

RESEARCH

Open Access



Did real economic uncertainty drive risk connectedness in the oil–stock nexus during the COVID-19 outbreak? A partial wavelet coherence analysis

Mohammad Al-Shboul¹ and Aktham Maghyereh^{2*}

*Correspondence:
a.almaghairah@uaeu.ac.ae

¹ Department of Finance & Economics, University of Sharjah, 27272 Sharjah, United Arab Emirates

² Department of Economics & Finance, United Arab Emirates University, Al Ain, United Arab Emirates

Abstract

This study explores the impact of real economic policy (business condition risk) on the oil–stock nexus risk connectedness during the COVID-19 pandemic. It uses multivariate wavelet coherency and partial wavelet coherency methods to isolate the effects of global risk indices, such as the US economic uncertainty index, the crude oil volatility index, and the geopolitical risk index, on risk connectedness. The study is based on daily data from January 2018 to December 2020 and finds a strong impact of real economic uncertainty indices on risk connectedness, with time-varying and frequency-sensitive patterns. The results also show that during the COVID-19 crisis, higher coherencies between oil and equity volatilities exist at lower frequencies. This research provides useful insights for regulators and portfolio diversifiers.

Keywords: Real economic uncertainty, Risk connectedness, Oil prices, Stock prices, Wavelet coherence analysis, COVID-19

JEL Classification: G12, G15, G18, G01, F3, E44

1 Introduction

The correlation between stock prices and other assets prices, particularly crude oil prices, is of great importance for portfolio investments and risk diversification. Crude oil has become a necessary asset for investment particularly to diversify or hedge against equity market volatility because it is driven by various business cycles generated by conventional financial markets (Roll 2013), and confirmed to have weak associations with stock markets (Boako et al. 2020). Accordingly, information transmission between oil and stock markets has become an issue of concern to researchers. The dilemma of economic policy uncertainty has become more important after the global crises such as the 2008 Global Financial Crisis (GFC), the European bond crisis and increasing policy disputes in the United States (Baker et al. 2016). Theoretically, Gomes et al. (2012) and Pástor and Veronesi (2012, 2013) demonstrated that the uncertainty in government policies can depress stock prices, and lead to higher volatilities and correlations in stocks via its

negative impact on investment decisions. The effects of oil prices on the global economy were examined by earlier studies, including Hamilton (1983), Balassa (1985), and Mork (1989). They suggested that shocks in oil prices influence exports and policies decisions. Since then, research studies have attempted to provide new empirical evidence on the impact of oil price shocks and other markets.

The integration of financial markets has greatly tightened linkages across oil and stock markets, raising widespread concerns about network risk transmission. This phenomenon is particularly evident during and following turbulent period. As the world's primary energy source, crude oil is the most important commodity which plays a key role in both production and consumption. Given the historical increase in the oil price variations since early 1970s, uncertainty in the oil market, therefore, influences the world economy and global financial markets as well (Aguilera and Radetzki 2017). However, different conclusions were found by the literature in which some papers found a negative effect of oil price shocks on stock returns (Papapetrou 2001; Driesprong et al. 2008; Yousaf and Hassan, 2019), while others reached to a positive impact (Boubaker and Raza 2017; Wang and Wang 2019; Cui et al. 2021a, b; Mensi et al. 2022, among others).

Oil price risk (measured by volatility) can transmit into equity markets through important channels. For instance, volatility in oil prices may cause variations in the earnings of oil-related companies, which may translate into high volatility in their equity prices (Maghyereh et al. 2016; You et al. 2017). Shocks in oil price, especially in recent years, due to the supply and demand mechanism may affect the discount rate. An increase in oil price shocks is often seen as an indication of inflationary pressure, where central banks raise the interest rate due to an increase in the inflation rate (Huang et al. 1996; Miller and Ratti 2009). As the relationship between changes in oil prices and stock markets has effects on portfolio management, the degree to which oil market volatility spreads to stock markets depends on how much oil market volatility affects real economic uncertainty and then economic growth.

Given the cyclical nature of the demand for both oil and equities, which may lead to a positive association between those assets, risk transmission across oil and equity markets could contribute to real economic shocks. As an increase in economic policy uncertainty (EPU) can cause economic downturns (Baker et al. 2016), it can be considered a main driver and/or an important source of the risk connectedness between oil and equities. Particularly, real economic uncertainty reflects the unpredictability and ambiguity surrounding economic conditions, such as GDP growth, inflation, employment, and fiscal policies. According to the portfolio theory, during periods of high economic uncertainty, market participants become more cautious and risk-averse, leading to increased correlations and interdependencies between different financial markets and assets, (Forbes and Rigobon 2002; Bekaert, et al. 2010; Frankel, and Saravelos 2012). This heightened risk aversion can result in a synchronized response to economic shocks, leading to a stronger link between financial assets including oil and stock market volatilities. In addition, uncertain economic conditions can lead to changes in consumer behavior, business investment decisions, and overall market sentiment. For example, during periods of economic uncertainty, consumers may reduce discretionary spending, which can impact oil demand, while businesses

may postpone investment plans, affecting stock market performance. These combined effects can lead to a higher level of risk connectedness between oil and stocks.

Furthermore, real economic uncertainty can also influence other macroeconomic variables and global risk factors that are known to affect both oil and stock markets (Bloom 2009; Jurado et al. 2015; Baker et al. 2016; Cesa-Bianchi and Rebucci 2017; Barbi and Macovei 2020). For instance, changes in economic uncertainty can influence currency exchange rates, interest rates, geopolitical tensions, or policy decisions, which, in turn, can impact directly impact both the oil and stock markets, leading to a higher degree of risk interconnectedness.

Despite the increase in the body literature that investigates the risk transfer between oil and equities (Arouri et al. 2012; Maghyereh et al. 2016; Awartani et al. 2016, 2018; Mensi et al. 2021a, 2021b; Liao et al. 2021; Hung and Vo 2021; Maghyereh and Abdoh 2022), it rarely investigates the effect of EPU on the risk transmission of the oil–stock nexus during turmoil periods. Studies in this case (Kang and Ratti 2013; You et al. 2017; Fang et al. 2018; Ali et al. 2022; Uddin et al. 2018; among others) focused mostly on the impact of economic uncertainty on the return spillovers among oil and stock returns. These studies have largely ignored the effect of real economic uncertainty (business condition risk, ADS) but mostly focused on using only the EPU index designed by Barker et al. (2016). While the news-based EPU index specifically targets economic policy uncertainty and aimed to quantify the degree of uncertainty arising from policy-related factors (Karanasos and Yfanti 2021) the ADS index primarily focuses on business conditions and provides a comprehensive measure of economic activity. It captures a wide range of macroeconomic variables related to employment, production, income, and sales. This broader coverage allows for a more holistic assessment of the overall state of the economy, making it particularly suitable for analyzing real economic uncertainty in real-time (Diebold 2020). Therefore, while the EPU index is relevance may be more pronounced when studying the effects of policy-related uncertainties on specific economic sectors or policy-driven events, the ADS index is more relevant when the impact of real economic shocks. Furthermore, the ADS index has been widely used and validated in empirical research, demonstrating its robustness and accuracy in capturing changes in business conditions (e.g., Diebold 2020; Uluceviz and Yilmaz 2021; Cenesizoglu 2022). It has been shown to have a strong correlation with key macroeconomic variables, such as GDP growth and industrial production. This makes it a reliable tool for assessing real economic uncertainty and its impact on the business environment.

Existing studies (Sharif et al. 2020; Bahloul and Khemakhem 2021; Belhassine and Karanti 2021, among others) have paid less attention in their analysis to isolate the effect of different global risks indices (the US economic uncertainty index (EPU), the crude oil volatility index (OVX) and the geopolitical risk index (GPR)) on risk connectedness. In addition, the bulk of the earlier studies calculated market volatility using low-frequency interval data (e.g., daily and weekly), thereby ignoring the information embedded in the latter. Indeed, high-frequency intraday data enables a more thorough examination of the pricing process as well as more accurate volatility estimates (Dhaene and Wu 2020). As a result, in this paper, we calculate market volatility using the continuous record of the return processes.

The contribution of this paper to the existing literature is in twofold. First, it is the first to explore the impact of the real economic uncertainty [the index of business conditions (ADS)], as proposed by Aruoba et al. (2009) on the volatility spillovers among oil and stock prices during the turbulent period of the COVID-19 pandemic. To perform the analysis, the partial wavelet coherency (PWC) and multivariate wavelet coherency (MWC), as suggested by Aguiar-Conraria et al. (2018a, 2018b) and Verona (2020), are implemented.¹ PWC is used when the influence of economic conditions and the economic policy uncertainty indices are filtered out. The MWC model is used to infer the coherence of multiple independents (i.e., the oil–stock nexus) on a dependent (i.e., economic conditions or economic policy uncertainty). Second, the risk connectedness between oil and equity is measured by “realized volatility” as a proxy measure of risk. The realized volatility is measured using high-frequency (intraday transaction prices) of the futures contracts rather than the spot prices of the underlying. Therefore, our volatility estimate is a consistent measure of the latent volatility process, and thus, it will be more suitable to use in a time series framework.

The paper finds evidence of strong multiple wavelet coherency (MWC) and partial wavelet coherency (PWC) between real-economy uncertainty index (ADS) and risk connectedness in the oil–stock nexus with event-specific patterns, time varying and frequency sensitive. During the coronavirus disease (COVID-19) crisis, higher multivariate coherencies between ADS and risk transmission with respect to other global factors (EPU and GRP) were found at higher frequencies. However, when isolating the other global risk factors, our results also show that during the COVID-19 crisis, higher coherencies between ADS and the risk transmission in the oil and equity nexus existed at lower frequencies. This observation is noteworthy as it suggests that the relationship between the two assets became more pronounced during this period of significant economic disruption. These results have practical implications for regulators and portfolio diversifiers. Regulators responsible for overseeing financial markets can benefit from understanding the increased interconnectedness between oil and equity risks during times of crisis. This knowledge can help in formulating appropriate risk management policies and interventions to mitigate potential systemic risks. For portfolio diversifiers, understanding the time-varying and frequency-sensitive patterns of risk connectedness allows for improved risk assessment and allocation strategies.

