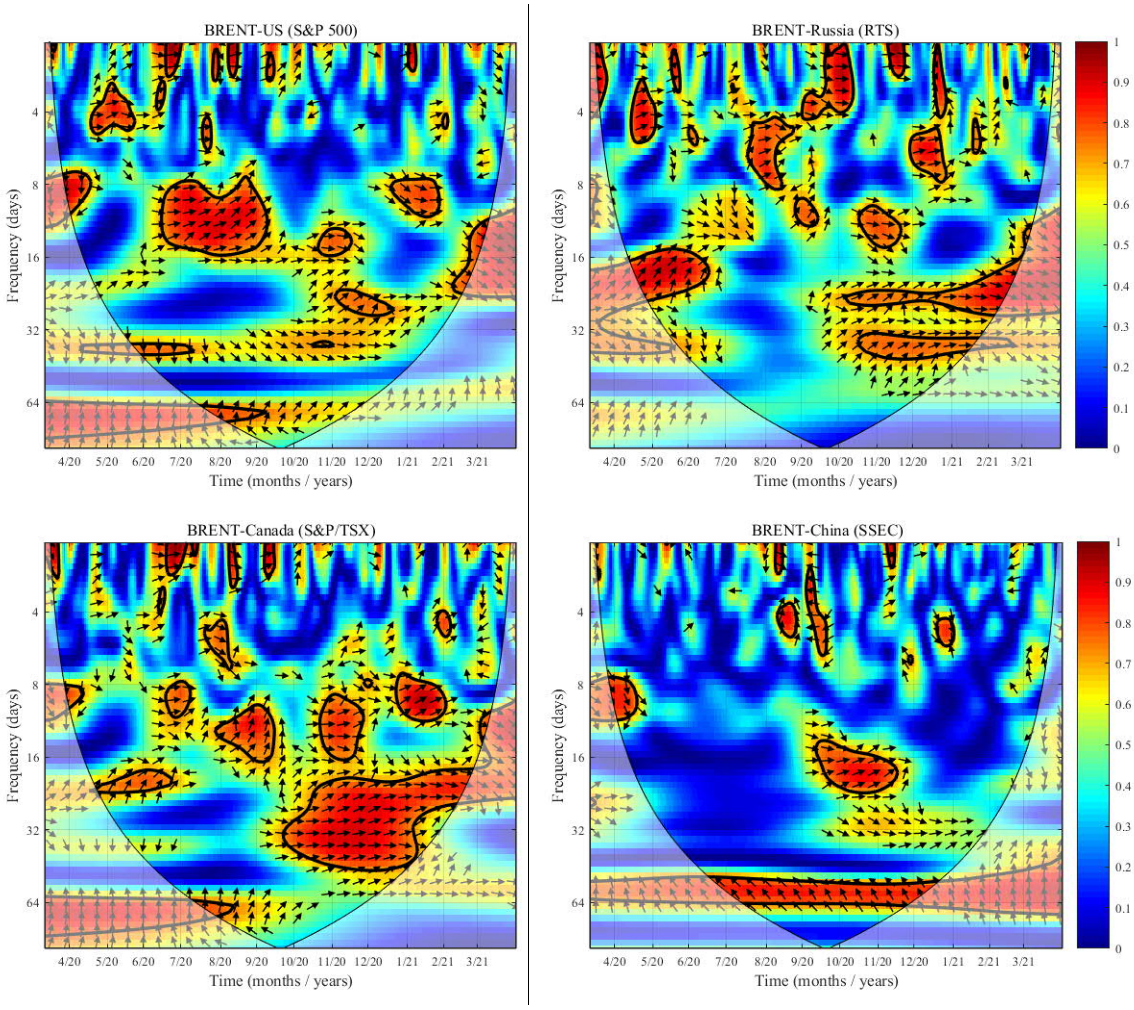
The horizontal axis shows the period, and the vertical axis shows the frequency in terms of days. The yellow color indicates strong coherence between oil prices and stock indices.

Panel A: WTI





Panel B: BRENT



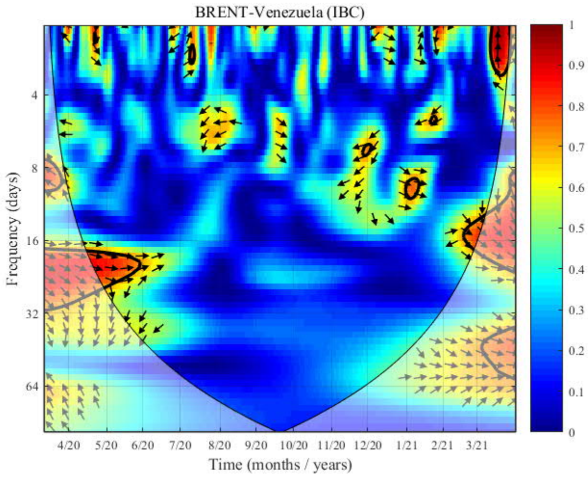


Fig. 6. Wavelet coherence between stock and oil price returns pre-COVID-19 (from January 1, 2019 to March 11, 2020)

5.2 Granger causality results

We first report the causality between WTI prices and five stock indices' returns in the original and decomposed return series for both the pre- and during-COVID-19 periods. Table 3 presents the pre-COVID-19 Granger causality results for the WTI oil index and the five stock indices. We observe that, for the Russian index, the F-statistics are highly significant, indicating that oil prices cause significant price changes in this market. By contrast, in the U.S., Canadian, and Chinese markets, the results are weakly significant in lag-1 and lag-2. Oil has an insignificant impact on the Venezuelan market in the pre-COVID-19 period. Oil prices cause the stock markets at low frequencies (D3). This indicates that oil prices influence the stock markets at the long term. This result is consistent with the results of wavelet coherence approach. Table 4 presents the during-COVID-19 Granger causality results for the WTI oil index and the five stock indices. We detect a significant impact of oil movement on the U.S., Canadian, and Chinese markets in lag-5. For the other closer lags, the results are insignificant.

We also report the time-scale-based results in this section. We observe that higher scale results show greater significance in the oil–stock nexus, particularly for US and Canada.

Table 5 shows the Granger causality results for the five stock indices and oil prices in the pre-COVID-19 period. The Canadian and U.S. markets have a significant effect on oil—even on a smaller scale, such as D1. By contrast, on a larger scale, almost all indices have a significant impact on oil prices. However, for the raw data, the results were somewhat insignificant. Additionally, in Table 6**,** we observe that the impact of the U.S. and Canadian index movement is significant in determining oil prices, even via the raw data. The results show a highly significant impact of the U.S. and Canadian indices on oil prices via all lags. Other markets, such as those of Russia, China, and Venezuela have a significant impact only on a higher scale.

Overall, the results suggest significant bidirectional causality—oil prices and stock indices mutually affect each other particularly at high scale (D3). In particular, the movements of the U.S. and Canadian markets have a larger impact on oil prices. Our evidence shows that oil prices and stock indices have less co-movement on a smaller scale, but more co-movement on a larger scale. In the COVID-19 period, these movements are insignificant for almost all countries on smaller scales. These results also demonstrate differences in the oil–stock index nexus between the pre-COVID-19 and during-COVID-19 periods. In the pre-COVID-19 announcement period, Salisu et al. (2020) find unidirectional causality from oil price returns to stock returns in the while causality between crude oil price and stock returns. On the other hand, they claim that the causality is bidirectional in the post-COVID-19 announcement period. However, our results demonstrate that there is an existence of bidirectional causality in both pre and during the COVID-19 period but the magnitude varies over countries and scales. Sharif et al. (2020) show that the spillover from oil price return to U.S. stock markets is the same in all frequencies, however, we show that bidirectional causality is higher in the larger scale than small scale and it is similar in both pre and during COVID-19 sample.

