Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Oil and Risk in a Pandemic: Time Frequency Evidence from WTI, OVX, SPX, and DXYs

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Funding information:
Institute of Technology and Business in České Budějovice

How to cite this article:
Vochozka, M., Kayathingal, H. and Shebalkova, Y. (2026). Oil and Risk in a Pandemic: Time Frequency Evidence from WTI, OVX, SPX, and DXYs. *Acta Monstanistica Slovaca,* Volume 31 (1), 102-110

DOI:
https://doi.org/10.46544/AMS.v31i1.08

Abstract
We study the comovements among oil prices, equities, the U.S. dollar, and oil-specific volatility both in the pre-COVID-19 and COVID-19 periods. Using daily data for 2018–2021 (WTI, S&P 500, DXY, OVX), we compare 2019 with 2020 and measure comovement with wavelet coherence, summarizing short (2–16 trading days), medium (16–64), and long (64–128) horizons. We filter out results that are not statistically significant and outside the cone of influence, and perform an approximate partial test whereby we purge oil and OVX of contemporaneous equity and dollar effects. First, oil–volatility comovement is strong in 2019 and even stronger in 2020, particularly at long horizons; phase arrows depict many anti-phase patches (oil down, volatility up). Second, the oil–equity relationship shifts toward longer horizons in 2020, but medium-horizon comovement is less pervasive after masking. Third, the oil–dollar relationship is more fragile and intermittent, with no stable long-horizon strength pattern in 2020. The partial test corroborates that the stronger oil–volatility association remains after controls. The results suggest that risk management depends on the time horizon: OVX is a strong hedging indicator for downside oil risk in crises, equity–oil comovement is higher for slower cycles, and the dollar provides limited long-horizon diversification in times of stress. Overall, these findings support horizon-dependent risk management, where OVX offers a strong hedge signal, equity–oil comovement matters mainly at slower cycles, and the dollar provides little long-horizon diversification under stress.

Keywords
Wavelet coherence, WTI, OVX, S&P 500, DXY, COVID-19

Introduction

Oil markets lie at the heart of macro-financial risk, as shocks ripple through growth, inflation, and portfolios. The average correlations can be misleading, as cross-market interdependence evolves over time and across horizons, suggesting the use of tools that capture time variation and frequency specificity (Rua & Nunes, 2009). Time–frequency techniques address this issue by estimating co-movement in time and scale, allowing the sign and persistence of co-movements to be monitored (Vacha & Barunik, 2012). Wavelet coherence is quite appropriate for this purpose as it adjusts cross-power by the local variance and exposes localised correlation, which can be compared across horizons (Torrence & Compo, 1998). The cross-wavelet and coherence framework also provides phase information that helps distinguish in-phase, anti-phase, and lead–lag behavior, which is crucial for interpretation and policy (Grinsted et al., 2004).

The COVID-19 shock induced strong and time-varying co-movements between oil, equities, uncertainty, and the dollar, which calls for an approach that extracts relevant time–frequency co-movement "islands" (Sharif et al., 2020). oil–dollar linkages are regime dependent, revolve around the nominal or real status of exchange rates, and causality is primarily from nominal exchange rates to nominal oil price (Beckmann & Czudaj, 2013). The recent literature on connectedness also reveals that transmission is different over short, medium, and long-term cycles, which again highlights the importance of frequency decomposition-based analysis (Baruník & Křehlík, 2018). Since the outbreak of the COVID-19 pandemic, global stock markets have plummeted to unprecedented levels of uncertainty (Lyócsa et al., 2020). A recent paper has shown that the COVID-19 pandemic has adverse effects on the economy and the financial markets, and reinforces the sensitivity, in particular between oil and stock markets, and economic condition and uncertainty (Managi et al., 2022).

Oil volatility indicators such as OVX hold information on risk premiums along the oil supply chain and have linkages with the rest of the economy, especially during periods of turmoil (Li et al., 2022). OVX is the main source of uncertainty in spot variances on both WTI and Brent, with a more pronounced impact on Brent and a relatively stronger feedback from WTI to OVX (Benedetto et al., 2020). Earlier studies report structural breaks and a post-break reduction in oil–equity correlations, which is evidence of time-varying transmission that warrants a time–frequency analysis for the WTI–S &P 500 linkage (Lu et al., 2021).

Studying oil market price fluctuations not only allows researchers to deepen the complex dynamics of the crude oil market, such as its overnight momentum and return patterns, but it also offers valuable information for high-frequency traders and investors considering trading or investing in oil products. It also presents more detailed information for policymakers to gain a better understanding of the process of high-frequency trading in the oil market. (Alqaralleh, 2024).