The rest of the paper is structured as follows: Sect. 2 presents the literature review, and Sect. 3 discusses the methodology used in the paper. In Sect. 4, the empirical findings are discussed, and the conclusion is addressed in Sect. 5.

2 Literature review

The modern portfolio theory by Markowitz (1952) suggests that the interrelation between various assets is vital for portfolio’s return maximization. Its main assumption is that investors can diversify the risk of their portfolios by allocating different asset classes with various levels of risks. In periods of high volatility, investors can diversify

¹ A number of studies have used the wavelet analyses (MWC and PWC) (among others, Das and Kumar 2018; Albulescu and Mutascu 2021; Choi 2022; Hkiri et al. 2018; Wu et al. 2020; Maghyereh et al. 2022a, b; Sharma et al. 2021; Kinkyo 2022).

the risk of their portfolios by investing in assets which are weakly correlated or not intercorrelated. Therefore, identifying the degree and the direction of risk transmission among assets are essential to identify the possible risk diversification opportunities during different periods.

Risk spillovers among different asset classes have been extensively examined in the literature, but existing studies have not been able to arrive at the consensus. Arouri et al. (2011a) found strong volatility spillovers among world oil prices and the Gulf Cooperation Council (GCC) stock markets, via the generalized VAR-GARCH approach. Using similar methodologies, Arouri et al. (2011b) found a strong volatility spillover among oil and stock markets in Europe and the US at the sectoral level. Arouri et al. (2012) found that risk spillovers between oil prices and sector stock returns are strong at both the aggregate and sector levels of European stock markets. By considering the 2014 oil price crash crisis, Awartani et al. (2016) argued that the risk transmission from oil to equity markets rose during this crisis. In a similar vein, Maghyereh et al. (2016) found that risk spillovers between oil and eleven major international equity markets were largely dominated by spillovers from the oil market to equity markets and not the other way around due to the start of global economic recovery after the 2008 global financial crisis (GFC).

Utilizing the multivariate ARMA-GARCH approach and the wavelet multiresolution analysis, Boubaker and Raza (2017) found that risk spillovers among oil prices and the BRICS stock markets were very strong due to the increase in demand on crude oil. Wang and Wang (2019) argued that risk spillovers between crude oil and China's sectoral stock markets are almost positive and that the China's 2015 financial crisis had a significant impact on the risk spillovers. However, Zhang (2017) argued that oil shocks rarely contribute to the shocks of the six major international stock markets. Yousaf and Hassan (2019) found that risk spillover transmitted from crude oil price changes to most of the emerging Asian stock markets decreases during the Chinese 2015 stock market crash, concluding that lesser investments in crude oil can lessen portfolio risks during the Chinese crisis.

Mensi et al. (2021), using the TVP-VAR approach, found strong risk spillover effects between oil and different global stock markets (the US, Europe, Asia and five vulnerable European Union countries) and the effects increased during GFC, the 2014 oil price crisis, and during COVID-19. When applying the same methodology, Bahloul and Khemakhem (2021) reported strong evidence of risk spillovers among oil and Islamic stock markets after the COVID-19 pandemic. Another analysis was performed by Belhassine and Karamti (2021) who reported that oil-exporting countries showed a higher correlation between oil prices and stock market indices in the long run compared to importing countries. Furthermore, Cui et al. (2021b) stated that the oil market received much more risk spillovers transmitted from different global stock markets and crises such as GFC, the 2014 oil price collapse, and COVID-19 had greatly contributed to the increase in the level of risk spillover. Another study by Mensi et al. (2022) confirmed the findings of Cui et al. (2021a, b) where spillover increased widely during the 2010 European debt crisis, the 2014 oil crash crisis, 2016 Brexit referendum, and during COVID-19. Thus, lesser investments in oil would reduce the overall portfolio risk.

Using the wavelet TVP-VAR approach, Younis et al. (2023) argued that the connectedness between oil, gold, and global equity markets increased widely, but at heterogeneous

levels, during the above-mentioned crises as well as during the Chinese stock market crash in 2015. Another study by Babar et al. (2022) found strong risk spillovers for the nexus between energy commodities and the nine net importers of energy Asian stock markets, especially during times of the turmoil events. In worldwide study, Razmi and Razmi (2023) argued that after the COVID-19 outbreak the US stock market lost its significant influence on the crude oil market, but the Chinese market did not. Escribano et al. (2022) reported that connectedness among crude oil and stock markets is significantly noticeable during crises periods and the information is conveyed mostly from crude oil to stock markets where crude oil acts as a diversifier for oil-exporters. In summary, while the literature is flooded with analyses on the risk connectedness among oil and stock markets, the literature has failed to provide conclusive evidence for the nature of risk transmission among oil and stock markets.

Contrary to the research conducted on the risk connectedness, the research effort concerning the determinants of connectedness, especially the effect of economic uncertainty on connectedness, was scant. Considering the growing concern about the impact of global recent economic uncertainties, crude oil volatility and geopolitical uncertainties on financial risk diversification, especially after the most recent global crises (the GFC, the 2010 Greek crisis, the COVID-19 outbreak, the Russian–Ukrainian conflict, the US geopolitical tension and increasing public policy disputes in the US), different global risk factors have been recently invented in the literature to examine, including the EPU index, geopolitical risk index by Caldara et al. (2022), and the trade policy uncertainty (TPU) index by Caldara et al. (2020), among others. Thus, the empirical literature examining the impact of such global indices on the oil–stock nexus have reached to mixed results and inconclusive evidence.

To critically analyze the literature relating to the impact of global policy uncertainties on the risk spillovers, the second strand of studies has been carried out in this section. The theoretical frameworks provided by Pástor and Veronesi (2012, 2013) and Gomes et al. (2012) argued that uncertainties in government policies adversely impact stock markets via causing more volatilities in portfolios and more correlations among financial assets. Caldara and Iacoviello (2022) and Baker et al. (2016) stated that EPU can impact the cross-asset correlations of portfolios of different financial assets via its negative impact on investment decisions. Although the impact of EPU, and other global risk factors, on the risk connectedness among the oil–stock nexus, this topic is still rather understudied and remains scarce to some extent due to the unreachable clear evidence of such impact.

Starting with Kang and Ratti (2015), an increase in EPU in China had led to a less negative effect on real oil prices and real stock market returns, concluding that volatility in oil prices causes a significant rise in China's EPU but reduces the real stock market returns. Another study by You et al. (2017) indicates that stock returns were highly correlated with oil price shocks and China's EPU. Fang et al. (2018) also reported a significant positive influence of EPU on the long-run oil–stock correlation. However, when other global risk factors (e.g., VIX, OVX and GPR) were used, they found a strong positive impact on the correlation except for the monetary policy uncertainty and national security uncertainty. Sharif et al. (2020) argued that the effect of the COVID-19 pandemic on the geopolitical risk (GPR) was substantially higher than on the US's EPU. By utilizing the

quantile connectedness method, Kamal et al. (2022) pointed out that EPU and GPR had a positive impact only on the stock market during extreme uncertain periods.

Using the multivariate quantile VAR approach, Yuan et al. (2022) argued that when the oil market was booming, EPU in China and India had a negative impact on the oil returns, whereas EPU in Russia and Brazil had a positive effect. Another study by Wang et al. (2022) reported that GPR and global EPU had a strong impact on the global oil market price variabilities. Using a quantile regression approach, Zhao and Wang (2022) found a strong impact of EPU and monetary policy uncertainty (MPU) in the US and China on the oil–stock correlations. Using a combination of Q-VAR and TVP-VAR approaches, Dai and Zhu (2023) found the risk spillovers among EPU, gold, oil and stock prices were much higher in extreme market states.

In the context of the wavelet multiple and partial coherency approaches (MWC and PWC), the impact of different uncertainty factors on the risk connectedness among different asset classes has been rarely examined. Ko and Lee (2015) argued that EPU is negatively associated with stock prices, exhibiting low- to high-frequency cycles. Wu et al. (2020) pointed out that crude oil is a major driver of co-movement between global stock markets in the median and long-term frequencies. Choi (2022) found evidence of interdependence between the global GPR and stock market volatilities of China, South Korea, and Japan in the short run. However, they found more co-movement between the global GPR and volatility of the Korean and Japanese stock market indices when filtering out for the Korean's GPR via the PWC method. Khan et al. (2023) found positive coherence in the oil and Islamic stocks nexus due to the global policy uncertainty. In general, they concluded that MWC provided a stronger correlation than PWC in the short, medium, and long term.

Mensi et al. (2023) showed evidence of time–frequency co-movements between the developed markets and the emerging BRICS economies with respect to other global risk factors at medium and low frequencies. Besides, they claimed that the degree of co-movement had increased during the 2008 global financial crisis as well as during COVID-19. Alkathery et al. (2023) reported that all global energy markets are weakly and positively correlated with the Gulf Cooperative Council (GCC) energy stock prices at lower frequencies. Besides, oil price was a stronger moderator for the GCC energy equities at lower frequencies relative to other global factors, especially for Kuwait's energy stock price. Mishra and Debasish (2022) found that the Chinese stock market experienced very little shocks in the short run and significant shocks in the long and medium run.

Altogether, although the existing studies have examined the impact of economic policy uncertainties with respect to other global risk factors on the connectedness among equity and oil markets, they have reported mixed and unconvincing evidence of such impact. The existing literature has mostly focused on the impact of economic uncertainty on price changes and returns, there is a lack of literature examining the effect of real economic uncertainty [business condition index (ADS) developed by Aruoba et al. (2009)] on the risk connectedness in the oil–equity nexus. Furthermore, one can also notice that they have not heavily focused on the effect of the COVID-19 crisis on the level of co-movements among global risk factors, and the risk spillover among oil and stock prices. Furthermore, although the literature has extensively used the EPU index

proposed by Baker et al. (2016), they overlooked the impact of the real economic uncertainty index [the business conditions index (ADS)] with respect to global risk factors on risk spillovers. Although the literature has focused on different methodologies, such as DCC-GARCH, the structural VAR model, the time-varying copula-GARCH-based CoVaR approach, the multivariate ARMA-GARCH approach, and wavelet multiresolution analysis, Quantile-VAR, and VAR-GARCH, the wavelet coherencies approaches (MWC and PWC) is still under-used in when it comes to the role of ADS on the risk transmission among oil and stock markets.