Table 3. Results of wavelet-based Granger causality analysis from oil prices to stock returns before the pandemic

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
WTI->US	R	7.68**	3.32*	2.05	1.6	1.52
WTI->Russia		19.16***	11.05***	8.62***	6.68***	5.63***
WTI->Canada		6.03*	3.94*	2.93*	2.67*	1.99
WTI->China		0.73	3.31*	2.27	1.78	1.42
WTI->Venezuela		0.7	0.52	0.33	1.08	1.52
WTI->US	D1	0.25	0.59	1.36	0.43	0.39
WTI->Russia		0.75	3.04*	2.53.	2.57*	2.69*
WTI->Canada		3.79.	2.39.	2.11.	0.86	0.56
WTI->China		3.84.	1.69	0.97	1.52	1.05
WTI->Venezuela		0.66	0.25	0.17	0.41	0.7
WTI->US	D2	4.18*	4.65*	4.91**	0.75	2.02.
WTI->Russia		18.54***	2.31	11.93***	2.36.	7.54***
WTI->Canada		7.49**	1.44	5.55**	1.36	4.97***
WTI->China		18.6***	4.05*	4.65**	0.92	1.8
WTI->Venezuela		5.78*	0.24	0.11	1.05	0.6
WTI->US	D3	21.62***	14.89***	10.79***	1.37	2.1.
WTI->Russia		92.57***	8.76***	11.8***	0.47	0.24
WTI->Canada		91.28***	6.33**	22.98***	0.96	0.62
WTI->China		3.85	7.72***	4.46**	1.52	1.88
WTI->Venezuela		7.23**	17.68***	13.83***	2.89*	2.1

Notes: The values of the table present wavelet-based Granger causality analysis results from oil prices to stock returns before the COVID-19 pandemic crisis (from January 1, 2019 to March 11, 2020). S&P 500 index refers to the US stock market, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela, WTI is the West Texas Intermediate crude oil price. Scales D1 (short term) present the time horizons of 2–4 days, scales 2 (medium-term) correspond with the time horizons of 4–8 days, and scales 3 (long term) correspond with the horizons of 8–16 days. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Results of wavelet-based Granger causality analysis from oil prices to stock returns during the pandemic

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
WTI->US	R	0.03	0.24	0.48	1.3	2.53*
WTI->Russia		1.72	1.12	0.77	1.29	1.65
WTI->Canada		1.26	0.79	1.5	1.72	3.29**
WTI->China		0.23	3.33*	3.02*	2.35.	3.12**
WTI->Venezuela		0.01	0.26	1.87	2.17.	1.97.

WTI->US	D1	1.43	0.17	0.48	1.94	1.83
WTI->Russia		0.13	0.64	4.69**	1.98.	2.94*
WTI->Canada		4.65*	0.2	1.54	1.31	0.46
WTI->China		5.3*	1.5	5.07**	2.02.	2.79*
WTI->Venezuela		0.07	1.04	2.3	1.47	2.02.
WTI->US	D2	0.7	7.33***	4.98**	2.94*	3.37**
WTI->Russia		8.75**	4.19*	1.42	0.51	0.96
WTI->Canada		1.98	8.76***	6.26***	1.81	1.61
WTI->China		3.76.	4.73**	3.62*	2.04	2.56*
WTI->Venezuela		1.98	8.2***	6.32***	4.64**	4.4***
WTI->US	D3	19.96***	14.83***	9.06***	0.73	0.59
WTI->Russia		0.7	4.68*	4.16**	0.82	1.3
WTI->Canada		24.18***	6.9**	6.05***	0.4	0.61
WTI->China		0.02	2.02	1.81	0.7	1.1
WTI->Venezuela		0.52	1.2	1.8	0.71	1.75

Notes: The values of the table present wavelet-based Granger causality analysis results from oil prices to stock returns during the COVID-19 pandemic crisis (from March 12, 2020 to March 31, 2021). See the notes of Table 3.

Table 5. Results of wavelet-based Granger causality analysis from stock returns to oil prices before the pandemic

Direction	Time scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->WTI	R	1.87	0.62	0.86	0.79	2.01
Canada->WTI		6.82**	2.93	2.11	1.77	2.02
China->WTI		0.39	0.8	0.55	0.91	0.7
Russia->WTI		1.67	2.2	2.22	1.68	3.46**
Venezuela->WTI		0.02	0.76	0.6	0.6	0.42
US->WTI1	D1	3.58.	2.57.	4.83**	6.8***	3.95**
Canada->WTI1		15.59***	7.39***	6.9***	8.34***	5.09***
China->WTI1		0.6	0.08	1.08	1.31	0.52
Russia->WTI1		5.14*	4.08*	2.72*	3.2*	3.4**
Venezuela->WTI1		2.3	0.67	0.82	0.7	0.35
US->WTI2	D2	0.61	5.28**	5.11**	3.58**	5.23***
Canada->WTI2		6.22*	0.38	5.41**	1.17	5.53***
China->WTI2		13.59***	0.78	4.67**	0.67	1.78
Russia->WTI2		10.9**	1.8	8.14***	2.57*	9.05***
Venezuela->WTI2		3.91*	0.13	0.88	2.29	0.89
US->WTI3	D3	33.62***	20.04***	10.86***	6.57***	7.01***
Canada->WTI3		105.12***	15.68***	23.92***	5.56***	6.09***
China->WTI3		3.86.	6.55**	3.68*	1.01	0.85
Russia->WTI3		86.33***	11.8***	13.41***	4.46**	4.19**
Venezuela->WTI3		1.16	13.17***	7.38***	2.59*	2.51*

Notes: The values of the table present wavelet-based Granger causality analysis results from stock return to oil price returns before the COVID-19 pandemic crisis (from January 1, 2019 to March 11, 2020). See the notes of Table 3.

Table 6. Results of wavelet-based Granger causality analysis from stock returns to oil prices during the pandemic

Direction	Time scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->WTI	R	18.35***	14.69***	4.51**	3.13*	2.65*
Canada->WTI		17.29***	14.4***	3.9**	3.44**	4.3***
China->WTI		0.57	1.19	1.97	2.23.	1.69
Russia->WTI		2.73.	2.99.	1.04	2.23.	3.89**
Venezuela->WTI		0.67	0.36	1.65	1.54	1.21
US->WTI1	D1	12.22***	13.3***	3.19*	4.42**	3.35**
Canada->WTI1		12.87***	6.6**	5.83***	6.05***	2.44*
China->WTI1		5.88*	3.19*	4.78**	1.32	1.77
Russia->WTI1		2.59	0.04	8.54***	7.27***	3.01*
Venezuela->WTI1		1.78	1.85	0.86	0.13	1.03
US->WTI2	D2	0.13	8.5***	4.44**	2.44*	2.37*
Canada->WTI2		0.01	18.83***	11.22***	3.94**	2.67*
China->WTI2		0.91	1.31	2.4.	1.75	2.63*
Russia->WTI2		5.42*	9.65***	4.79**	2.55*	2.03.
Venezuela->WTI2		0.02	4.53*	3.84*	1.95	1.96.
US->WTI3	D3	15.98***	9.06***	10.33***	1.62	1.24
Canada->WTI3		18.93***	8.31***	12.28***	2.4.	2.25*
China->WTI3		0.09	1.63	1.97	0.88	1.81
Russia->WTI3		0.21	7.9***	11.96***	4.84***	3.55**
Venezuela->WTI3		0.35	0.02	1	2.39.	3.29**

Notes: The values of the table present wavelet-based Granger causality analysis results from stock return to oil price returns during the COVID-19 pandemic crisis (from March 12, 2020 to March 31, 2021). See the notes of Table 3.