Most of the analyses either focus on the oil–equity or oil–dollar relationships in isolation, are based on single-horizon models, and rarely account for oil-implied volatility (OVX), and as a consequence, they do not capture how these markets co-move over time and across horizons, mostly during the COVID-19. Few studies report on whether the WTI–OVX connection holds when controlling for the effect of equities (S&P 500) and the dollar (DXY), and provide phase-based interpretation (in-/anti-phase, lead–lag) with COI and significance filters. We employ wavelet coherence with masked band-averages and an approximate partial step (controlling for SPX and DXY) to establish statistically strong, horizon-specific evidence on WTI's interactions with OVX, SPX, and DXY before vs during COVID-19.

Global financial markets are significantly impacted by the COVID-19 epidemic (Zhang et al., 2020). So our first research question is:

RQ1: How did the comovement between oil prices and the three markets, oil volatility, equities, and the dollar change from 2019 to 2020 across short, medium, and long horizons?

Oil option-implied volatility predicts weaker economic growth and is contemporaneously related to flightcen-tral oil inventories, lower oil consumption and oil products, and lower equity prices, suggestive of a precautionary-inventory channel through oil (Gao et al., 2022).

RQ2: Does the strong oil volatility link in 2020 remain after controlling for equities and the dollar, and at which horizons is it most pronounced?

Literature Review

Crude oil is a key commodity, but also a significant driver of economic activity, affecting the prices of inflation, costs of production, and profits of businesses (Cui et al., 2025). Rising crude oil prices affect oil-importing nations severely, and their GDP moves closely with the US dollar (Bilal et al., 2024). Over the past decades, many researchers have analyzed crude oil prices through different empirical methods. (Yang et al., 2022). The volatile crude oil price, which is consumed as a production cost or a component of production cost directly or indirectly in many industries, complicates the business investment decision. (Chen et al., 2024).

Wavelet coherence plots localized co-movement and phase so researchers can analyze strength, direction, and lead–lag over horizons (Grinsted et al., 2004). In energy markets, wavelet coherence offers scale-dependent, dynamic relationships among leading commodities (Vacha & Barunik, 2012). Using transfer entropy and wavelet partial coherence, evidence shows two-way information flow between EU ETS carbon prices and crude oil volatility—carbon-price surges raise oil volatility, while pandemic oil volatility pushed carbon prices down (Olasehinde-Williams, 2024).

Sharma & Rani, (2025) Use wavelet coherence to examine time- and scale-dependent co-movements in crude oil prices and ESG indices between leading Asian economies and discover dynamic interconnectedness. Using partial and multiple wavelet coherence, Wu et al., (2020) illustrates how global equity markets co-move once the effect of crude oil is controlled for over time and scale. Muhmmad & Ali, (2024) uses wavelet coherence on Saudi daily data and determines that COVID-19 and oil price shocks raise stock-market volatility overwhelmingly at short/low-frequency horizons, and the effect of COVID-19 is stronger compared to oil, revealing a sharp crisis and triggering policy responses.

The global economy has been severely impacted by the COVID-19 pandemic (Olujobi et al., 2022).The COVID-19 global pandemic has caused widespread economic and social disruption (McKibbin & Fernando, 2023). COVID-19 studies using wavelet tools record abrupt, time-varying linkages between oil, equities, uncertainty, and the dollar (Sharif et al., 2020). Global crude oil prices dropped by 65.96% from $69.25/barrel in January 2020 to $23.57/barrel in June 2020. West Texas Intermediate (WTI) reached −$36.98/barrel in March 2020, one of the highest in recent times (Mwape et al., 2024). Sectoral evidence suggests that pandemic uncertainty altered volatilities in equity horizons in specific ways (Choi, 2020). The oil-dollar relationship is dependent on the regime and is sensitive to whether it is measured in nominal or real terms (Beckmann & Czudaj, 2013). The oil-exchange rate dependence is significant but changing across different market phases and tails (Aloui et al., 2013). Reboredo & Rivera-Castro, (2014) employs wavelet multi-resolution decomposition and wavelet cross-correlation and indicates no effect of oil on stock returns pre-crisis (except oil & gas); but during the global financial crisis uncovers contagion and positive interdependence, a bidirectional lead–lag relationship that is scale-dependent. Ghazani et al., (2024) applies Diebold–Yilmaz spillover indices and Baruník–Křehlík frequency-domain connectedness, along with rolling-window estimation and wavelet coherence to capture the time- and frequency-varying connectedness in returns and volatilities among oil, equity, and crypto markets in COVID-19.