3 Methodology

Time-series analysis is conducted using the novel wavelet analysis, including partial wavelet coherency (PWC) and multivariate wavelet coherency (MWC), as suggested by Aguiar-Conraria et al. (2018a, 2018b) and Verona (2020). The PWC is used to examine for such effects when the influence of economic conditions as well as the economic policy uncertainty indices are filtered out. This methodology captures not only the time-varying information of spillovers but also allows one to estimate the magnitude across frequencies in a multivariate setting. PWC helps identify the resulting wavelet coherence between two-time series after eliminating the influence of their common dependence. Furthermore, PWC estimates the correlation and causal relationship between oil volatility and equity volatility, controlling for the influence of real economic activity. From the MWC model, it is possible to infer the wavelet coherence of multiple independents (i.e., the oil–stock nexus) on a dependent (i.e., economic conditions or economic policy uncertainty).

3.1 Realized volatility

The risk of oil and equity is measured by their realized volatility. The realized volatility is measured using the high-frequency (5-min intraday data) of the futures contracts. The quadratic variation method of Barndorff-Nielsen and Shephard (2004, 2006) is used to calculate the realized volatility of both markets. The existing body of literature widely concurs that employing high-frequency data for calculating realized volatility demonstrates superior performance compared to relying solely on daily returns (e.g., Martens 2001; Andersen et al. 2003; Koopman et al. 2005; Lyócsa, et al. 2021), and it has subsequently become popular in empirical studies for forecasting the volatility of oil and equity returns (e.g., Bollerslev and Zhou 2006; Corsi et al. 2008; Wei 2012; Souček and Todorova 2013; Sévi 2014; Luo and Ji 2018; Bonato et al. 2020; Cui et al. 2021a; Grønborg et al. 2022; Maghyereh et al. 2022a,b; Cui and Maghyereh 2022, 2023a,b; among many others).

Consider a logged price process p_t that evolves as a continuous Brownian motion:

$$p_t = \int_0^T \mu_s ds + \int_0^T \sigma_s dW_s \quad (1)$$

where μ_s is a predictable drift and locally bounded, σ_s is the continuous part of volatility, and W_s is a standard Brownian motion. If we sample M intraday observations for T days,

then over a fixed time span \bar{T} we have $M\bar{T}$ observations and the realized volatility (RV) at time t is defined as

$$RV_{t,\bar{T},M} = \sum_{i=1}^{M\bar{T}} \left(p_{t,\frac{i}{M}} - p_{t,\frac{i-1}{M}} \right)^2 \tag{2}$$

3.2 Wavelet methods

In this paper, we apply two wavelet-based techniques: PWC and MWC, as recently suggested by Aguiar-Conraria et al. et al. (2018a, 2018b) and Verona (2020). While MWC is useful for determining the coherence of multiple independent variables on the dependent variable, PWC can help to identify the wavelet coherence after removing the power of common dependence between two time series on the dependent variable.

Let x_{t1}, x_{t2} , and y_t be three-time series representing the realized volatility, respectively, and s refers to the smoothing operator on the cross-spectrum for both time and of oil, the realized volatility of equity, and the real economy/uncertainty proxies, respectively. The wavelet transformations of these time series are correspondingly defined as $W_t^{x1}(s)$, $W_t^{x2}(s)$, and $W_t^y(s)$, respectively, and s refers to the smoothing operator on the cross-spectrums for both time and frequency. Smoothing can be attained by complexity over time and scale, represented by $s(w) = s_{scale}(s_{time}(w(s)))$, where s_{scale} and s_{time} are smoothing on the wavelet scale axis and time, respectively. The cross-wavelet spectrum is correspondingly defined as W_t^{x1x2} , W_t^{yx1} , and W_t^{yx2} . According to Aguiar-Conraria et al. (2018a, 2018b) and Verona (2020), the PWC squared between x_{t1} and x_{t2} , after controlling for the third series y_t , can be defined as follows:

$$R_{x_{t1}x_{t2},y_t}^2 = \frac{R_{x_{t1},x_{t2}}^2 - R_{x_{t1},y_t} \overline{R_{x_{t2},y_t}}}{\sqrt{\left(1 - R_{x_{t2},y_t}^2\right)\left(1 - R_{x_{t2},y_t}^2\right)}} \tag{3}$$

where $R_{x_{t1},x_{t2}}$ is the wavelet coherency of x_{t1} and x_{t2} given by $R_{x_{t1},x_{t2}} = |S(W_{x_{t1},x_{t2}})| / \left[S(|W_{x_{t1}}|^2) S(|W_{x_{t2}}|^2) \right]^{0.5}$.

A similar interpretation to squared wavelet coherency $R_{x_{t1},x_{t2}}^2$, the squared PWC coefficient $R_{x_{t1}x_{t2},y_t}^2$ would satisfy $0 \leq R_{x_{t1}x_{t2},y_t}^2 \leq 1$ in the time–frequency space. A low level of $R_{x_{t1}x_{t2},y_t}^2$ at a high level of $R_{x_{t1},x_{t2}}^2$ implies that series x_{t1} has a no significant power (impact) on series x_{t2} and time series y_t dominates the variance of x_{t2} .

To extend and refine our results, we apply the squared MWC analysis. The MWC between the series y_t and the two series x_{t1} and x_{t2} with continuous wavelet transforms denoted by $R_{x_{t1}x_{t2},y_t}^2$ can be given by:

$$R_{x_{t1}x_{t2},y_t}^2 = \frac{R_{x_{t1},x_{t2}}^2 + R_{x_{t1},y_t}^2 - 2\Re(R_{x_{t1},x_{t2}} R_{x_{t1},y_t} \overline{R_{x_{t2},y_t}})}{1 - R_{x_{t2},y_t}^2} \tag{4}$$

where $R_{x_{t1},x_{t2}}$ is the wavelet coherency of x_{t1} and x_{t2} are as defined earlier.

Finally, since the theoretic distribution of the PWC and MWC coefficients is unknown, the statistical significance level of both analyses is estimated using Monte Carlo simulations.

4 Empirical findings

4.1 Data and preliminary analysis

The data cover two markets: the US equity market and the oil market. To measure the realized volatility for both markets, we use the intraday transaction prices of the futures contracts rather than the spot prices of the underlying assets. To represent US equity, we obtain the S&P 500 E-Mini Futures contract listed on the CME.² The oil market is represented by the oil 3-month futures traded on NYMEX, which control the future price per 1000 barrels of WTI crude oil.

The 5-min prices from the traded 3-month futures contracts are extracted using the last tick method. In particular, if the intraday price is not available at the 5-min time stamp, we use the last observed price. Near the maturity of each contract, we roll forward and extend the time series using the prices of the next 3-month traded contract. The continuous record of the transaction prices of the futures contracts on the two markets is obtained from Olsen Financial Technologies. From the continuous record, we compute the intraday returns and then the daily realized volatilities. The sample of daily volatility under study spans the period from January 2, 2007, to December 22, 2020, giving a total of 1087 days. For all days on which there are no prices (i.e., holidays), we assume that the previous day's volatility has not changed.

We use the ADS index of business conditions, proposed by Aruoba et al. (2009), as a proxy for the real economy of the United States. The index is designed to track real business conditions at a daily frequency. It is constructed from the (seasonally adjusted) high- and low-frequency blending of 50 economic indicators.³ The daily data for the ADS index are obtained from the Federal Reserve of Philadelphia.⁴ A number of recent studies have used this index, including Uluceviz and Yilmaz (2021) and Barunik et al. (2021).

For uncertainty proxies, we use the Baker et al. (2016) economic policy uncertainty (EPU) index and the Caldara and Iacoviello (2022) geopolitical risk (GPR) index. Both of these are available from the Federal Reserve Bank of St. Louis. The EPU index is derived from textual data in the form of news articles and media coverage of policy-related economic uncertainty.⁵ The GPR index is derived from automated text-search results that count the occurrence of words related to geopolitical tensions in leading international newspapers.⁶

² An index point move on the S&P500 contract represents \$250 profit and loss. The exposure to this contract is 250 times the index. This index is more liquid than traditional S&P500 futures contract.

³ The ADS index measures the state of the economy; a progressively higher positive value indicates that current real business conditions are progressively better than average conditions, whereas a progressively higher negative value indicates that real business conditions are progressively worse than average conditions.

⁴ <https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads>.

⁵ Detailed information about the calculation of the EPU is available at www.policyuncertainty.com and in the work of Baker et al. (2016).

⁶ For details about the calculation of the GPR, see the work of Caldara and Iacoviello (2022).