5.3 Causality between oil and stock markets during Russia-Saudi oil price war period

Russia-Saudi Arabia oil price war began at the same time (early March 2020) when the COVID-19 crisis also started and both events put a huge impact on the global economy. Therefore, it is difficult to say which event led to the extraordinary volatility of the oil market. However, this Russia-Saudi oil price war did not last long and it ended in April 2020 when Russia and Saudi Arabia finally reached an agreement. But the impact of the COVID-19 crisis lasts and the initial uncertainty from the COVID-19 crisis caused oil prices to remain low till the end of 2020. After that, the oil price gradually raises in 2021. We investigate the multiscale bidirectional causalities from oil to stocks during the Russia-Saudi oil price war period. The estimate results of wavelet-based Granger causality from oil to stock markets and from stock to oil markets are presented in Tables 7 and 8, respectively. As we can see in Table 7, we observe limited or insignificant causality from oil to stock markets in raw series as well as in a smaller scale (D1). However, in the higher scales the impact of WTI is very high pronounced in the US, Canadian and Chinese markets. These results also demonstrate that US, China and Canada are highly influenced by oil price changes in the larger scale, suggesting a long-term unidirectional causality. At high scale, Canadian market is highly influenced by oil price movements followed by US and China whereas as Russia is the least affected. As for the causality from stock market to oil (Table 8), we find significant causality from the five stocks to oil at high scale (D3). The results of wavelet-based Granger causality during the Russian-Saudi oil price war is similar to the findings before COVID-19 crisis. Ma et al. (2021) show that oil price war exhibits asymmetric impacts on the stock markets. They show that information leakage plays a significant role in the impacts generated by the price war.

Table 7. Results of wavelet-based Granger causality analysis from oil prices to stock returns during Russia-Saudi oil price war (from March 8, 2020 to April 30 2020)

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
WTI->US	R	0	0.89	3.85*	3.42*	3.75*
WTI->Russia		3.33.	0.53	0.78	0.89	0.96
WTI->Canada		0.62	1.62	3.34*	2.34.	3.36*
WTI->China		0.21	0.97	1.4	0.72	2.4.
WTI->Venezuela		0.75	0.42	0.19	0.46	0.7
WTI->US	D1	3.91.	2.88.	1.19	3.47*	2.04
WTI->Russia		2.31	0.53	1.92	4.87**	5.27**
WTI->Canada		11.71**	3.19.	3.32*	1.28	1.84
WTI->China		6.03*	0.34	1.84	1.9	1.34
WTI->Venezuela		0.27	0.05	1.61	1.29	1.13
WTI->US	D2	24.36***	13.13***	9.1***	10.75***	7.66***
WTI->Russia		2.03	1.65	0.81	0.98	1.43
WTI->Canada		9.23**	12.16***	7.86***	10.53***	8.01***
WTI->China		5.05*	3.88*	2.68.	2.81*	2.76*
WTI->Venezuela		1.46	1.94	1.32	2.2.	1.76
WTI->US	D3	19.73***	127.14***	52.31***	21.08***	19.77***

WTI->Russia	1.47	5.61**	6.8**	0.58	0.66
WTI->Canada	20.6***	45.02***	25.79***	5.46**	1.85
WTI->China	10.92**	14.53***	5.21**	10.25***	16.69***
WTI->Venezuela	5.16*	5.92**	4.34*	2.33	1.28

Notes: The values of the table present wavelet-based Granger causality analysis results from oil prices to stock returns during oil price war (from March 8, 2020 to April 30, 2020). S&P 500 index refers to the US stock market, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela, WTI is the West Texas Intermediate crude oil price. Scales D1 (short term) present the time horizons of 2–4 days, scales 2 (medium-term) correspond with the time horizons of 4–8 days, and scales 3 (long term) correspond with the horizons of 8–16 days. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Results of wavelet-based Granger causality analysis from stock prices to oil returns from March 8, 2020 to April 30 2020 (within the Saudi Russia oil price war period)

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->WTI	R	2.94.	1.98	1.7	1	1.07
Russia->WTI		0.26	0.29	0.59	2.86*	3.19*
Canada->WTI		4.38*	2.82.	1.89	1.54	2.42.
China->WTI		0.98	0.55	0.46	0.45	0.25
Venezuela->WTI		0.71	0.55	0.33	0.25	0.14
US->WTI	D1	2.62	2.69.	1.68	0.95	0.91
Russia->WTI		0.65	0.02	5.21**	1	1.48
Canada->WTI		6.41*	0.87	3.44*	1.45	1.98
China->WTI		4.39*	0.16	0.86	0.55	0.61
Venezuela->WTI		1.42	1.03	0.98	0.17	0.86
US->WTI	D2	3.3.	9.56***	6.28**	3.52*	5.34**
Russia->WTI		10.45**	9.95***	7.49***	1.82	1.33
Canada->WTI		0.29	14.42***	10.53***	5.12**	5.05**
China->WTI		2.46	0.1	0.53	2.62.	3.64*
Venezuela->WTI		0.57	0.14	0.09	0.56	0.81
US->WTI	D3	14.88***	14.56***	16.32***	2.99*	1.51
Russia->WTI		0.76	18.02***	9.05***	4.31**	3.28*
Canada->WTI		9.49**	36.74***	17.28***	3.02*	0.94
China->WTI		15***	2.63.	5.05**	4.63**	2.6.
Venezuela->WTI		5.67*	6.62**	3.99*	2.6	4.88**

Notes: The values of the table present wavelet-based Granger causality analysis results from stock return to oil price returns during the oil price war (from March 8, 2020 to April 30, 2020). See the notes of Table 7.

5.4. Portfolio management implications

The wavelet analysis provides evidence of strong co-movement between oil prices and five important stock markets, both before and during the COVID-19 pandemic. Major global crises—such as the COVID-19 pandemic and the oil price war between Saudi Arabia and

Russia—have had a significant multiscale effect on the oil–stock index nexus. The relationships differ across frequencies and over time. These results require more analysis, such as portfolio analysis. Owing to the growing integration between oil and stock market movements due to global crises, investors would like to explore potential substitutes to construct efficiently diversified portfolios and ensure optimal risk management. Accordingly, we calculate the optimal portfolio weights, hedge ratios, and hedging effectiveness so as to determine the proper hedging strategy. To offer investors a clear picture for crises periods, we analyze these measures in the context of the COVID-19 pandemic.

Table 9 shows the values of the optimal portfolio weights, hedge ratios, and hedge effects for oil and stock markets for the raw series in the pre- and during-COVID-19 periods. For the entire period (Panel A), the results indicate that investors should hold more oil assets than stocks for all countries. However, the Venezuelan market has a less optimal portfolio weight ratio. The optimal weight values range from 1% for S&P 500 stocks to 99% for oil. This result shows that the optimal allocation for oil in a one-dollar S&P 500–oil portfolio should be 99 cents, with the remainder (1 cent) invested in stocks. Similarly, for the Canadian market, investors should invest 99% of their budget in oil and 1% in the S&P/TSX Composite Index. In the case of the Chinese market, the results show that investors should have a portfolio composition of about 5% stock as derived from the SSE Composite Index and 95% worth of oil futures. Finally, in the Venezuelan market, investors should hold 60% oil-related instruments and around 40% of the IBC stocks in their portfolios.