Granger causality in risk by using VaR and detects significant asymmetric risk spillovers between the S&P 500 and WTI: pre-crisis, the spillovers from stocks to oil are positive and from oil to stocks are negative; post-crisis, bidirectional positive spillovers are much stronger and spillovers can be contemporaneous or with lags (Du & He, 2015). Choi & Hong,(2020) Applied implied volatility indices and found that OVX and VIX have two-way causality solely in the shale-revolution era, OVX leads to VKOSPI only in the shale-revolution era, and VIX unidirectionally causes VKOSPI in both eras, indicating time-varying volatility linkages of interests to risk management. Siddiqui & Hasim, (2024) tests the transmission of COVID-19's infectivity to crude oil using MS-GARCH and BEKK-GARCH, enriched with PCA-based risk factors and controlled regressions.

The wavelet coherence method is based on wavelet analysis and serves as a measure of the extent of causal or dynamical dependencies between two time series across different time scales. That is, it shows the interaction of the variables on low, medium, and high temporal scales. (Magzumov & Kumral, 2024). Compared with other traditional econometric models that estimate the parameters either at one or at most two time scales, wavelet analysis is free of any model assumptions and enables one to analyze the time series simultaneously in the frequency and time domains. These all contribute to making the wavelet framework much better than the traditional frequency methods (Tiwari et al., 2020). Therefore, we adopt wavelet coherence in this study to capture time- and scale-specific linkages that classic models miss, providing a model-free, joint time–frequency view of oil, equities, the dollar, and oil-volatility dynamics.

Material and Methods

All data were obtained only from Yahoo Finance with a daily frequency. The data set consists of (i) WTI front-month futures, continuous series (ticker CL=F), (ii) the S&P 500 price index (ticker ^GSPC), (iii) the U.S. Dollar Index (DXY) (Yahoo Finance listings: DX-Y.NYB, DX=F, or ^DXY), and (iv) the Cboe Crude Oil Volatility Index (OVX) (ticker ^OVX). The observation period is from 1 January 2018 to 31 December 2021, which gives a broad enough window to reduce the end effect in the time–frequency analysis while accommodating a regime comparison between pre-COVID (2019) and during-COVID (2020). For each sequence, the closing quotation is kept, the series are synchronized on the common trading days, and the log-returns are calculated for further processing.

For a standardized series $x(t)$, the CWT with complex Morlet mother wavelet is

$$W_x(r,s) = \int x(t) \frac{1}{\sqrt{s}} \psi_0^* \left(\frac{t-r}{s}\right) dt \tag{1}$$

Where:

$W_x(r,s)$ complex wavelet coefficient at time r and scale s.

ψ_0 Mother Wavelet
$(.)^*$ Complex conjugate
t Sampling step in trading days

We use the complex Morlet wavelet,

$$\psi_0(\eta) = \pi^{-1/4}\, exp(i\omega_0\eta)\, exp\,(^{-n^2}/_2) \tag{2}$$

Where:
η Is the nondimionsinal time
ω_0 Central frequancy
i Is the imaginary unit

Scale is mapped to Fourier period via the Morlet Fourier factor:

$$\lambda\,(s) = s\frac{4\pi}{\omega_0 + \sqrt{2+\omega_0^2}} \tag{3}$$

, which allows us to label the vertical axis in period (days) rather than scale. The wavelet power of x is $|W_x(r,s)|^2$.

Finite-length samples induce edge effects; the cone of influence (COI) indicates the region where estimates are reliable. For the Morlet wavelet, the e-folding time of the autocorrelation of the wavelet is $\sqrt{2}\,s$; outside the COI, power and coherence are down-weighted in inference and masked in summaries.

Cross-wavelet transform, phase, and coherence

The cross-wavelet transform between x and y is

$$W_{xy}(r,s) = W_x(r,s)W_s^*(r,s) \tag{4}$$

Its modules $\left|W_{xy}(r,s)\right|$ measure localized co-variation, and its argument

$$\phi_{xy}(r,s) = arg\,(W_{xy}(r,s)) \tag{5}$$

is the phase difference, which we visualize with arrows: rightward ≈ in-phase (positive comovement), leftward ≈ anti-phase (negative), and up/down ≈ lead–lag near a quarter cycle.

We use squared wavelet coherence, a localized squared correlation after smoothing in time and scale. Let S { · } denote the standard smoothing operator (convolution in time and in log-scale appropriate to the Morlet wavelet). Squared coherence is

$$R_{xy}^2 = (r,s) = \frac{\left|S\{s^{-1}W_{xy}(r,s)\}\right|^2}{S\{s^{-1}|W_x(r,s)|^2\}S\{s^{-1}\left|W_y(r,s)\right|^2\}}, 0 \le R_{xy}^2 \le 1. \tag{6}$$

Where:
R_{xy}^2 squared coherence
S standard PyCWT smoothing operator
s^{-1} scale normalization used by PyCWT.