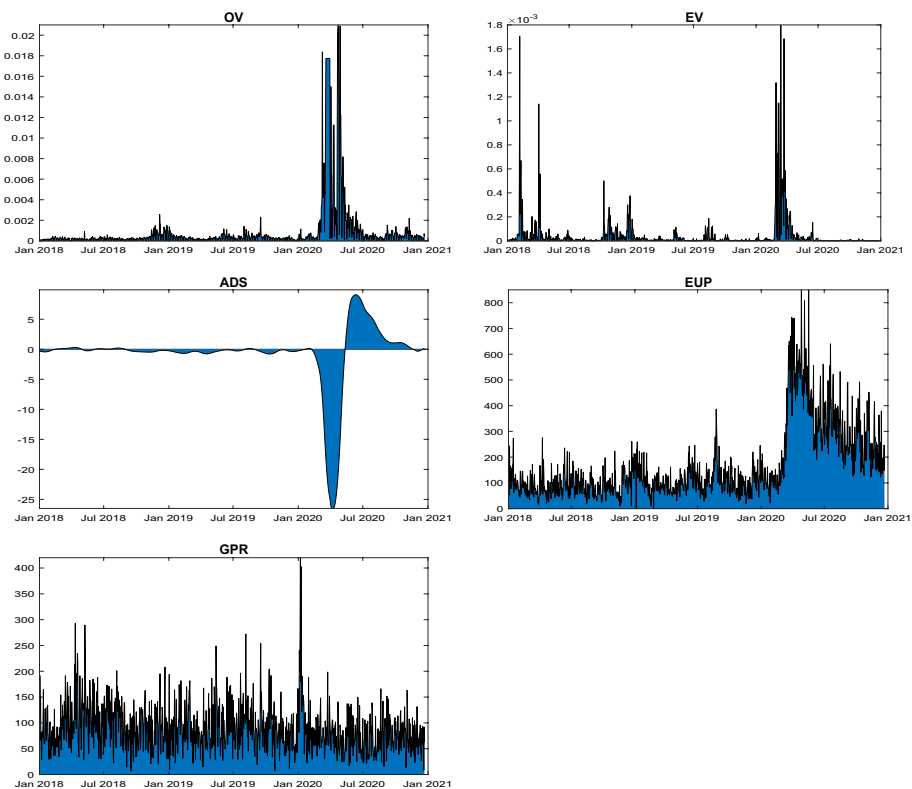


Fig. 1 Time series plot of daily data. The top two figures display the daily realized volatility of oil (OV) and equity (EV) estimated using high-frequency data from futures contracts, with a resolution of 5-min intervals. The bottom figures illustrate the daily business conditions index (ADS) proposed by Aruoba et al. (2009), the economic policy uncertainty index (EPU) developed by Baker et al. (2016), and the geopolitical risk index (GPR) introduced by Caldara and Iacoviello (2022)

Table 1 Descriptive statistics

	OV	EV	ADS	EPU	GPR
Mean	9.05E−04	4.46E−05	− 0.6328	167.0736	89.6235
Median	2.81E−04	6.42E−06	− 0.1860	115.0700	83.5358
Maximum	2.13E−02	2.00E−03	9.0799	861.1000	420.2932
Minimum	2.35E−07	0.0000	− 26.6504	4.0500	6.8074
Std. Dev	2.66E−03	1.61E−04	5.2141	138.5362	44.6327
Skewness	5.5261	7.8518	− 3.1545	1.8224	1.4660
Kurtosis	34.8817	76.5461	15.6965	6.3413	8.6619
Jarque–Bera	51568.8***	256153.1***	9103.8***	1107.4***	1841.3***

OV realized volatility of crude oil, EV realized volatility of equity, ADS Aruoba–Diebold–Scotti index of business conditions, EPU economic policy uncertainty index, GPR geopolitical risk index

*** Indicates significant 1% level

Figure 1 plots the daily evolution of each variable over the sample period. All the series show positive and significant return shocks, particularly during the COVID-19 crisis. The exception is ADS, which has more high shocks in relation to negative returns than positive shocks. This indicates that the COVID-19 pandemic played a significant role in the behavior of all the series. Table 1 gives the summary descriptive

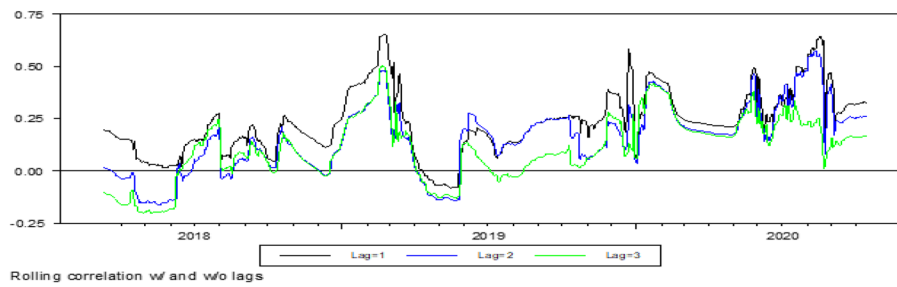


Fig. 2 Rolling window correlation. This figure presents 365-day rolling correlation at different lags length between realized volatility of oil (OV) and equity (EV)

statistics. Almost all of the series show positive mean values, and ADS is the only variable with a negative mean value and negative skewness. EPU has the lightest standard deviation, while equity volatility (EV) has the lowest standard deviation and the highest kurtosis value. We note that all of our series show significant evidence of non-normality.

Figure 2 shows a 360-day rolling correlation between realized volatilities in the two markets [oil (OV) and equity (EV)] at different lag lengths. The figure shows a bivariate of both the direction and strength of correlation between variables over time. The direction of correlation among these variables is mostly positive over the sample period, including during the early stages of the COVID-19 pandemic period, except in some cases where the correlation was negative and weak (e.g., in the first part of 2018 and around the middle of 2019). The strong positive correlations among of oil and equity volatilities indicate that shocks of both assets move in the same direction, which can be considered disadvantages to investors who always attempt to diversity of the risk of their portfolios via allocating assets with weak and negative correlations in their portfolios. In general and in normal markets conditions, investors in the US market can trade-off between oil and equity, to reduce investment weight in one of these assets, or substitute one another, obtain the optimal risk-return profile. Our results are consistent with the findings of Cui et al. (2021a, b), Mensi et al. (2022), Younis et al. (2023) and Escribano et al. (2022) who argued that correlation between crude oil and international equity markets increased widely in normal and crises conditions, but contradict the findings of Razmi and Razmi (2023) who pointed out that the US stock market lost its significant influence on the crude oil market after COVID-19.

However, it seems that the US investors were advantageous when investing in both assets at once during the 2018–2019 US–China trade war due to the negative correlation among oil and equity markets. Given the US is considered as an oil producer and at the same time a heavy importer of oil and has highly developed stock markets, whereas China is mostly a crude oil importer with emerging stock markets, the US investors could be given the opportunities to efficiently trade-off between crude oil and stocks when allocating their assets for profitable investments. Thus, due to the global pressure placed on oil and stock prices during 2018 and 2019, in some cases

the correlation between both assets turned to be negative and weak, allowing investors to use both assets as hedgers to portfolio risk.

We also see evidence of a strong correlation among the subject variables from the beginning of the COVID-19 crisis (confirmed as a health crisis by the World Health Organization in March 2020) up to June 2020. From that point on, which saw an increase in the number of people around the world vaccinated against COVID-19, the correlation remained positive and strong. However, the correlation later dropped significantly, with a noticeable difference between the level of correlation of lag = 3 and the level of correlation of lags = 1 and 2. This indicates that the shocks caused by the crisis following the introduction of the vaccine had a slower effect on the volatilities in comparison to the early stages of the crisis. The interpretation of the strong positive correlation in the first stage of the COVID-19 crisis is that people were subject of fear and anxiety during the crises where the epidemic trend refused to smooth out. The coronavirus sharply increased spread generating in a substantial number of death cases around the globe, where the total number of death cases suddenly increased from 17 to around 4700 cases within January 2020 and then to around 6,500,600 cases in the mid of March 2020 (the day of confirming coronavirus as a pandemic).

Furthermore, the reaction of the global healthcare system to COVID-19 was very weak due to being entirely overwhelmed by the infected cases. During COVID-19, people were required to reside at home (and do their work duties from home) with very limited social interactions. People around the globe were cautious about spread of the virus because they were unable to pay for healthcare services. They were also facing a deliberate suspension of normal healthcare procedures, a less care for COVID-19 patients, and the general lockdown of the healthcare services that prevent hospitals from providing the normal service provision. All these negative consequences caused a higher pressure in all markets, particularly the crude oil and stock markets. The impact of COVID-19 led to a sharp increase in the price volatilities of many assets including crude oil and stocks, where in some dates crude oil prices dropped to below than zero during the pandemic period.

However, when the coronavirus vaccination was introduced at a later time, investors seemed to start re-gaining their confidence in both markets (equity and crude oil) where prices of crude oil and stocks were started to recover, leading to a large reduction in the correlation among both markets. Our results are confirmed by the findings of Cui et al. (2021a, b) and Mensi et al. (2022) who stated that global crises, such as, GFC, the 2014 oil price collapse and COVID-19 had greatly contributed to the increase in correlation between oil and equity markets. To conclude, the correlation among oil and equity volatility behave differently across the sample periods, especially within periods of trade tension and health crises, supporting the possibility of the presence correlation waves and the use of wavelet coherence analysis.

To investigate the stationarity of our series, we apply four conventional unit root tests. The outputs of the stationarity tests are presented in Table 2. The results reveal that our series are all stationary at I(0). Further, we investigate the stationary of our series using the wavelet-based Fourier ADF (WADF) unit root test recently proposed by Aydin (2019) and Aydin and Pata (2020). Table 3 reports the results of the WADF test and shows that, for all the time series, we are unable to reject the null hypothesis of a unit

Table 2 Conventional unit root tests

	ADF	PP	KPSS	DF-GLS
OV	- 4.2866***	- 9.4769***	0.5720	0.4937
EV	- 5.2893***	- 23.0522***	0.0965	0.7417
ADS	- 3.6788***	- 3.0951**	0.1051	1.0564
EPU	- 2.9261**	- 8.3792***	0.0780	1.8874
GPR	- 5.8253***	- 25.2106***	0.3788*	0.5795

ADF augmented Dickey-Fuller test with null hypothesis that a unit root is present, PP Phillips-Perron test with null hypothesis that a unit root is present, KPSS Kwiatkowski-Phillips-Schmidt-Shin test with null hypothesis of stationary around a deterministic trend, DF-GLS Elliott-Lothberg-Stock test with the null hypothesis of a unit root against the alternative of stationarity. The optimal lag lengths (p) were selected automatically using the SIC

*, **, and *** denote the significant levels at 10%, 5%, and 1%, respectively

Table 3 Wavelet-based Fourier ADF unit root test

	Test statistics	t-statistics	k	p
OV	- 5.2134	- 2.8602***	1	2
EV	- 6.5952	- 2.8762***	3	2
ADS	- 7.1965	- 3.1538***	2	7
EPU	- 4.9619	- 2.6509**	3	5
GPR	- 3.8291	- 2.0825**	1	6