In the year leading up to the COVID-19 pandemic, the distribution of funds to oil assets remained more or less the same, as the optimal weight value for oil remained almost the same throughout this period, except in the Venezuelan market. Before the pandemic, in the Venezuelan market, the optimal allocation for oil instruments in a one-dollar S&P 500–oil portfolio was 45 cents, with the remainder (55 cents) invested in stocks, equating to a 55%

weighting on stocks and 45% on oil. However, during the pandemic, the allocations relating to the Venezuelan market index were lower than those for oil assets. Hence, in most cases, we observe that oil is a safe-haven asset in both crisis and non-crisis periods. In both the pre- and during-COVID-19 periods, we find that oil can be considered a good investment compared to stock index portfolios. We note that portfolio structure weights are not sensitive to market conditions. Overall, investors hold more oil-related instruments and assets than stocks in their portfolios. This result confirms the finding that oil, as an asset class, is important for hedging purposes during normal periods and as a safe-haven asset during crisis periods.

A low hedge ratio, indicating that hedging effectiveness in the oil and stock markets is quite good, is in line with the idea that the inclusion of oil-based instruments in a diversified portfolio of stocks increases the risk-adjusted performance of the resulting portfolio. In Table 9, we see that the Chinese market has a lower beta coefficient than other countries, indicating a better combination for risk diversification. China and Venezuela also display lower beta coefficients during the COVID-19 period, meaning that oil-based instruments are even better portfolio-diversifying assets in the crisis period for these two counties. The values of the hedge ratio between oil instruments and stock indices range from 0.05 in the WTI/Canada portfolio to 0.14 in the WTI/Venezuela portfolio before the COVID-19 crisis. These results are important in establishing that a $1 long position in WTI can be hedged for 0.09 cents with a short position in the US index. Similarly, a $1 long position in WTI can be hedged for 0.05 cents with a short position in the Canada index, for 0.05 cents with a short position in the China index, for 0.05 cents with a short position in the Russia index, and for 0.14 cents with a short position in the Venezuela index in the pre-pandemic period.

During the COVID-19 crisis, the values of the hedge ratios between oil prices and stock indices range from 0.02 in the WTI/Canada portfolio to 0.10 in the WTI/US portfolio. The results demonstrate that a $1 long position in the WTI can be hedged for 0.10 cents with a short position in the US index. Similarly, a $1 long position in WTI can be hedged for 0.09 cents with a short position in the Canada index, for 0.02 cents with a short position in the China index, for 0.05 cents with a short position in the Russia index, and for 0.03 cents with a short position in the Venezuela index in the pre-pandemic period. We also estimate that the hedge ratios range between 0.0035 for the oil/China stock portfolio and 0.15 for the oil/US portfolio in the pre-COVID-19 sample. In the during-COVID-19 sample, the hedge ratios range from 0.0009 for the oil/Venezuela stock portfolio to 0.0217 for the oil/US portfolio.

The effect of the corona pandemic on the oil price is unique and unprecedented as it caused the largest price slump since the Gulf war. The rapid fall of oil prices due to travel restrictions and the lockdown was exacerbated by a price war between Saudi Arabia and Russia at the same time led oil prices fell spectacularly by 30 percent. It is documented that the effect of the COVID-19 pandemic on stock market volatility was greater than that of the 2008 global financial crisis (Li et al. 2021). Our research suggests that there is an impact of this crisis on the spillover between oil and stock, but this impact is not similar for all countries. We see that the Russian market is significantly influenced by oil's price even on a small scale before the COVID-19 pandemic; however, this effect disappears during the pandemic. Since the Covid pandemic put an impact on the overall sentiment level of investors, there is a possibility that Russian individual investors who are driven by the higher sentiment may overprice or underprice the stocks and therefore it dilutes the magnitude of the oil-stock nexus. Djalilov and Ülkü (2021) demonstrate that the COVID-19 pandemic has carried a notable increase of individual investor presence in stock markets especially in Russia. They show that Russian individual investors increase their buying when price has dropped due to COVID crash in March–April 2020. During Covid period individual investors account for 38% of the trading value in the Russian stock market. Youssef et al. (2021) also demonstrate the evidence that Russian stock market is one of the most affected markets by the spread of the new infectious shock and face an unprecedented shutdown of their indices' spot prices. By contrast, the Canadian and U.S. markets influence oil prices on a small scale during the COVID-19 pandemic, but the effect is not visible for the U.S. market in the pre-COVID-19 sample.

Table 9. Optimal portfolio weight, hedge ratios, and hedging effectiveness

Portfolio	W_t^c	β_t^c	***HE (%)***
Panel A: Whole sample period (January 01, 2019, to March 30, 2021)			
WTI/US	0.9941	0.0918	0.0212
WTI/Canada	0.9988	0.0698	0.0142
WTI/China	0.9586	0.0308	0.0017
WTI/Russia	0.9960	0.0536	0.0057
WTI/Venezuela	0.5970	0.0800	0.0054
Panel B: Before COVID-19 (January 01, 2019, to March 11, 2020)			
WTI/US	0.9940	0.0912	0.0159
WTI/Canada	0.9999	0.0527	0.0063
WTI/China	0.9449	0.0467	0.0035
WTI/Russia	0.9956	0.0487	0.0041
WTI/Venezuela	0.4565	0.1375	0.0048
Panel C: During COVID-19 (March 12, 2020, to March 30, 2021)			
WTI/US	0.9942	0.1018	0.0217
WTI/Canada	0.9939	0.0866	0.0166
WTI/China	0.9774	0.0245	0.0011
WTI/Russia	0.9995	0.0695	0.0096
WTI/Venezuela	0.7462	0.0256	0.0009

Notes: S&P 500 index refers to the US stock market, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela, WTI is the West Texas Intermediate crude oil price. β_t is the risk-minimizing hedge ratio, W_t^c is the optimal portfolio weight and HE is the hedging effectiveness.

For additional robustness, we report results of wavelet-based granger causality as well as Optimal portfolio weight, hedge ratios, and hedging effectiveness from appendix Tab.A.1 to Tab.A.5 by using Brent oil price. We observe that the results of wavelet-based granger causality from Brent oil price are very much similar with the results with WTI oil price. We find that there is the existence of significant bidirectional causality—oil prices and stock indices mutually affect each other particularly at high scale (D3). The movements of the U.S. and Canadian markets have a larger impact on oil prices as well. At the same way the oil prices and stock indices have less co-movement on a smaller scale, but more co-movement on a larger scale. In Tab.A.5, we find that like WTI portfolios, Brent also have large $\boldsymbol{W_t^c}$ values for US, Canada, China and Russia. However, the size of $\boldsymbol{W_t^c}$ is smaller in case of Venezuela. We also report the war period granger causality test with Brent oil price in Tab.A.6 and Tab.A.7.

6. Conclusions

Both international oil prices and stock indices declined considerably in the initial stages of the COVID-19 pandemic; this was followed by a considerable increase in prices, attracting intensive research on the complicated oil–stock interactions. The impact of this oil–stock nexus makes decision making among stock traders, the governments of oil-based countries, and policymakers much riskier. The main objective of this research was to check patterns of differences in the oil–stock connection between two sample periods (the pre- and during-COVID-19 periods) and to provide a clear picture of the complex, dynamic, and multiscale co-movements of oil and stocks at the onset of this pandemic-induced crisis. Hence, this study examined the multiscale relationships between oil price and stock markets in major oil-dependent countries and explored the extent to which the COVID-19 crisis has affected the spillovers between the oil and stock markets.