Significance testing and masking

Statistical significance is assessed scale-by-scale against a red-noise null (AR(1)) following Torrence–Compo-style inference. Le R_{crit}^2(s) denote the 95% critical coherence at scale s. A time–scale point is (r,s) deemed significant if $R_{xy}^2(r,s) \ge R_{crit}^2(s)$ and (r,s) lies inside the COI. We overlay significance contours and the COI on all WTC plots, and we enforce both when constructing band summaries.

Band-averaged coherence

To produce interpretable metrics, we compute band-averaged coherence over three bands commonly used in financial applications:

- Short: $B_1 = (2,16)$ trading days
- Medium: $B_2 = (16,24)$ trading days
- Short: $B_3 = (64,128)$ trading days

Where:
B_1, B_2, B_3 Bands chosen to reflect commontrading/investment horizons

For a band B, define the set of admissible points

$$\mathcal{A}_B = \{(r,s){:}\lambda\,(s) \in B, R_{xy}^2(r,s) \ge R_{crit}^2(s)\ inside\ COI$$

and compute the masked band average

$$\overline{R_{xy}^2}(B) = \frac{1}{|\mathcal{A}_B|} \sum_{(R,S)\epsilon\mathcal{A}_B} R_{xy}^{(r,s)} \tag{7}$$

Where,

COI	safe time–scale points with period in B
$\overline{R_{xy}^2}(B)$	Band level summary

Approximate partial wavelet coherence

To account for contemporaneous linear effects of equity and dollar factors on WTI and OVX, we compute WTC on residuals after regression on controls:

$$y_t = Z_1\beta_y + \varepsilon_t^y, \qquad x_t = Z_t\beta_x + \varepsilon_t^x \tag{8}$$

$$\widetilde{y_t} = \varepsilon_t^y, \quad \widetilde{x_t} = \varepsilon_t^x \Rightarrow R_{\tilde{x}\,\tilde{y}}^2(r,s) \tag{9}$$

Where,

y_t	WTI returns
x_t	OVX returns
$\beta_y\beta_x$	OLS coefficents
$\varepsilon_t^y, \varepsilon_t^x$	Residuals
$\widetilde{y_t}, \widetilde{x_t}$	standardized residual series used in place of y_t and x_t
$R_{\tilde{x}\,\tilde{y}}^2$	wavelet coherence of residuals

All transforms and statistics are computed with PyCWT's wct using the Morlet wavelet with ω_0 scale resolution $d_j = 1/12$, sampling step $\Delta t = 1$ trading day, and the library default smallest scale s 0 s 0 implied by the Fourier factor. Plots use a logarithmic period axis (inverted so longer periods plot lower). Significance contours and the COI boundary are overlaid; arrows indicate phase only within significant regions.

Results

Figure 1 shows how each pair moves together over time and across different horizons. The colors denote the intensity of the connection.. The white lines indicate significance at the 5% level. The dashed curve shows areas near the edges where results are less reliable in the WTI–OVX panels; the significance regions are wide in 2019 and become wider in 2020. The color is deeper in 2020, particularly in the long run. Arrows often point left in significant regions. This means WTI and OVX move in opposite directions in those patches. When oil prices fall, implied oil volatility tends to rise. In the WTI–SPX panels, strong regions appear and disappear over time. In 2020, they appeared more at long periods. This shows the equity–oil link shifted toward slower cycles during the pandemic. In the WTI–DXY panels, there are fewer strong regions. The long-period area in 2020 does not remain significant inside the cone of influence. This means the dollar–oil relationship is weaker and not persistent at low frequencies in 2020.