The optimal lag lengths (p) were selected automatically using the SIC. k indicates the frequency of the Fourier term. %1, %5, and %10 critical values of t-statistics are 2.85, 2.01, and 1.60, respectively. All critical values were obtained using Monte Carlo Simulation with 250 observations and 10,000 replications and k = 1, 2, 3, 4, 5

*, **, and *** denote the significant levels at 10%, 5%, and 1%, respectively

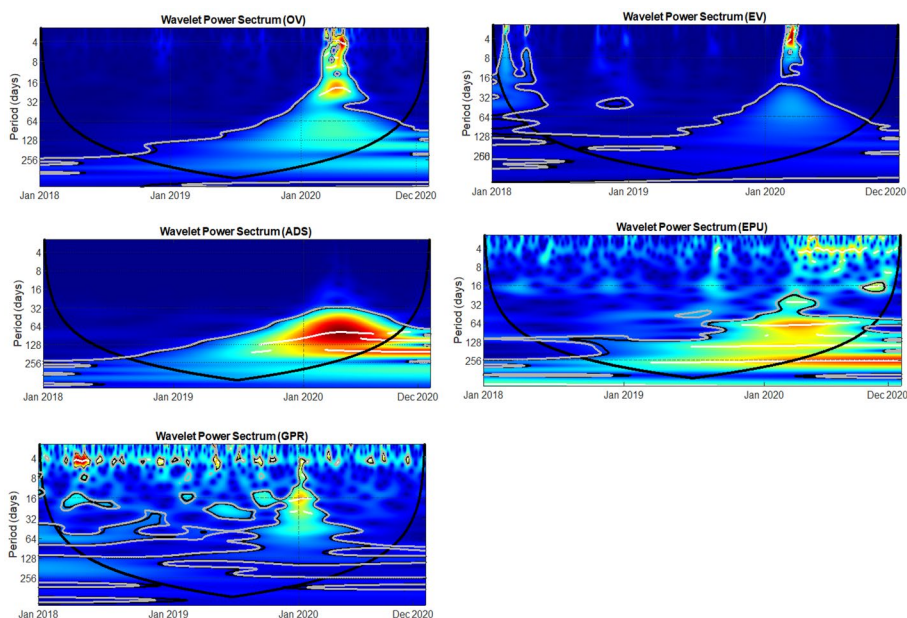


Fig. 3 Wavelet power spectrums (WPS) of the time series. The hotter colors such as yellow and red correspond to higher volatility level, and colder colors such as green and blue correspond to lower volatility level. A contours black line represents statistically significant areas at 5% level, where the significance values are generated through Monte Carlo simulations

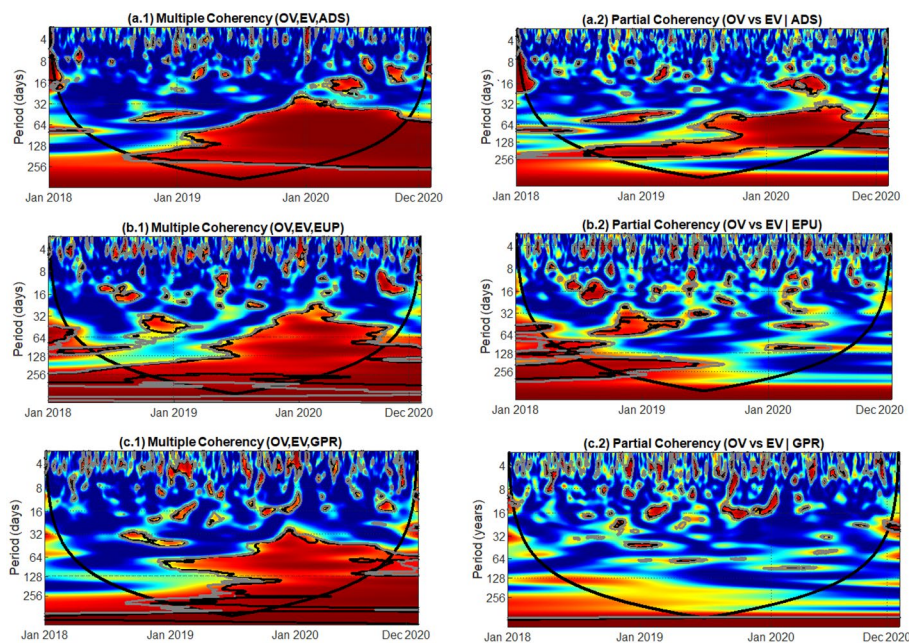


Fig. 4 Multiple wavelet coherence (MWC) and partial wavelet coherence (PWC). The figure plots the multiple wavelet coherence (left graph)) and partial wavelet coherence (right graph) between the oil and equity volatilities. The hotter colors such as yellow and red correspond to higher coherence, and colder colors such as green and blue correspond to lower coherence. A contours black line represents statistically significant areas at 5% level, where the significance values are generated through Monte Carlo simulations

root, even after accounting for the influence of nonlinear factors. This confirms that the adoption of wavelet analysis is more appropriate than the use of regression-based econometric methods.

In Fig. 3, we plot the wavelet power spectrums (WPS) of each time series. In these charts (as well as in the coherency in the following section), the horizontal axis represents time, and the vertical axis reports period frequency (in days). The warm/hot colors (yellow and red) correspond to higher variability accumulation and coherency level, the colder colors (green and blue) correspond to lower variability accumulation and coherency level, and the white lines indicate the local maxima of the WPS. The significance level of the WPS at 5% against red noise is represented by the contours of the black line. We see both OV and EV, as well as GPR, exhibit statistically significant high levels of local variability, with a frequency range of less than 16 days, which corresponds to the entire first wave of COVID-19 from March 15 to June 30. Similarly, the WPS of ADS and EPU was high and statistically significant, with a frequency of 32–128 days between the period of the first wave of COVID-19 and around October 2020. This indicates that difference in the degree of coherencies across the variability of the subject variables at lower and higher frequencies is present even within the COVID-19 crisis wave.

4.2 Wavelet analysis

This section presents the results of partial and multiple wavelet analyses. The left side of Fig. 4 shows the MWC of the volatility oil–stock nexus and the ADS, EUP, and GPR indices. The MWC represents the combined impact of the OV and each of the ADS,

EUP, and GPR indices on equity volatility. In general, in the first wave of the period, the MWC graphs (a.1, b.1, and c.1) show higher coherencies for the combined impact of the OV and each of the ADS, EPU, and GPR indices on EV in the short run (at a lower frequency of 1–16 days). However, the intensity of coherencies is different across indices, as the combined impact of the OV and each of EPU and GPR on EV is more intense than the cone of coherency for the combined impact of the OV and ADS on EV. This due to the serious impact of the COVID-19 pandemic on GPR which was largely higher than on the US's EPU and ADS, confirming the findings of Sharif et al. (2020) and Kamal et al. (2022). We also notice higher coherency at the top left of the ADS and GPR graphs for the period between the end of 2017 and 2018, which reflects the serious political and trade tensions between the US and North Korea at the time, as well as the US–China trade war. This is can be interpreted as that ADS and GPR had a quicker and a higher impact of the transmission among oil and stocks in the short run in periods of trade and political tensions compared to the impact of the US's EPU which had a higher impact in the period of health crisis. This is due to that ADS has the ability to track the daily real business conditions, is highly liquid compared to futures contracts and is constructed from the (seasonally adjusted) high- and low-frequency blending of 50 economic indicators. One reason for the quicker impact of ADS relates the federal government's attempt to report on regulatory activities and speed up regulatory approvals for businesses and the other relates to the financial compensations offered to businesses due to devastating cyclones and their followed geopolitical and geographical disasters between 2017 and 2019. Furthermore, given the US geopolitical tension and increasing public policy disputes in the US, GRP seems to be highly correlated with the risk transmission of the oil–stock nexus more than EPU at lower frequencies.

In the medium and high range of frequencies (from more than 16 to 256), we see strong coherency in the period of the health crisis for the combined impact of OV and all the uncertainty indices on EV. This strong MWC is found from the beginning of 2019 until the end of October 2020, which is consistent not only with the severe effects of the COVID-19 pandemic but also with the other economic and trade conflicts across the globe, especially between China and the US, the two largest economies. Other causes underlying the high sensitivity (coherencies) are the multiple tropical cyclones in the US and the US presidential election. At frequencies in the long run (more than 128 days), we notice that coherency remains strong for the whole sample period, but that the level of coherency increases during the COVID-19 pandemic, from the beginning of 2020 until October 2020. In the long run, therefore, there is strong evidence that MWC is driven not only by transitory short-term shocks but also by fundamental factors. Our results are consistent with the findings of Choi (2022), who reported strong coherencies between GRP and stock market volatility in East Asian countries. The COVID-19 pandemic caused major negative consequences to the global community which had led all the US risk factors to greatly correlate with the risk transmission among crude oil and stock prices in the long run. The negative consequences are the temporary lockdown of business daily actions, work from home with very limited social contacts and reduction in employees' income. In some cases, people were also encountering deliberate suspensions of healthcare from obtaining the normal service provision, particularly for COVID-19 infected individuals.

The right side of Fig. 4 shows the PWC between the volatility oil–stock nexus of each of the ADS, EUP, and GPR indices in graph form (a.2, b.2, and c.2, respectively). The PWC represents the wavelet coherence between OV and EV after filtering out the effect of each on the real economic uncertainty variable. The PWC between the risk connect- edness oil–stock nexus conditional to the ADS index is shown in (a.2), conditional to EPU in (b.2) and conditional to GRP in (c.2).

Although the PWC is strong and significant for the entire sample period up to fre- quencies of 16 days, its intensity increases in comparison to the MWC for all the graphs in Fig. 4. This means that using one of the real economic uncertainty indices while filter- ing out the effect of the other two indices leads to a slight increase in the wavelet coher- encies at low frequencies. However, at medium term (frequencies of 16–64 days), we see different results for PWC across the sample period. The results of PWC for the oil–stock volatility conditional on ADS (as in a.2) exhibit greater coherence during the COVID- 19 crisis. However, although the PWC for the oil–stock volatility conditional on ADS increases in the long run (frequencies of 64–256), isolating EPU and GRP reduces the magnitude of PWC in the long term to less than those reported in MWC.