Our main findings can be summarized as follows: First, the wavelet graphs indicate strong co-movement, particularly from March 2020 to May 2020 (the initial period of the COVID-19 outbreak) between oil prices and stock returns, demonstrating that the bearish trend of stock markets is associated with a downward movement in oil prices. Therefore, the significant positive co-movements between the stock markets of the US, China, Russia, Canada, and Venezuela and oil prices indicate that oil is not an appropriate asset class for diversifying portfolios, but that oil futures can be a possible asset for cross-hedging during a crisis. Second, from the portfolio analysis, we find that investors should keep more oil-related instruments than stocks in their portfolios. These findings prove that oil is important for hedging during normal periods and acts as a safe-haven asset during a crisis. Third, as demonstrated via the wavelet results, not only does the oil price influence these countries' stock movements, but the stock indices' movement also impact the oil price. In particular, the fluctuations in the U.S. and Canadian indices have a larger influence on oil prices. Our evidence also indicates that oil prices and stock indices have less co-movement on a smaller scale, but greater co-movement on a larger scale. In the COVID-19 pandemic period, these movements are insignificant for almost all countries on smaller scales. These results also demonstrate differences in the oil–stock index nexus between the pre- and during-COVID-19 periods. Using the wavelet-based Granger causality approach, the results show that, although oil prices and stock indices have less co-movement on a smaller scale and greater movement on a larger scale for all periods, the Russian market is significantly influenced by oil's price even on a small scale before the COVID-19 pandemic; however, this effect disappears during the pandemic. By contrast, the Canadian and U.S. markets influence oil prices on a small scale during the COVID-19 pandemic period, but the effect is not visible for the U.S. market in the pre-COVID-19 sample. The results reveal significant bidirectional causality from oil to stock markets and vice versa during Russian-Saudi oil price war at high scale (64 trading days). Oil prices have a much more sporadic effect on the Russian stock market (Korhonen and Peresetsky, 2016). Jalolov and Miyakoshi (2007) also demonstrate that oil and gas price has a significant influence on the Russian market. The reason for the greater influence of oil price in the Russian market is that in this market, the price of currency risk is found to be time-varying and therefore the Russian market is highly affected by the price of oil (Saleem and Vaihekoski, 2010). On the other hand, oil has a higher influence on the US market during the COVID-19 pandemic because there is evidence that the US market is highly influenced by oil price volatility

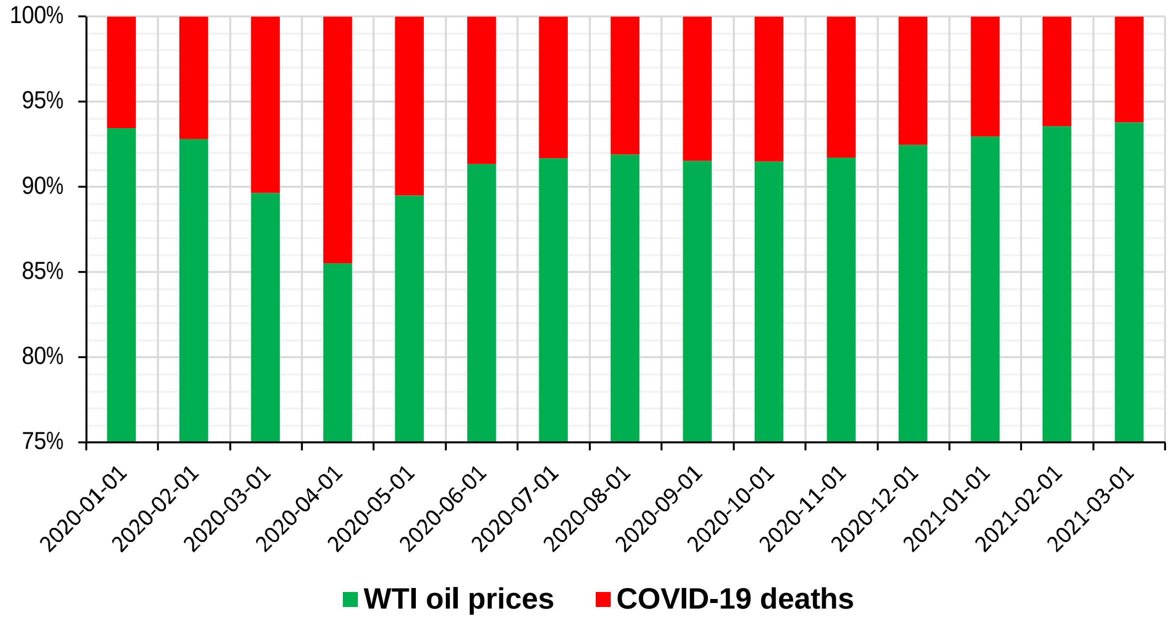
(Rehman, 2021). Since COVID-19 brings unprecedented volatility in both oil and stock price, it is not surprising that the US market will be hugely affected by oil during the pandemic periods.

Our results have significant implications for the financial and energy economics literature, since policymakers and investors can use this information in policymaking and investment decisions. Moreover, people can tackle future pandemic-like crises using our findings. Stock investors should be aware that time-varying movements are crisis-sensitive and asymmetric. Hence, they can use these results in their hedging strategies, especially in any future crisis period and particularly in the short term, when the co-movements are very high. Such investors may also correct their hedging strategies according to market movements and the time–investment horizon factor. Portfolio managers can use this information on the oil–stock nexus when predicting future co-movements, especially during crisis periods. They also need data and evidence on oil volatility when predicting stock price volatility and when designing equity portfolios. Policymakers need information on oil–stock co-movements during financial, energy, and health crises because these events can weaken cross-market linkages.

International stock markets and oil have recently become more integrated due to financial crises and greater globalization. These trends and events have made hedging more difficult, thereby reducing the benefits from diversification. However, understanding the risk spillovers between oil and stocks is of great importance for asset allocation and portfolio risk management. In this study, for higher scales, there is a strong bi-directional spillover effect between the five stock markets under consideration and the international oil market. Hence, the dynamics (or Granger causality) of risk transmissions will stimulate market participants to precisely evaluate, and efficiently guard against, extreme market risks. For instance, a positive risk spillover from the stock to the oil market indicates that a long trader in oil futures markets might face big margin calls after an extreme crash in the stock market. Similarly, the negative risk spillover from the oil to the stock market indicates that, after any positive shock in the oil market, traders who hold well-diversified portfolios can consider hedging the whole market risk in the following month. This information on the spillover of risk can be used for appropriate decision-making relating to energy storage and purchase, especially for major oil-dependent countries. This research offers exciting prospects for future papers, which can extend this work by considering the impact of the oil–stock linkage for the short, medium, and long runs.

Appendix

Fig. A.1: Monthly WTI oil prices and COVID-19 deaths



Tab.A.1. Results of wavelet-based Granger causality analysis from oil prices (Brent) to stock returns before the pandemic

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
Brent->US	R	1.14	4.29*	2.39.	1.84	1.19
Brent->Russia		42.92***	22.15***	15.38***	11.74***	9.67***
Brent->Canada		4.75*	4.44*	2.92*	2.	1.45
Brent->China		0.81	1.3	0.91	0.73	0.85
Brent->Venezuela		0.55	0.44	0.76	1.39	1.37
Brent->US	D1	0	3.46*	0.84	1.13	1.19
Brent->Russia		1.53	5.81**	6.42***	4.44**	3.99**
Brent->Canada		5.19*	5.13**	2.15.	2.05.	1.79
Brent->China		3.01.	0.31	1.76	1.16	0.97
Brent->Venezuela		5.89*	0.48	0.26	0.27	0.54
Brent->US	D2	20.38***	4.04*	9.15***	1.39	1.78
Brent->Russia		15.14***	9.39***	21.62***	6.36***	10.08***
Brent->Canada		11.58***	0.23	1.47	0.6	0.59
Brent->China		0.2	5.04**	3.13*	0.67	0.42
Brent->Venezuela		11.74***	1.78	1.1	0.42	3.39**
Brent->US	D3	0	5.75**	5.86***	0.7	1.01
Brent->Russia		101.87***	0.86	7.25***	2.4.	1.31
Brent->Canada		8.71**	1.9	3.89**	0.59	0.83
Brent->China		1.25	1.12	0.83	0.69	0.58
Brent->Venezuela		38.56***	9.36***	3.75*	1.74	2.81*