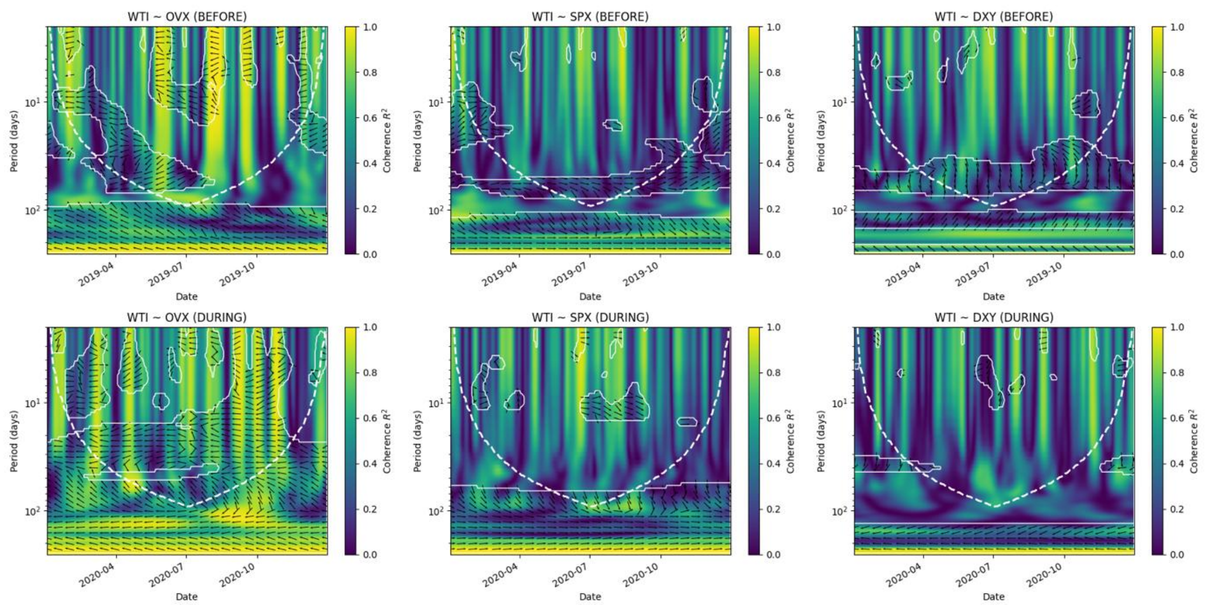

Figure 1. WTI with OVX, SPX, and DXY (2019 vs 2020)

Note: Pairwise wavelet coherence between WTI and OVX, SPX, and DXY. 2019 is the top row, and 2020 is the bottom row. Colors show coherence R^2. White contours mark 95% significance. The dashed curve is the cone of influence. Arrows show the phase.

Table 1 corroborates this visual message. For WTI and OVX, we observe a rising trend in averages in all bands from 2019 to 2020, and the strongest average at long periods in 2020 for both series. For WTI and SPX, the long band is elevated in both years, but the medium band is lower and less pervasive in 2020. For WTI and DXY, the long band is not significant in 2020, indicating weak long-term co-movement with the dollar at low frequencies.

Table 1. Band-averaged WTC (COI- & 95% significance-masked)

Regime	Pair	Short (2–16d)	Medium (16–64d)	Long (64–128d)
BEFORE	WTI ~ OVX	0.749	0.679	0.615
BEFORE	WTI ~ SPX	0.691	0.685	0.721
BEFORE	WTI ~ DXY	0.685	0.731	0.665
DURING	WTI ~ OVX	0.769	0.797	0.881
DURING	WTI ~ SPX	0.694	0.613	0.722
DURING	WTI ~ DXY	0.689	0.631	n.s.

Notes: n.s. is the no time–time-scale points in the band that survive the COI and 95% significance mask. Periods are trading days. Parameters as in Figure 1.

Figure 2 illustrates co-movement between oil prices (WTI) and oil implied volatility (OVX) once we remove the influence of two major market factors: the stock market (SPX) and the dollar (DXY). First, we regress WTI and OVX on SPX and DXY. We then calculate coherence on the residuals. The left panel is from 2019. The right panel is 2020. Color shows the magnitude of the connection (R2). Warm colors represent stronger connections. White contours delineate regions in which a five-percent level of statistical significance is attained. The dashed curve shows the cone of influence, which confines areas near the borders where the computations have higher edge effects. Arrows represent the phase: the right arrow is moving together, the left arrow is moving opposite, up or down arrows indicate a lead-lag of approximately a quarter cycle.

In 2019, there are prominent patches, but they are smaller and more dispersed. They occur multiple times and in a variety of horizons. In 2020, substantial patches turned out to be larger and more persistent, in particular at medium (roughly 16–64 trading days) and long (roughly 64–128 trading days) horizons. These bands have deeper colors, which indicates more time–frequency coupling. The pattern suggests the oil volatility link has strengthened during COVID, despite the comovement of equities and the dollar. Several arrows within the major clusters point to the left, showing an anti-phase relation: the oil price fall co-occurs with volatility surges. In sum, the figure shows a strong and increasing oil volatility connection in 2020, particularly at the medium and long horizons, and robust to the inclusion of stocks and the dollar.