The results of PWC conditional only on the effect of EPU (as in 2.b) show a decrease in coherency in the medium term at frequencies of 64–128 days, and the level of coher- ency varies over the sample period. In the long-run, we notice a significant decrease in the partial coherencies after controlling only for the effect of EPU at the second stage of the COVID-19 crisis (mid 2019 until October 2020). However, during the first wave of the crisis, the PWC clearly increased at higher frequencies (greater than 128 days). Thus, the isolation of the effects of ADS and GRP led to a change in the PWC results during the COVID-19 crisis. The decrease in the PWC during 2019 and 2020 is also caused by filtering out the effects of ADS and GRP.

When the effect of GRP is included (after removing the effects of ADS and EPU), our results reveal that the PWC between the OV and EV significantly decreases in both the medium term (at frequencies less than 64 days) as well as the long term (at frequencies greater than 64 days) for the entire sample period, including the COVID- 19 crisis. Therefore, our results are conditional only on the effect of GRP, which gives a significantly lower partial wavelet coherence during the health crisis in comparison to MWC. This shows that ADS and EPU had a big impact on the increase in the intensity of PWC during the crisis. This suggests that the PWC is caused by more than just the COVID-19 effect, such as by the real economic uncertainty indices. The most influen- tial uncertainties during the health crisis are the risk of business conditions and the US economic policy uncertainty. During the crisis period, increased uncertainties related to business conditions and economic factors led to higher risk aversion among investors. This heightened risk aversion, in turn, resulted in increased volatility in both the oil and stock markets. The higher volatility in these markets, stemming from the uncertainties, enhanced the coherence between the volatility of the oil–stock nexus. Our results are in- line with the findings of Mensi et al. (2023), Wnag et al. (2022), Yuan et al. (2022), Khan et al. (2023) and Choi (2022).

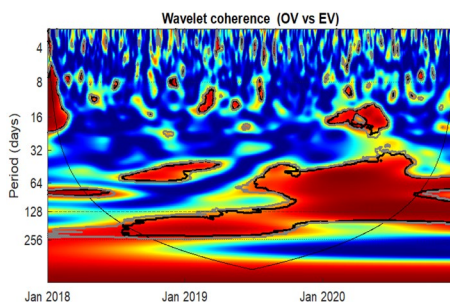


Fig. 5 Bivariate wavelet coherence (WTC). The figure plots the bivariate wavelet coherence (WTC) between the oil and equity volatilities. The hotter colors such as yellow and red correspond to higher coherence, and colder colors such as green and blue correspond to lower coherence. A contours black line represents statistically significant areas at 5% level, where the significance values are generated through Monte Carlo simulations

4.3 Robustness check

To check the robustness of our findings we perform bivariate wavelet coherence (WTC). This method estimates the wavelet coherence between the volatility oil–stock nexus without filtering out the effect of the real economic uncertainty. In brief, let x_t and y_t be two time series that reflect the realized volatility of oil and realized volatility of stock, respectively. The wavelet transformation of these time-series is correspondingly defined as $W_t^x(s)$, and $W_t^y(s)$, respectively. Then the wavelet coherence squared between x_t and y_t can be defined as follows (See, for instance, Maghyereh et al., et al. (2020), Maghyereh and Abdoh (2021), Kartal et al. (2023), and Cui and Maghyereh (2023a,b) for further technical details):

$$R^2_{x_t,y_t} = \frac{|S(W_{x_t,y_t})|^2}{S(|W_{x_t}|^2 S|W_{y_t}|^2)} \tag{5}$$

The squared wavelet coherence coefficient $R^2_{x_t,y_t}$ is ranged between 0 and 1 (with 1 representing the highest coherence). The statistical significance of WTC is calculated using Monte Carlo simulations.

Figure 5 plots the WTC among the two variables. We notice significant risk connect- edness in the oil–stock nexus in the medium run (16–64-week cycles), which becomes stronger around turbulence episodes. These findings confirm the results from the MWC shown in Fig. 4. As in the previous results, volatility transmission between oil and equi- ties increased significantly and was much higher than PWC, thereby confirming the prior findings that real economic uncertainty is a crucial factor driving the risk connect- edness among stock markets and the oil market.

5 Conclusion

The paper contributed to the time–frequency domain by examining the impact of real economic uncertainty on the risk connectedness among oil and stock prices during the COVID-19 pandemic period, using the multiple and the partial wavelet coherence anal- yses. The wavelet methods allow to isolate the effect of different global risk indices (such

as the US economic uncertainty index (EPU), the crude oil volatility index (OVX) and the geopolitical risk index (GPR)) on the level of risk connectedness. Our analysis found that the real economic uncertainty has strong multiple and partial wavelet coherencies on the risk connectedness in the equity–oil nexus during the COVID-19 crisis. Although strong evidence of multiple wavelet coherencies was detected during the health crisis, different results were found for the partial wavelet coherencies analysis. Conditional to each uncertainty indices individually, we found significant and higher PWC at lower frequencies in the entire sample period, but the intensity of PWC became lesser at the medium frequencies with an evidence during the crisis. However, conditional to of the effect of ADS, PWC increased at higher frequencies during the crisis.

Overall, our findings provide some interesting and useful recommendations for investors, regulatory authorities, and policymakers. For investors, the strong coherencies between real economic uncertainty and risk connectedness in the equity–oil nexus during the COVID-19 crisis suggest that investors should carefully consider economic uncertainty indicators when making investment decisions. Monitoring and analyzing these indicators can provide valuable insights into the interconnectedness of risks and help investors anticipate and navigate market fluctuations more effectively. During periods of high uncertainty, investors can hedge the unsystematic risk of their investments, by hold more stocks that are not highly influenced by oil prices. For regulatory authorities and policymakers, the strengthening regulations related to market surveillance, risk assessment, and disclosure requirements can enhance market transparency and resilience, particularly during times of crisis. Furthermore, the increase coherencies at higher frequencies during the crisis, conditional on the effect of business conditions, suggests the importance of implementing timely crisis-specific interventions that fostering investor confidence and ensuring stable economic indicators to manage short-term risks and support market resilience.

Acknowledgements

The authors thank and are incredibly grateful to the Journal's editor and for anonymous referees for their effort and valuable comments. Their suggestions and recommendations have significantly improved the quality of the paper. The Article Processing Charge was covered by the funds of PAPAIOIS and JSPS (KAKENHI Grant Number JP 21HP2002).

Author contributions

MA-S: conceptualization, investigation, methodology, literature review, results and discussion, validation, resources, writing—original draft, Writing—review and editing. AM: conceptualization, data curation, methodology, formal analysis, results and discussion, writing—review and editing, software, validation.

Funding

The Article Processing Charge was covered by the funds of PAPAIOIS and JSPS (KAKENHI Grant Number JP 21HP2002).

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests

The authors declare that they have no known competing financial and nonfinancial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 9 November 2022 Revised: 23 August 2023 Accepted: 24 August 2023