Notes: The values of the table present wavelet-based Granger causality analysis results from oil prices to stock returns before the COVID-19 pandemic crisis (from January 1, 2019, to March 11, 2020). S&P 500 index refers to the US stock market, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela, Brent is the spot oil price. Scales D1 (short term) present the time horizons of 2–4 days, scales 2 (medium-term) correspond with the time horizons of 4–8 days, and scales 3 (long term) correspond with the horizons of 8–16 days. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Tab.A.2. Results of wavelet-based Granger causality analysis from oil (Brent) prices to stock returns during the pandemic

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5

Brent->US	R	1.61	3.55*	4.11**	2.53*	1.88.
Brent->Russia		2.39	1.36	0.93	0.83	0.82
Brent->Canada		0.04	1.57	3.67*	2.87*	2.18.
Brent->China		0.01	0	1.15	0.89	0.81
Brent->Venezuela		1.18	1.95	2.69*	2.19.	1.97.
Brent->US	D1	0	0.36	0.5	1.64	1.39
Brent->Russia		0.99	0.36	0.58	2.69*	1.22
Brent->Canada		0.19	0.53	0.3	7.23***	4.7***
Brent->China		0.14	0.98	0.64	0.68	1.42
Brent->Venezuela		4.82*	2.11	2.24.	1.45	4.17**
Brent->US	D2	4.6*	4.13*	14.51***	7.07***	12.13***
Brent->Russia		20.48***	8.16***	6.17***	2.47*	3.08*
Brent->Canada		0.76	4.46*	6.63***	11.06***	14.74***
Brent->China		4.23*	1.18	1.03	1.6	1.34
Brent->Venezuela		6.99**	2.95.	4.45**	7.8***	8.08***
Brent->US	D3	162.26***	37.76***	38.03***	4.86***	7.75***
Brent->Russia		3.61.	5.56**	7.92***	2.28.	7.52***
Brent->Canada		128.03***	36.51***	26***	5.21***	11.55***
Brent->China		28.32***	0.73	0.66	1.29	2.64*
Brent->Venezuela		5.54*	6.47**	8.93***	1.45	2.11.

Notes: The values of the table present wavelet-based Granger causality analysis results from oil (Brent) prices to stock returns during the COVID-19 pandemic crisis (from March 12, 2020, to March 31, 2021). See the notes of Table 3.

Tab.A.3. Results of wavelet-based Granger causality analysis from stock returns to oil (Brent) prices before the pandemic

Direction	Time scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->Brent	R	2.35	4.14*	2.74*	2.15.	3.07*
Russia->Brent		5.97*	3.24*	2.15.	2.3.	3.38**
Canada->Brent		2.28	2.43.	1.83	1.4	1.41
China->Brent		1.86	1.3	0.86	1.27	1.04
Venezuela->Brent		4.76*	4.3*	3.11*	2.82*	2.56*

US->Brent	D1	0.49	0.37	1.78	5.18***	5.14***
Russia->Brent		2.19	1.43	1.1	2.21.	5.17***
Canada->Brent		7.6**	1.69	1.68	7.77***	6.18***
China->Brent		1.24	1.17	1.98	1.67	2.22.
Venezuela->Brent		14***	3.89*	3.32*	2.81*	1.8
US->Brent	D2	37.58***	18.6***	14.08***	4.99***	4.28***
Russia->Brent		0.28	3.73*	14.36***	6.22***	11.16***
Canada->Brent		21.13***	9.87***	7.66***	7.75***	4.16**
China->Brent		2.55	6.75**	4.91**	1.89	1.5
Venezuela->Brent		6.55*	0.24	1.69	3.47**	5.41***
US->Brent	D3	0.01	17.17***	12.09***	5.57***	5.65***
Russia->Brent		103.61***	12.99***	11.69***	3.77**	4.85***
Canada->Brent		6.5*	10.18***	10.06***	3.93**	5.49***
China->Brent		2.07	2.5.	1.84	0.24	0.59
Venezuela->Brent		17.91***	3.83*	3.63*	0.96	2.69*

Notes: The values of the table present wavelet-based Granger causality analysis results from the stock return to oil (Brent) price returns before the COVID-19 pandemic crisis (from January 1, 2019, to March 11, 2020). See the notes of Table 3.

Tab.A.4. Results of wavelet-based Granger causality analysis from stock returns to oil (Brent) prices during the pandemic

Direction	Time scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->Brent	R	5.64*	3.3*	2.77*	2.82*	3.95**
Russia->Brent		1.19	2.01	0.71	2.25.	2.64*
Canada->Brent		3.	2.19	0.74	0.87	2.68*
China->Brent		0.33	0.3	0.11	0.04	0.43
Venezuela->Brent		0.18	1.8	1.48	1.67	3*
US->Brent	D1	0.64	2.08	3.47*	6.16***	3.48**
Russia->Brent		0.77	2.73.	3.08*	9.76***	7.15***
Canada->Brent		0.46	1.77	1.87	8.13***	6.76***
China->Brent		0.07	0.13	0.62	2.09.	1.84
Venezuela->Brent		1.63	0.15	4.48**	2.71*	5.65***
US->Brent	D2	4.5*	2.18	16.87***	13.95***	15.58***

Russia->Brent		7.21**	1.34	2.75*	2.81*	3.31**
Canada->Brent		0.56	0.3	5.04**	11.58***	13.99***
China->Brent		2.34	0	0.47	1.66	1.65
Venezuela->Brent		2.96.	5.86**	6.59***	8.96***	8.13***
US->Brent	D3	107.99***	6.29**	31.7***	4.89***	5.29***
Russia->Brent		0.08	31.76***	37.46***	6.45***	10.62***
Canada->Brent		82.15***	3.21*	19.1***	2.66*	5.38***
China->Brent		21.56***	1.58	5**	1.32	3.02*
Venezuela->Brent		5.46*	1.23	7.12***	1.48	1.15

Notes: The values of the table present wavelet-based Granger causality analysis results from the stock return to oil (Brent) price returns during the COVID-19 pandemic crisis (from March 12, 2020, to March 31, 2021). See the notes of Table 3.

Tab.A.5. Optimal portfolio weight, hedge ratios, and hedging effectiveness (With Brent oil)

Portfolio	W_t^c	β_t^c	*HE (%)*
Panel A: Whole sample period (January 01, 2019, to March 30, 2021)			
Brent/US	0.9460	0.1338	0.0221
Brent/Canada	0.9831	0.0982	0.0165
Brent/China	0.8338	0.0578	0.0033
Brent/Russia	0.9434	0.1080	0.0121
Brent/Venezuela	0.3735	0.0120	0.0000
Panel B: Before COVID-19 (January 01, 2019, to March 11, 2020)			
Brent/US	0.9530	0.1198	0.0269
Brent/Canada	0.9932	0.0801	0.0158
Brent/China	0.7991	0.0730	0.0090
Brent/Russia	0.9389	0.0817	0.0098
Brent/Venezuela	0.2199	0.0864	-0.0190
Panel C: During COVID-19 (March 12, 2020, to March 30, 2021)			
Brent/US	0.9329	0.1570	0.0216
Brent/Canada	0.9684	0.1223	0.0153
Brent/China	0.8683	0.0533	0.0020
Brent/Russia	0.9402	0.1402	0.0142
Brent/Venezuela	0.5390	-0.0517	0.0010

Notes: S&P 500 index refers to the US stock market, the S&P/TSX Composite index for Canada, the SSE Composite Index for China, the RTS Index for Russia, and the Índice Bursátil de Capitalización (IBC) for Venezuela, Brent is the crude oil spot price. β_t is the risk-minimizing hedge ratio, W_t^c is the optimal portfolio weight and HE is the hedging effectiveness.