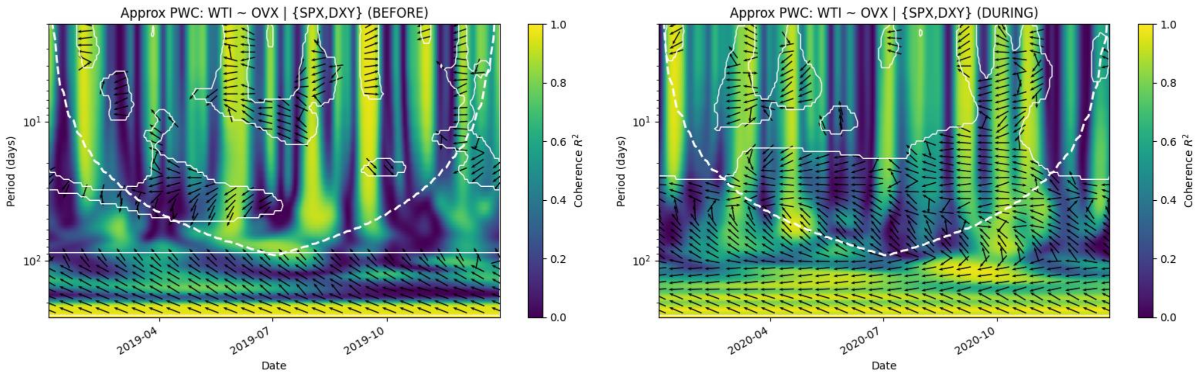

Figure 2. WTI–OVX Coherence After SPX & DXY Controls

Table 2 shows the mean coherence between oil prices (WTI) and oil implied volatility (OVX) once the contemporaneous linear influence of the stock market (SPX) and the U.S. dollar (DXY) is partialled out. Coherences are averaged over three time bands, expressed in trading days: short (2–16), medium (16–64), and long (64–128). Only the points falling within the cone of influence and significant at the 5% level are reported. The 2019 averages are 0.744 for the short band, 0.679 for the medium band, and 0.659 for the long bandIn 2020, averages increase to 0.760 in the short band, 0.807 in the medium band, and 0.894 in the long band. These figures indicate that the oil–volatility relationship intensifies during COVID, controlling for equities and the dollar. The upward bias is small over short horizons, but is large over medium and long horizons. The long-horizon value of approximately 0.89 in 2020 suggests a very strong and persistent relationship at a slower cycle. Therefore, Table 2 suggests that crisis-period forces specific to oil markets deepened the WTI–OVX relationship beyond what can be explained by stock and dollar movements.

Table 2. Partial Wavelet Coherence (WTI–OVX) Controlling for SPX and DXY: Band Averages

Regime	Short (2–16d)	Medium (16–64d)	Long (64–128d)
BEFORE	0.744	0.679	0.659
DURING	0.760	0.807	0.894

Discussion

RQ1: How did the comovement between oil prices and the three markets—oil volatility, equities, and the dollar-change from 2019 to 2020 across short, medium, and long horizons?

The oil prices (WTI) and the oil implied volatility (OVX) co-movement became stronger in 2020 for all horizons. Much was moved at long horizons. The wavelet coherence plots show more significant regions in 2020. This is in line with a crisis situation where oil price drops conform to volatility spikes. The band-averaged results confirm this pattern. For WTI–OVX, short, medium, and long bands all increase, with the largest increase at long horizons.

The comovement of WTI and the S&P 500 (SPX) moves toward the long end of the horizon in 2020. Significant regions at medium horizons are less pervasive after we apply masking. This says that slow-moving, macro channels were predominant in equity-oil transmission in the year of the pandemic.

The correlation between WTI and the U.S. Dollar Index (DXY) is relatively weak in 2020. Long-horizon coherency will no longer be significant after applying the cone-of-influence and significance mask. This implies that the sustained low-frequency dollar–oil connection did not persist in the year of the pandemic.

In short, the crisis re-formulated cross-market dependencies. Oil and oil volatility were more strongly correlated over the time–frequency domain. Oil and equities co-moved but only at long horizons. The relationship between oil and the dollar is much weaker and sporadic, particularly in the low frequencies.

RQ2: Does the strong oil volatility link in 2020 remain after controlling for equities and the dollar, and at which horizons is it most pronounced?

Yes. The oil volatility link remains strong after we remove the contemporaneous linear effects of the stock market and the dollar. We achieve this by regressing WTI and OVX on SPX and DXY and calculating coherence on the residuals. The residual-based coherence maps indicate that significant areas remain in 2019 and even grow in 2020. The expansion is most evident at medium and long-term horizons.

The band-averaged partial results the largest such increases are indeed found at medium and long horizons. The numbers for 2020 are elevated and show a substantial increase from 2019. So, the stronger link is not just a result of co-movement with equities or the dollar. These are oil-specific factors that turned out to be more important in the crisis era. These have included disruptions to supply, storage , and inventories, as well as reassessments of risk premia in oil options.

In general, the partial analysis favors a strong conclusion. The oil- volatility link strengthened in 2020, and the impact is even stronger in slower cycles. This lends further support to the economic interpretation that in times of crisis, oil market mechanisms strengthen the relationship between oil price and implied volatility more than broad equity and dollar factors are able to capture.

Conclusion

This paper studied the comovements in oil prices, equities, the U.S. dollar, and oil-specific volatility pre- and during COVID-19 through the wavelet coherence. We concentrate on 2019 (pre-COVID) and 2020 (during COVID). We condense the time–frequency maps via band-averaged quantities at the short, medium, and long term horizons. We also incorporate an approximate partial step to account for simultaneous equity and dollar influences while examining the oil–volatility relationship.