Published online: 07 September 2023

References

- Aguiar-Conraria L, Martins MMF, Soares MJ (2018a) Estimating the Taylor rule in the time-frequency domain. *J Macroecon* 57:122–137. <https://doi.org/10.1016/j.jmacro.2018.05.008>
- Aguiar-Conraria L, Soares MJ, Sousa R (2018b) California's carbon market and energy prices: a wavelet analysis. *Philos Trans R Soc A Math Phys Eng Sci* 376:20170256. <https://doi.org/10.1098/rsta.2017.0256>
- Aguilera RF, Radetzki M (2017) The synchronized and exceptional price performance of oil and gold: explanations and prospects. *Resour Policy* 54:81–87. <https://doi.org/10.1016/j.resourpol.2017.09.005>
- Albulescu CT, Mutascu MI (2021) Fuel price co-movements among France, Germany and Italy: a time-frequency investigation. *Energy* 225:120236. <https://doi.org/10.1016/j.energy.2021.120236>
- Ali SRM, Mensi W, Anik KI (2022) The impacts of COVID-19 crisis on spillovers between the oil and stock markets: evidence from the largest oil importers and exporters. *Econ Anal Policy* 73:345–372. <https://doi.org/10.1016/j.eap.2021.11.009>
- Alkathery MA, Chaudhuri K, Nasir MA (2023) Dependence between the GCC energy equities, global clean energy and emission markets: evidence from wavelet analysis. *Energy Econ* 121:106659. <https://doi.org/10.1016/j.eneco.2023.106659>
- Andersen TG, Bollerslev T, Diebold FX, Labys P (2003) Modeling and forecasting realized volatility. *Econometrica* 71:579–625
- Arouri MEH, Jouini J, Nguyen DK (2011a) Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *J Int Money Financ* 30:1387–1405
- Arouri MEH, Lahiani A, Nguyen DK (2011b) Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Econ Model* 28:1815–1825. <https://doi.org/10.1016/j.econmod.2011.03.012>
- Arouri MEH, Jouini J, Nguyen DK (2012) On the impacts of oil price fluctuations on European equity markets: volatility spillover and hedging effectiveness. *Energy Econ* 34:611–617. <https://doi.org/10.1016/j.eneco.2011.08.009>
- Aruoba SB, Diebold FX, Scotti C (2009) Real-time measurement of business conditions. *J Bus Econ Stat* 27:417–427. <https://doi.org/10.1198/jbes.2009.07205>
- Awartani B, Maghyereh A, Cherif G (2016) The connectedness between crude oil and financial markets: evidence from implied volatility indices. *J Commod Mark* 4:56–69. <https://doi.org/10.1016/j.jcomm.2016.11.002>
- Awartani B, Javed F, Maghyereh A, Virk N (2018) Time-varying transmission between oil and equities in the MENA region: New evidence from DCC-MIDAS analyses. *Rev Dev Financ* 8:116–126. <https://doi.org/10.1016/j.rdf.2018.11.001>
- Aydin M, Pata UK (2020) Are shocks to disaggregated renewable energy consumption permanent or temporary for the USA? Wavelet based unit root test with smooth structural shifts. *Energy* 207:118245. <https://doi.org/10.1016/j.energy.2020.118245>
- Bahloul S, Khemakhem I (2021) Dynamic return and volatility connectedness between commodities and Islamic stock market indices. *Resour Policy* 71:101993. <https://doi.org/10.1016/j.resourpol.2021.101993>
- Baker SR, Bloom N, Davis SJ (2016) Measuring economic policy uncertainty. *Q J Econ* 131:1593–1636. <https://doi.org/10.1093/qje/qjw024>
- Barbi M, Macovei OI (2020) The impact of macroeconomic uncertainty on the stock-bond nexus: evidence from the G7 countries. *J Int Finan Markets Inst Money* 67:101169
- Barndorff-Nielsen OE (2004) Power and bipower variation with stochastic volatility and jumps. *J Financ Econom* 2:1–37. <https://doi.org/10.1093/jffnec/nbh001>
- Barndorff-Nielsen OE, Shephard N (2006) Econometrics of testing for jumps in financial economics using bipower variation. *J Financ Econom* 4:1–30. <https://doi.org/10.1093/jffnec/nbi022>
- Barunik J, Bevilacqua M, Faff RW (2021) Dynamic industry uncertainty networks and the business cycle. *SSRN Electron J*. <https://doi.org/10.2139/ssrn.3768370>
- Babar M, Ahmad H, Yousaf I (2022) Information transmission between energy commodities and emerging Asian stock markets during crises: an analysis of oil importing countries. *Asia-Pacific Journal of Business Administration*. <https://doi.org/10.1108/APJBA-02-2022-0061>
- Bekaert G, Engstrom E, Grenadier S (2010) Stock and bond returns with Moody investors. *J Empir Financ* 17(5):867–894
- Belhassine O, Karamti C (2021) Volatility spillovers and hedging effectiveness between oil and stock markets: evidence from a wavelet-based and structural breaks analysis. *Energy Econ* 102:105513. <https://doi.org/10.1016/j.eneco.2021.105513>
- Bin KJ, Wohar M, Bin KK (2022) Do gold, oil, equities, and currencies hedge economic policy uncertainty and geopolitical risks during covid crisis? *Resour Policy* 78:102920. <https://doi.org/10.1016/j.resourpol.2022.102920>
- Bloom N (2009) The impact of uncertainty shocks. *Econometrica* 77(3):623–685
- Boako G, Alagidede IP, Sjo B, Uddin GS (2020) Commodities price cycles and their interdependence with equity markets. *Energy Econ* 91:104884. <https://doi.org/10.1016/j.eneco.2020.104884>
- Bollerslev T, Zhou H (2006) Volatility puzzles: a sample framework for gauging return-volatility regressions. *J Econom* 131(1e2):123e50
- Bonato M, Gupta R, Lau CKM, Wang SX (2020) Moments-based spillovers across gold and oil markets. *Energy Econ* 2020(89):104799
- Boubaker H, Raza SA (2017) A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. *Energy Econ* 64:105–117. <https://doi.org/10.1016/j.eneco.2017.01.026>
- Balassa B (1985) Exports, policy choices, and economic growth in developing countries after the 1973 oil shock. *J Dev Econ* 18: 23–35. [https://doi.org/10.1016/0304-3878\(85\)90004-5](https://doi.org/10.1016/0304-3878(85)90004-5)
- Caldara D, Iacoviell M (2022) Measuring geopolitical risk. *Am Econ Rev* 112:1194–1225. <https://doi.org/10.1257/aer.20191823>
- Caldara D, Iacoviello M, Molligo P (2020) The economic effects of trade policy uncertainty. *J Monet Econ* 109:38–59. <https://doi.org/10.1016/j.jmoneco.2019.11.002>
- Cenesizoglu T (2022) Return decomposition over the business cycle. *J Bank Financ* 143:106592

- Cesa-Bianchi A, Rebucci A (2017) Uncertainty spillovers from Japan to the US: evidence from the stock and bond markets. *J Int Money Financ* 77:205–223
- Choi SY (2022) Evidence from a multiple and partial wavelet analysis on the impact of geopolitical concerns on stock markets in North-East Asian countries. *Financ Res Lett* 46:102465. <https://doi.org/10.1016/j.frl.2021.102465>
- Corsi F, Mittnik S, Pigorsch C, Pigorsch U (2008) The volatility of realized volatility. *Econ Rev* 27(1e3):46e78
- Cui J, Maghyereh A (2022) Time–frequency co-movement and risk connectedness among cryptocurrencies: new evidence from the higher-order moments before and during the COVID-19 pandemic. *Financ Innov* 8:90. <https://doi.org/10.1186/s40854-022-00395-w>
- Cui J, Maghyereh A (2023) Time-frequency dependence and connectedness among global oil markets: fresh evidence from higher-order moment perspective. *J Commod Markets* 30:100323. <https://doi.org/10.1016/j.jcomm.2023.100323>
- Cui J, Maghyereh A (2023) Higher-order moment risk connectedness and optimal investment strategies between international oil and commodity futures markets: insights from the COVID-19 pandemic and Russia-Ukraine conflict. *Int Rev Financ Anal* 86:102520. <https://doi.org/10.1016/j.irfa.2023.102520>
- 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. <https://doi.org/10.1016/j.energy.2020.119302>
- Cui J, Maghyereh Goh M, Zou H (2021) Risk spillovers and time-varying links between international oil and China's commodity futures markets: fresh evidence from the higher-order moments. *Energy* 238:121751. <https://doi.org/10.1016/j.energy.2021.121751>
- Dai Z, Zhu H (2023) Dynamic risk spillover among crude oil, economic policy uncertainty and Chinese financial sectors. *Int Rev Econ Financ* 83:421–450. <https://doi.org/10.1016/j.iref.2022.09.005>
- Das D, Kumar SB (2018) International economic policy uncertainty and stock prices revisited: multiple and Partial wavelet approach. *Econ Lett* 164:100–108. <https://doi.org/10.1016/j.econlet.2018.01.013>
- Dhaene G, Wu J (2020) Incorporating overnight and intraday returns into multivariate GARCH volatility models. *J Econom* 217:471–495. <https://doi.org/10.1016/j.jeconom.2019.12.013>
- Diebold FX (2020). Real-time real economic activity: exiting the great recession and entering the pandemic recession, PIER Working Paper Archive 20–023, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania
- Driesprong G, Jacobsen B, Maat B (2008) Striking oil: another puzzle? *J Financ Econ* 89:307–327. <https://doi.org/10.1016/j.jfneco.2007.07.008>
- Escribano A, Koczar MW, Jareno F, Esparcia C (2022) Shock transmission between crude oil prices and stock markets. *SSRN Electron J* 83:103754. <https://doi.org/10.2139/ssrn.4065300>
- Fang L, Chen B, Yu H, Xiong C (2018) The effect of economic policy uncertainty on the long-run correlation between crude oil and the U.S. stock markets. *Financ Res Lett* 24:199–220. <https://doi.org/10.1016/j.frl.2017.07.007>
- Forbes KJ, Rigobon R (2002) No contagion, only interdependence: measuring stock market comovements. *Journal of Finance* 57(5):2223–2261
- Frankel JA, Saravelos G (2012) Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis. *J Int Econ* 87(2):216–231
- Gomes FJ, Kotlikoff LJ, Viceira LM (2012) The excess burden of government indecision. *Tax Policy Econ* 26:125–164. <https://doi.org/10.1086/665505>
- Grønberg NS, Lunde A, Olesen KV, Elst HV (2022) Realizing correlations across asset classes. *J Financ Markets* 59:100729
- Hamilton JD (1983) Oil and the macroeconomy since World War II. *J Polit Econ* 91:228–248. <https://doi.org/10.1086/261140>
- Hkiri B, Hammoudeh S, Aloui C, Shahbaz M (2018) The interconnections between U.S. financial CDS spreads and control variables: New evidence using partial and multivariate wavelet coherences. *Int Rev Econ Financ* 57:237–257. <https://doi.org/10.1016/j.iref.2018.01.011>
- Huang RD, Masulis RW, Stoll HR (1996) Energy shocks and financial markets. *J Futur Mark* 16:1–27. [https://doi.org/10.1002/\(sici\)1096-9934\(199602\)16:1%3c1::aid-fut1%3e3.3.co;2-g](https://doi.org/10.1002/(sici)1096-9934(199602)16:1%3c1::aid-fut1%3e3.3.co;2-g)
- Hung NT, Vo XV (2021) Directional spillover effects and time-frequency nexus between oil, gold and stock markets: evidence from pre and during COVID-19 outbreak. *Int Rev Financ Anal* 76:101730. <https://doi.org/10.1016/j.irfa.2021.101730>
- Jurado K, Ludvigson SC, Ng S (2015) Measuring uncertainty. *Am Econ Rev* 105(3):1177–1216
- Kang W, Ratti RA (2013) Oil shocks, policy uncertainty and stock market return. *J Int Financ Mark Inst Money* 26:305–318. <https://doi.org/10.1016/j.intfin.2013.07.001>
- Kang W, Ratti RA (2015) Oil shocks, policy uncertainty and stock returns in China. *Econ Transit* 23:657–676. <https://doi.org/10.1111/ecot.12062>
- Karanasos M, Yfanti S (2021) On the economic fundamentals behind the dynamic equicorrelations among asset classes: global evidence from equities, real estate, and commodities. *J Int Financ Markets Inst Money* 74:101292
- Kartal MT, Kirikkaleli D, Ayhan F (2021) Nexus between non-performing loans and economic growth in emerging countries: evidence from Turkey with wavelet coherence approach. *Int J Financ Econ* 28:1250–1260
- Khan MA, Khan F, Sharif A, Suleman MT (2023) Dynamic linkages between Islamic equity indices, oil prices, gold prices, and news-based uncertainty: new insights from partial and multiple wavelet coherence. *Resource Policy* 80:103213. <https://doi.org/10.1016/j.resourpol.2022.103213>
- Kinkyo T (2022) The intermediating role of the Chinese renminbi in Asian currency markets: evidence from partial wavelet coherence. *North Am J Econ Financ* 59:101598. <https://doi.org/10.1016/j.najef.2021.101598>
- Ko J-H, Lee C-M (2015) International economic policy uncertainty and stock prices: wavelet approach. *Econ Lett* 134:118–122. <https://doi.org/10.1016/j.econlet.2015.07.012>
- Koopman SJ, Jungbacker B, Hol E (2005) Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *J Empir Financ* 12(3):445–475