Tab.A.6. Results of wavelet-based Granger causality analysis from oil prices to stock returns during Russia-Saudi oil price war

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
Brent->US	R	0.31	0.82	2.02	1.09	0.76
Brent->Russia		0	0.52	0.51	0.18	0.14
Brent->Canada		0	0.27	0.93	0.71	0.67
Brent->China		0.08	0.03	0.45	0.73	0.58
Brent->Venezuela		0.5	1.14	1.36	1.12	0.87
Brent->US	D1	0.02	0.25	0.23	0.33	1.43
Brent->Russia		0.05	0.47	0.19	1.07	0.4
Brent->Canada		0.02	0.18	0.06	1.02	4.41**
Brent->China		0.01	1.57	1.29	0.36	4.24**
Brent->Venezuela		5.4*	1.39	1.56	1.58	2.35.
Brent->US	D2	1.09	1.65	4.63**	1.93	2.25.
Brent->Russia		2.51	0.89	1.16	1.68	2.13.
Brent->Canada		0.48	1.23	2.12	4.36**	2.92*
Brent->China		7.19*	1.26	4.61**	3.6*	2.79*
Brent->Venezuela		3.33.	1.19	1.72	9.25***	10.48***
Brent->US	D3	62.05***	11.61***	13.1***	4.62**	4.92**
Brent->Russia		1.11	4.05*	5.22**	3.11*	3.4*
Brent->Canada		35.25***	12.59***	5.72**	1.17	6.23***
Brent->China		39.22***	0.11	5.12**	4.75**	4.6**
Brent->Venezuela		54.94***	5.45**	9.41***	2.26.	1.78

Notes: The values of the table present wavelet-based Granger causality analysis results from oil (Brent) prices to stock returns during Soudi Russian oil war (from March 8, 2020 to April 30 2020).

Tab.A.7. Results of wavelet-based Granger causality analysis from oil prices to stock returns during Russia-Saudi oil price war

Direction	Time Scale	Lag-1	Lag-2	Lag-3	Lag-4	Lag-5
US->Brent	R	0.61	0.42	0.25	0.23	0.14
Russia->Brent		0.42	0.59	0.34	0.71	0.98
Canada->Brent		0.33	0.3	0.14	0.1	0.16

China->Brent		0.06	0.08	0.16	0.14	0.23
Venezuela->Brent		0	1.76	1.23	1.19	1.26
US->Brent	D1	0	0.19	0.8	0.64	0.57
Russia->Brent		0.01	0.53	0.86	1.58	1.56
Canada->Brent		0	0.14	0.47	0.58	0.69
China->Brent		0.78	0.38	0.54	1.25	3.22*
Venezuela->Brent		2.08	0.13	2.07	1.38	7.21***
US->Brent	D2	0.88	0.86	4.49*	4.99**	6.94***
Russia->Brent		1.61	0.26	0.13	0.39	0.56
Canada->Brent		0.27	0.04	0.87	2.35.	2.03
China->Brent		4.96*	0.03	3.77*	10.38***	7.21***
Venezuela->Brent		1.77	2.06	2.05	7.34***	7.83***
US->Brent	D3	0.61	0.42	0.25	0.23	0.14
Russia->Brent		0.42	0.59	0.34	0.71	0.98
Canada->Brent		0.33	0.3	0.14	0.1	0.16
China->Brent		0.06	0.08	0.16	0.14	0.23
Venezuela->Brent		0	1.76	1.23	1.19	1.26

Notes: The values of the table present wavelet-based Granger causality analysis results from oil (Brent) prices to stock returns during Saudi Russian oil war (from March 8, 2020 to April 30 2020).

References

Abuzayed, B., & Al-Fayoumi, N. (2021). Risk spillover from crude oil prices to GCC stock market returns: New evidence during the COVID-19 outbreak. *The North American Journal of Economics and Finance*, *58*, 101476.

Akhtaruzzaman, M., Boubaker, S., Chiah, M., & Zhong, A. (2021). COVID− 19 and oil price risk exposure. *Finance Research Letters*, *42*, 101882.

Albulescu, C. T., Demirer, R., Raheem, I. D., & Tiwari, A. K. (2019). Does the US economic policy uncertainty connect financial markets? Evidence from oil and commodity currencies. *Energy Economics*, *83*, 375-388.

Ali, M., Afas, N., & Rivzi, S. (2020). Coronavirus (COVID-19) — An epidemic or pandemic for financial markets. *Journal of Behavioral and Experimental Finance*, *27*, 100341.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance*, *30*(7), 1387-1405.

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2012). On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. *Energy Economics*, *34*(2), 611-617.

Arouri, M. E. H., & Rault, C. (2012). Oil prices and stock markets in GCC countries: empirical evidence from panel analysis. *International Journal of Finance & Economics*, 17(3), 242-253.

Ashfaq, S., Tang, Y., & Maqbool, R. (2020). Dynamics of spillover network among oil and leading Asian oil trading countries' stock markets. *Energy*, *207*, 118077.

Awartani, B., & Maghyereh, A. I. (2013). Dynamic spillovers between oil and stock markets in the Gulf Cooperation Council Countries. *Energy Economics*, *36*, 28-42.

Badeeb, R. A., & Lean, H. H. (2018). Asymmetric impact of oil price on Islamic sectoral stocks. *Energy Economics*, *71*, 128-139.

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*(4), 742–758.

Baker, S. R., Bloom, N., Davis, S. J., & Terry, S. J. (2020). COVID-induced economic uncertainty. *NBER working paper series*,

Baruník, J., & Křehlík, K. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*, 271-296.

Bastianin, A., & Manera, M. (2018). How does stock market volatility react to oil price shocks? *Macroeconomic Dynamics*, *22*(3), 666-682.

Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis*, *33*, 58–69.

Bjørnland, H. C. (2009). Oil price shocks and stock market booms in an oil exporting country. *Scottish Journal of Political Economy*, *56*(2), 232-254.

Bouri, E. (2015). Oil volatility shocks and the stock markets of oil-importing MENA economies: A tale from the financial crisis. *Energy Economics*, *51*, 590-598.

Cohen, A. (2020, April 20). Oil Plummets Over 300% To Almost -$40 A Barrel In Historic Collapse. *Forbes*.

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, 35, 101554.

Cui, J., Goh, M., Li, B., & Zou, H. (2021). Dynamic dependence and risk connectedness among oil and stock markets: New evidence from time-frequency domain perspectives. *Energy*, *216*, 119302.

Diebold, F.X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*, 57-66.

Djalilov, A., & Ülkü, N. (2021). Individual investors' trading behavior in Moscow Exchange and the COVID-19 crisis. *Journal of Behavioral and Experimental Finance*, *31*, 100549.

Du, L., & He, Y. (2015). Extreme risk spillovers between crude oil and stock markets. *Energy Economics*, *51*, 455-465.

Ewing, B. T., & Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal*, *29*, 12-23.

Feng, J., Wang, Y., & Yin, L. (2017). Oil volatility risk and stock market volatility predictability: Evidence from G7 countries. *Energy Economics*, *68*, 240-254.