Three results stand out. First, the link between WTI and OVX strengthened in 2020 across all horizons and was strongest at long horizons. Phase patterns in significant regions showed many anti-phase patches, which is consistent with oil price declines coinciding with volatility spikes. Second, the WTI–SPX link shifted toward longer horizons in 2020, while medium-horizon comovement became less pervasive once we enforced the cone of influence and significance masks. Third, the WTI–DXY link was weaker and more episodic, and it did not persist at long horizons in 2020 under strict masking. The residual-based (approximate partial) analysis showed that the stronger WTI–OVX connection in 2020 remained after controlling for SPX and DXY, with the largest gains at medium and long horizons.

These findings suggest horizon-dependent and regime-dependent risk management. OVX is a robust hedge indicator of negative oil movements in crisis; equity–oil co-movement is mainly slow-moving, and the dollar provides poor long-horizon diversification in stress. From a methodological standpoint, wavelet coherence with tight masking and band summaries provides a clear picture of when connections are strong and dependable, while the partial stage isolates oil-specific channels. Limitations are that it depends on choices of proxies and a partial residual-based approach; future research can extend the time periods, include sectors and alternative FX measures, and apply multivariate/partial wavelet coherency with phase and coverage summaries.

Reference

Aloui, R., Ben Aïssa, M. S., & Nguyen, D. K. (2013). Conditional dependence structure between oil prices and exchange rates: A copula-GARCH approach. Journal of International Money and Finance, 32, 719–738. https://doi.org/10.1016/j.jimonfin.2012.06.006

Alqaralleh, H. S. (2024). Analyzing Overnight Momentum Transmission: The Impact of Oil Price Volatility on Global Financial Markets. International Journal of Financial Studies, 12(3), 75. https://doi.org/10.3390/ijfs12030075

Baruník, J., & Křehlík, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk*. Journal of Financial Econometrics, 16(2), 271–296. https://doi.org/10.1093/jjfinec/nby001

Beckmann, J., & Czudaj, R. (2013). Oil prices and effective dollar exchange rates. International Review of Economics & Finance, 27, 621–636. https://doi.org/10.1016/j.iref.2012.12.002

Benedetto, F., Mastroeni, L., Quaresima, G., & Vellucci, P. (2020). Does OVX affect WTI and Brent oil spot variance? Evidence from an entropy analysis. Energy Economics, 89, 104815. https://doi.org/10.1016/j.eneco.2020.104815

Bilal, M., Aamir, M., Abdullah, S., & Khan, F. (2024). Impacts of crude oil market on global economy: Evidence from the Ukraine-Russia conflict via fuzzy models. Heliyon, 10(1), e23874. https://doi.org/10.1016/j.heliyon.2023.e23874

Chen, Y., Dong, S., Qian, S., & Chung, K. (2024). Impact of oil price volatility and economic policy uncertainty on business investment—Insights from the energy sector. Heliyon, 10(5), e26533. https://doi.org/10.1016/j.heliyon.2024.e26533

Choi, S.-Y. (2020). Industry volatility and economic uncertainty due to the COVID-19 pandemic: Evidence from wavelet coherence analysis. Finance Research Letters, 37, 101783. https://doi.org/10.1016/j.frl.2020.101783

Choi, S.-Y., & Hong, C. (2020). Relationship between uncertainty in the oil and stock markets before and after the shale gas revolution: Evidence from the OVX, VIX, and VKOSPI volatility indices. https://doi.org/10.1371/journal.pone.0232508

Cui, J., Maghyereh, A., & Ziadat, S. (2025). Crude oil, forex, and stock markets: Unveiling the higher-order moment and cross-moment risk spillovers in times of turmoil. Humanities and Social Sciences Communications, 12(1), 1158. https://doi.org/10.1057/s41599-025-05308-7

Du, L., & He, Y. (2015). Extreme risk spillovers between crude oil and stock markets. Energy Economics, 51, 455–465. https://doi.org/10.1016/j.eneco.2015.08.007

Gao, L., Hitzemann, S., Shaliastovich, I., & Xu, L. (2022). Oil volatility risk. Journal of Financial Economics, 144(2), 456–491. https://doi.org/10.1016/j.jfineco.2021.08.016

Ghazani, M. M., Malekshah, A. A. M., & Khosravi, R. (2024). Analyzing time–frequency connectedness between cryptocurrencies, stock indices, and benchmark crude oils during the COVID-19 pandemic. Financial Innovation, 10(1), 119. https://doi.org/10.1186/s40854-024-00645-z

Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Processes in Geophysics, 11(5/6), 561–566. https://doi.org/10.5194/npg-11-561-2004