- Liao J, Zhu X, Chen J (2021) Dynamic spillovers across oil, gold and stock markets in the presence of major public health emergencies. *Int Rev Financ Anal* 77:101822. <https://doi.org/10.1016/j.irfa.2021.101822>
- Luo J, Ji Q (2018) High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. *Energy Econ* 76:424e38
- Lyócsa S, Molnár P, Výrost T (2021) Stock market volatility forecasting: do we need high-frequency data? *Int J Forecast* 37:1092–1110
- Maghyereh A, Abdoh H (2021) Time–frequency quantile dependence between Bitcoin and global equity markets. *North Am J Econ Financ* 56:101355
- Maghyereh A, Abdoh H (2022) Connectedness between crude oil and US equities: the impact of COVID-19 pandemic. *Ann Finan Econ* 17(4):2250029
- Maghyereh A, Awartani B, Bouri E (2016) The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes. *Energy Econ* 57:78–93
- Markowitz H (1952) Portfolio selection. *The Journal of Finance* 7:77–91. [www.jstor.org.proxy.lib.chalmers.se/stable/10.2307/2975974?origin=api\(2012-1030\)](http://www.jstor.org.proxy.lib.chalmers.se/stable/10.2307/2975974?origin=api(2012-1030))
- Maghyereh A, Basel A, Abdoh H (2020) The effects of investor emotions sentiments on crude oil returns: a time and frequency dynamics analysis. *Int Econ* 162:110–124
- Maghyereh A, Abdoh H, Basel A (2022a) Have returns and volatilities for financial assets responded to implied volatility during the COVID-19 pandemic? *J Commod Mark* 26:100194
- Maghyereh A, Awartani B, Virk NV (2022b) Asymmetric risk transmissions between oil, gold and US equities: recent evidence from the realized variance of the futures prices. *Resour Policy* 79:103108
- Martens M (2001) Forecasting daily exchange rate volatility using intraday returns. *J Int Money Financ* 20(1):1–23
- Mensi W, Al-Yahyaee KH, Vo XV, Kang SH (2021) Modeling the frequency dynamics of spillovers and connectedness between crude oil and MENA stock markets with portfolio implications. *Econ Anal Policy* 71:397–419. <https://doi.org/10.1016/j.eap.2021.06.001>
- Mensi W, Al Rababaa AR, Vo XV, Kang SH (2021) Asymmetric spillover and network connectedness between crude oil, gold, and Chinese sector stock markets. *Energy Econ* 98:105262. <https://doi.org/10.1016/j.eneco.2021.105262>
- Mensi W, Naeem MA, Vo XV, Kang SH (2022) Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: implications for risk management. *Econ Anal Policy* 73:331–344. <https://doi.org/10.1016/j.eap.2021.11.015>
- Mensi W, Rehman MU, Al-Yahyaee KH, Vo XV (2023) Frequency dependence between oil futures and international stock markets and the role of gold, bonds, and uncertainty indices: evidence from partial and multivariate wavelet approaches. *Resour Policy* 80:103161. <https://doi.org/10.1016/j.resourpol.2022.103161>
- Miller JI, Ratti RA (2009) Crude oil and stock markets: Stability, instability, and bubbles. *Energy Econ* 31:559–568. <https://doi.org/10.1016/j.eneco.2009.01.009>
- Mishra S, Debasish SS (2022) Exploring relationship between crude oil price volatility and stock indices movement using wavelet analysis: evidence from India and China. *Vilakshan XIMB J Manag* 19:69–86. <https://doi.org/10.1108/xjm-11-2020-0204>
- Mork KA (1989) Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. *J Polit Econ* 97:740–744. <https://doi.org/10.1086/261625>
- Papapetrou E (2001) Oil price shocks, stock market, economic activity and employment in Greece. *Energy Econ* 23:511–532. [https://doi.org/10.1016/S0140-9883\(01\)00078-0](https://doi.org/10.1016/S0140-9883(01)00078-0)
- Pástor L, Veronesi P (2012) Uncertainty about government policy and stock prices. *J Financ* 67:1219–1264. <https://doi.org/10.1111/j.1540-6261.2012.01746.x>
- Pástor L, Veronesi P (2013) Political uncertainty and risk premia. *J Financ Econ* 110:520–545. <https://doi.org/10.1016/j.jfineco.2013.08.007>
- Razmi SF, Razmi SMJ (2023) The role of stock markets in the US, Europe, and China on oil prices before and after the COVID-19 announcement. *Resour Policy* 81:103386. <https://doi.org/10.1016/j.resourpol.2023.103386>
- Roll R (2013) Volatility, correlation, and diversification in a multi-factor world. *J Portf Manag* 39:11–18. <https://doi.org/10.3905/jpm.2013.39.2.011>
- Sévi B (2014) Forecasting the volatility of crude oil futures using intraday data. *Eur J Oper Res* 235(3):643–659
- Sharif A, Aloui C, Yaroyaya L (2020) COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int Rev Financ Anal* 70:101496. <https://doi.org/10.1016/j.irfa.2020.101496>
- Sharma GD, Tiwari AK, Jain M et al (2021) Unconditional and conditional analysis between covid-19 cases, temperature, exchange rate and stock markets using wavelet coherence and wavelet partial coherence approaches. *Heliyon* 7:e06181. <https://doi.org/10.1016/j.heliyon.2021.e06181>
- Souček M, Todorova N (2013) Realized volatility transmission between crude oil and equity futures markets: a multivariate HAR approach. *Energy Econ* 40:586–597
- Uddin GS, Rahman ML, Shahzad SJH, Rehman MU (2018) Supply and demand driven oil price changes and their non-linear impact on precious metal returns: a Markov regime switching approach. *Energy Econ* 73:108–121. <https://doi.org/10.1016/j.eneco.2018.05.024>
- Uluvezir E, Yilmaz K (2021) Measuring real–financial connectedness in the U.S. economy. *North Am J Econ Financ* 58:101554. <https://doi.org/10.1016/j.najef.2021.101554>
- Verona F (2020) Investment, Tobin's Q, and cash flow across time and frequencies. *Oxf Bull Econ Stat* 82:331–346. <https://doi.org/10.1111/obes.12321>
- Wang X, Wang Y (2019) Volatility spillovers between crude oil and Chinese sectoral equity markets: evidence from a frequency dynamics perspective. *Energy Econ* 80:995–1009. <https://doi.org/10.1016/j.eneco.2019.02.019>
- Wang Y, Wei M, Bashir U, Zhou C (2022) Geopolitical risk, economic policy uncertainty and global oil price volatility—an empirical study based on quantile causality nonparametric test and wavelet coherence. *Energy Strateg Rev* 41:100851. <https://doi.org/10.1016/j.esr.2022.100851>

- Wei Y (2012) Forecasting volatility of fuel oil futures in China: GARCH-type, SV or realized volatility models? *Physica A* 391:5546–5556
- Wu K, Zhu J, Xu M, Yang L (2020) Can crude oil drive the co-movement in the international stock market? Evidence from partial wavelet coherence analysis. *North Am J Econ Financ* 53:101194. <https://doi.org/10.1016/j.najef.2020.101194>
- You W, Guo Y, Zhu H, Tang Y (2017) Oil price shocks, economic policy uncertainty and industry stock returns in China: asymmetric effects with quantile regression. *Energy Econ* 68:1–18. <https://doi.org/10.1016/j.eneco.2017.09.007>
- Younis I, Shah WU, Yousaf I (2023) Static and dynamic linkages between oil, gold and global equity markets in various crisis episodes: evidence from the Wavelet TVP-VAR. *Resour Policy* 80:103199. <https://doi.org/10.1016/j.resourpol.2022.103199>
- Yousaf I, Hassan A (2019) Linkages between crude oil and emerging Asian stock markets: New evidence from the Chinese stock market crash. *Finance Research Letters* 31 (4):207–217. <https://doi.org/10.1016/j.frl.2019.08.023>
- Yuan D, Li S, Li R, Zhang F (2022) Economic policy uncertainty, oil and stock markets in BRIC: evidence from quantiles analysis. *Energy Econ* 110:105972. <https://doi.org/10.1016/j.eneco.2022.105972>
- Zhang D (2017) Oil shocks and stock markets revisited: measuring connectedness from a global perspective. *Energy Econ* 62:323–333. <https://doi.org/10.1016/j.eneco.2017.01.009>
- Zhao W, Wang YD (2022) On the time-varying correlations between oil-, gold-, and stock markets: the heterogeneous roles of policy uncertainty in the US and China. *Pet Sci* 19:1420–1432. <https://doi.org/10.1016/j.petsci.2021.11.015>

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Mohammad Al-Shboul is currently working as an Associate Professor of Finance. His research work is published in well-respectable international academic Journals in different areas of Research, including Financial Economics, Banking Performance, Islamic Banking, International Finance and Corporate Finance.

Aktham Maghyereh is currently working as a Professor in Finance and Banking with more than 100 publications in well-respectable international Journals, which are distributed in different areas of Research, including Financial Economics, Energy Economics, International Finance, Banking Performance and Islamic Banking.

Submit your manuscript to a SpringerOpen[®] journal and benefit from:

- ▶ Convenient online submission
- ▶ Rigorous peer review
- ▶ Open access: articles freely available online
- ▶ High visibility within the field
- ▶ Retaining the copyright to your article

Submit your next manuscript at ▶ [springeropen.com](https://www.springeropen.com)