Filis, G., Degiannakis, S., & Floros, C. (2011). Dynamic correlation between stock market and oil prices: The case of oil-importing and oil-exporting countries. *International Review of Financial Analysis*, *20*(3), 152-164.

Financial Times. (2020). Oil prices hit lowest level in 17 years as demand plunges. *The Financial Times Limited.*

Furceri, D., Loungani, P., Ostry, J. D., & Pizzuto, P. (2020). Will covid-19 affect inequality? Evidence from past pandemics. *Covid Economics*, *12*(1), 138-157.

Guesmi, K., & Fattoum, S. (2014). Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. *Economic Modelling*, *38*, 305-310.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy*, 91(2), 228-248.

Huang, S., An, H., Gao, X., & Hao, X. (2016). Unveiling heterogeneities of relations between the entire oil–stock interaction and its components across time scales. *Energy Economics*, *59*, 70-80.

Hung, N.T, & Vo, X.V. (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*, *76*, 101730.

Jalolov, M., & Miyakoshi, T. (2005). Who drives the Russian financial markets? *The Developing Economies*, *43*(3), 374-395.

Jammazi, R., & Reboredo, J. C. (2016). Dependence and risk management in oil and stock markets. A wavelet-copula analysis. *Energy, 107*, 866-888.

Jones, C. M., & Kaul, G. (1996). Oil and the stock markets. *The Journal of Finance*, *51*(2), 463-491.

Jung, H., & Park, C. (2011). Stock market reaction to oil price shocks: A comparison between an oil-exporting economy and an oil-importing economy. *Journal of Economic Theory and Econometrics*, *22*(3), 1-29.

Karuppiah, J. & Los, C.A. (2005). Wavelet multi resolution analysis of high-frequency Asian FX rates, summer 1997. *International Review of Financial Analysis*, 14, 211-246.

Korhonen, I., & Peresetsky, A. (2016). What influences stock market behavior in Russia and other emerging countries? *Emerging Markets Finance and Trade*, *52*(5), 1210-1225.

Kroner, K. F., & Ng, V. K. (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, *11*(4), 817-844.

Kroner, K. F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, *28*(4), 535-551.

Ku, Y. H. H., Chen, H. C., & Chen, K. H. (2007). On the application of the dynamic conditional correlation model in estimating optimal time-varying hedge ratios. *Applied Economics Letters*, *14*(7), 503-509.

Lehkonen, H., & Heimonen, K. (2014). Timescale-dependent stock market comovement: BRICs vs. Developed markets. *Journal of Empirical Finance*, *28*, 90–103.

Li, W., Chien, F., Kamran, H. W., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2021). The nexus between COVID-19 fear and stock market volatility. *Economic Research-Ekonomska Istraživanja*, 1-22.

Li, Y., Mittoo, U. R., Yu, X., & Zhang, Z. (2021). The impact of global financial crisis on regulation S private debt market. *International Review of Economics & Finance*, *73*, 231-248.

Li, X., & Wei, Y. (2018). The dependence and risk spillover between crude oil market and China stock market: New evidence from a variational mode decomposition-based copula method. *Energy Economics*, *74*, 565-581.

Lin, L., Kuang, Y., Jiang, Y., & Su, X. (2019). Assessing risk contagion among the Brent crude oil market, London gold market and stock markets: Evidence based on a new wavelet decomposition approach. *The North American Journal of Economics and Finance*, *50*, 101035.

Lin, L., Zhou, Z., Jiang, Y., & Ou, Y. (2021). Risk spillovers and hedge strategies between global crude oil markets and stock markets: Do regime switching processes combining long memory and asymmetry matter? *The North American Journal of Economics and Finance*, *57*, 101398.

Ma, R., Xiong, T., & Bao, Y. (2021). The Russia-Saudi Arabia oil price war during the COVID-19 pandemic. *Energy Economics*, 102, 105517.

Mensi, W., Al-Rababa'a, A. R., Vo, X. V., & Kang, S. H. (2021c). Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. *Energy Economics*, *98*, 105262.

Mensi, W., Al-Yahyaee, K. H., Vo, X. V., & Kang, S. H. (2021a). Modeling the frequency dynamics of spillovers and connectedness between crude oil and MENA stock markets with portfolio implications. *Economic Analysis and Policy*, *71*, 397–419.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling*, *32*, 15-22.

Mensi, W., Hammoudeh, S., Shahzad, S. J. H., & Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*, *75*, 258–279.

Mensi, W., Hammoudeh, S., & Tiwari, A. (2016). New evidence on hedges and safe havens for Gulf stock markets using the wavelet-based quantile. *Emerging Markets Review*, 28, 155-183.

Mensi, W., Rehman, M. U., Maitra, D., Al-Yahyaee, K. H., & Vo, X. V. (2021b). Oil, natural gas and BRICS stock markets: Evidence of systemic risks and co-movements in the time-frequency domain. *Resources Policy*, *72*, 102062.

Mukanjari, S., & Sterner, T. (2020). Charting a “green path” for recovery from COVID-19. *Environmental and Resource Economics*, *76*(4), 825-853.

Qiao, X., Zhu, H., & Hau, L. (2020). Time-frequency co-movement of cryptocurrency return and volatility: evidence from wavelet coherence analysis. *International Review of Financial Analysis*, *71*, 101541.

Rahman, S. (2021). Oil price volatility and the US stock market. *Empirical Economics*, *61*(3), 1461-1489.

Roubaud, D., & Arouri, M. (2018). Oil prices, exchange rates and stock markets under uncertainty and regime-switching. *Finance Research Letters*, *27*, 28-33.

Saleem, K., & Vaihekoski, M. (2010). Time-varying global and local sources of market and currency risks in Russian stock market. *International Review of Economics & Finance*, *19*(4), 686-697.

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.

Sarwar, S., Tiwari, A. K., & Tingqiu, C. (2020). Analyzing volatility spillovers between oil market and Asian stock markets. *Resources Policy, 66*, 101608.

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

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological society, 79*(1), 61-78.

Vidya, C. T. & Prabheesh, K. P. (2020) Implications of COVID-19 pandemic on the global trade networks. *Emerging Markets Finance and Trade, 56,* 2408–2421.

Wagner, A. F. (2020). What the stock market tells us about the post-COVID-19 world. *Nurture Human Behaviour, 4,* 440.

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*(4), 1220-1239.

Wen, D., Wang, G. J., Ma, C., & Wang, Y. (2019). Risk spillovers between oil and stock markets: A VAR for VaR analysis. *Energy Economics, 80,* 524–535.

Wu, B., Wang, L., Wang, S., & Zeng, Y.R. (2021). Forecasting the U.S. oil markets based on social media information during the COVID-19 pandemic. *Energy 226,* 120403.

Xiao, J., Zhou, M., Wen, F., & Wen, F. (2018). Asymmetric impacts of oil price uncertainty on Chinese stock returns under different market conditions: Evidence from oil volatility index. *Energy Economics, 74,* 777-786.

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.

Youssef, M., Mokni, K., & Ajmi, A. N. (2021). Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter?. *Financial Innovation, 7*(1), 1-27.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters, 36*, 101528.

Zhang, W., & Hamori, S. (2021). Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany. *International Review of Financial Analysis, 74,* 101702.

Zhang, Y. J., & Ma, S. J. (2019). How to effectively estimate the time-varying risk spillover between crude oil and stock markets? Evidence from the expectile perspective. *Energy Economics, 84,* 104562.

Zhu, P., Tang, Y., Wei, Y., & Lu, T. (2021). Multidimensional risk spillovers among crude oil, the US and Chinese stock markets: Evidence during the COVID-19 epidemic. *Energy*, *231*, 120949.