Li, C., Wang, Y., & Wu, C. (2022). Oil implied volatility and expected stock returns along the worldwide supply chain. Energy Economics, 114, 106322. https://doi.org/10.1016/j.eneco.2022.106322

Lu, X., Liu, K., Lai, K. K., & Cui, H. (2021). The Relationship between Crude Oil Futures Market and Chinese/US Stock Index Futures Market Based on Breakpoint Test. Entropy, 23(9), 1172. https://doi.org/10.3390/e23091172

Lyócsa, Š., Baumöhl, E., Výrost, T., & Molnár, P. (2020). Fear of the coronavirus and the stock markets. Finance Research Letters, 36, 101735. https://doi.org/10.1016/j.frl.2020.101735

Magzumov, Z., & Kumral, M. (2024). Application of Wavelet Coherence and Connectedness Approaches to Unearth Nickel Price Dynamics. Mining, Metallurgy & Exploration, 41(6), 2901–2919. https://doi.org/10.1007/s42461-024-01121-z

Managi, S., Yousfi, M., Ben Zaied, Y., Ben Mabrouk, N., & Ben Lahouel, B. (2022). Oil price, US stock market and the US business conditions in the era of COVID-19 pandemic outbreak. Economic Analysis and Policy, 73, 129–139. https://doi.org/10.1016/j.eap.2021.11.008

McKibbin, W., & Fernando, R. (2023). The global economic impacts of the COVID-19 pandemic. Economic Modelling, 129, 106551. https://doi.org/10.1016/j.econmod.2023.106551

Muhmmad, R., & Ali, S. (2024, July 28). Exploring the Relationship Between the COVID-19 Pandemic, Crude Oil Prices, and the Stock Market in Saudi Arabia: Insights from Wavelet-Based Analysis. https://doi.org/10.1007/978-3-031-67434-1_19

Mwape, M. C., Mpofu, N. S., Malanda, C. H., & Kimutai, I. K. (2024). Early Impacts of COVID-19 Pandemic on the Crude Oil Prices and Demand in Sub-Saharan Africa: A Review. International Journal of Energy Research, 2024(1), 5548311. https://doi.org/10.1155/2024/5548311

Olasehinde-Williams, G. (2024). Crude oil price volatility—An unintended consequence of carbon pricing: Evidence from transfer entropy and wavelet-partial wavelet coherence analyses. Energy & Environment, 0958305X241246195. https://doi.org/10.1177/0958305X241246195

Olujobi, O. J., Olarinde, E. S., Yebisi, T. E., & Okorie, U. E. (2022). COVID-19 Pandemic: The Impacts of Crude Oil Price Shock on Nigeria's Economy, Legal and Policy Options. Sustainability, 14(18), 11166. https://doi.org/10.3390/su141811166

Reboredo, J. C., & Rivera-Castro, M. A. (2014). Wavelet-based evidence of the impact of oil prices on stock returns. International Review of Economics & Finance, 29, 145–176. https://doi.org/10.1016/j.iref.2013.05.014

Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. Journal of Empirical Finance, 16(4), 632–639. https://doi.org/10.1016/j.jempfin.2009.02.002

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. International Review of Financial Analysis, 70, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Sharma, C., & Rani, P. (2025). Dynamic Interconnectedness of ESG Indices and Crude Oil Prices: A Wavelet Coherence Approach in Asia-Pacific Markets. Australian Economic Papers, 64(3), 289–298. https://doi.org/10.1111/1467-8454.12392

Siddiqui, N., & Hasim, H. M. (2024). Risk contagion of COVID-19 to oil prices: A Markov switching GARCH and PCA approach. PLOS ONE, 19(12), e0312718. https://doi.org/10.1371/journal.pone.0312718

Tiwari, A. K., Nasreen, S., Shahbaz, M., & Hammoudeh, S. (2020). Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Economics, 85, 104529. https://doi.org/10.1016/j.eneco.2019.104529

Torrence, C., & Compo, G. P. (1998). A Practical Guide to Wavelet Analysis. Bulletin of the American Meteorological Society, 79(1), 61-78. https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2

Vacha, L., & Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. Energy Economics, 34(1), 241–247. https://doi.org/10.1016/j.eneco.2011.10.007

Wu, K., Zhu, J., Xu, M., & Yang, L. (2020). Can crude oil drive the co-movement in the international stock market? Evidence from partial wavelet coherence analysis. The North American Journal of Economics and Finance, 53, 101194. https://doi.org/10.1016/j.najef.2020.101194

Yang, T.-Y., Chen, S.-H., Yang, Y.-T., & Chang, H.-H. (2022). Frontiers | Relationship between crude oil price and production levels—An empirical study of OPEC and non-OPEC states. https://doi.org/10.3389/fenvs.2022.933431

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. Finance Research Letters, 36, 101528. https://doi.org/10.1016/j.frl.2020.101528