Theoretical and Applied Economics
Volume XXXI (2024), No. 3(640), Autumn, pp. 253-266

Do gold, oil and bitcoins possess safe heaven attributes in times of crisis? Empirical evidence using a wavelet-based time-frequency dependency approach from the pandemic to the Russia–Ukraine crisis

Akshay SAKHARKAR
Government College of Arts & Commerce, India
Dr.Akshaysakharkar@gmail.com

Abstract. *In the context of two important global events, i.e., the health crisis arising from the COVID-19 pandemic and the geopolitical tension resulting from the Russia-Ukraine war, the present study examines the existence of safe haven attributes of gold, oil and bitcoins against equities from five major countries i.e. US, China, India, Europe and Japan. Using daily observations from 1st January, 2020 to 31st December, 2023 and the wavelet coherence methodology the study finds persistent and strong correlations between gold, oil, and bitcoin returns vis-à-vis stock returns during periods of tranquility and turmoil. Gold exhibits safe haven features only over a long-term investment horizon, acting as a portfolio diversifier against stock market risk in short-term and medium-term periods. Both oil and bitcoins, on the contrary, are highly correlated with equities, suggesting they are viable diversifiers in turmoil and as hedges, but not as safe havens to mitigate stock market risk. Nevertheless, under normal circumstances, all examined assets possess the capacity to function as hedging assets and diversifiers against equities across different investing horizons.*

Keywords: wavelet analysis, cryptocurrency, stock market, safe haven, hedge, Russia–Ukraine war.

JEL Classification: C22, G01, G11, G15.

1. Introduction

A common feature of the global financial market is its risk, volatility, and great level of unpredictability during times of crisis. The recent COVID-19 epidemic in 2020 and the Russia-Ukraine war in 2022 are notable examples of how crises can disrupt markets and result in a massive loss of value for investors worldwide (Pandey and Kumari, 2021). This unprecedented increase in the volatility has sparked resurgence in the hedging, diversification, and safe haven instruments. Investors and portfolio managers mostly use risk-mitigation measures such as hedging or diversification, whereas investment in safe havens happens mostly during periods of extreme market circumstances and crises (Baur and Lucey, 2010). Numerous empirical and theoretical studies have highlighted gold, commodities, and most recently, cryptocurrencies, as alternative assets for portfolio risk management (Yousfi, Farhani and Bouzgarrou, 2024). Gold, also known as yellow metal, has always outperformed other asset classes; the literature has consistently documented its hedge and safe-haven property against stock indices (Baur and Lucey, 2010; Bouri *et al.*, 2020; Hussain Shahzad *et al.*, 2020; Mensi *et al.*, 2023; Velip, Jambotkar and Velip, 2023; Yousfi, Farhani and Bouzgarrou, 2024). The empirical literature also suggest alternative assets such as oil and other commodities, as well as cryptocurrency, as desirable safe havens and effective hedges (Shahzad *et al.*, 2019; Ali *et al.*, 2022; Boubaker and Larbi, 2022). While (Hussain Shahzad *et al.*, 2020) vouches for gold to be superior and most desirable safe haven and hedge, (Selmi *et al.*, 2018; Bouri *et al.*, 2020) suggest that cryptocurrency such as bitcoins exhibits superior hedge and safe haven properties over traditional assets such as gold and oil. In contrast, (Kliber *et al.*, 2019; Smales, 2019; Conlon and McGee, 2020) suggest that bitcoins do not offer any significant safe haven or hedge attributes as well as diversification benefits to investors in comparison to gold and commodities. Building on these findings, it is worth noting that the crisis phase can have a substantial impact on the performance of alternative assets that could serve as hedges, diversifiers, or safe havens. The current study intends to investigate the prevalence of safe haven features in gold, oil, and cryptocurrency in light of two significant global events: the health crisis caused by the COVID-19 pandemic and the geopolitical tension caused by the Russia-Ukraine war, this research will contribute to a better understanding of their role in investors' portfolios.

2. Data and Methods

The study considers daily prices of three potential safe-haven assets namely gold, oil and Bitcoin alongside the stock market indices of three major gold consuming countries USA, China and India for empirical analysis. The data pertaining to the stock indices and oil prices are sourced from (www.investing.com), while the data for gold in respective currencies is sourced from (www.gold.org) and the data for the bitcoin is sourced from website (www.coinmarketcap.com) in US dollars. The sample period is considered from 1st January, 2020 to 31st December, 2023 covering a period of COVID-19 and the Russia-Ukraine War. The daily price series for each variable is transformed into returns using the function $Rt = \ln (Pt/Pt\text{-}1)*100$.

Subsequently, a robust method of wavelet coherence (WTC) is applied to measure the relationship between two time series i.e. stock and gold, stock and oil and stock and bitcoin. This method allows detecting significant co-movement on a time frequency domain. Following (Torrence and Compo, 1998) a cross-wavelet power of two distinct time series x(t) and y(t) is estimated using the continuous wavelet transform $W_x(\tau,s) = W_x(\tau,s).W_y^*(\tau,s)$ where, $W_x(\tau,s)$ are continuous wavelet transforms and τ and s are the position index and scale.

Based on the above the squared wavelet coherence between x and y time series is defined as:

$$R_{xy}^2(\tau,s) = \frac{\left|S(s^{-1}W_{xy}(\tau,s))\right|^2}{S(s^{-1}|W_x(\tau,s)|^2.S(s^{-1}\left|W_y(\tau,s)\right|^2))} \quad (1)$$

The R_{xy}^2 represents the squared coherence Following (Torrence and Compo, 1998). The squared coherence fluctuates between 0 and 1 where value close to 1 indicates strong co-movement while a 0 represents no co-movement. Furthermore the lead and lag relationship within the coherence of the time series is drawn using the wavelet phase angle difference following the technique proposed by (Torrence and Webster, 1999) as:

$$\emptyset_{x,y}(\tau,s) = arctan\left(\frac{I(W_{xy}(\tau,s))}{R\left(W_{xy(\tau,s)}\right)}\right) \quad (2)$$

Where R and I corresponds to the real and imaginary parts of the wavelet coherence plot and the difference phase arrows are indicated in the wavelet coherence spectrum plot.

Additionally, to analyze the dynamic interconnectedness in the time series and cross validate the results from the wavelet coherence the study adopts the TVP-VAR ("Time-Varying Parameter Vector Autoregressive") directional pairwise connectedness approach proposed by (Antonakakis, Chatziantoniou and Gabauer, 2020; Gabauer, 2021) based on (Diebold and Yılmaz, 2015) is adopted.

3. Results and Discussion

Table 1 presents the descriptive statistics. The mean values of all the assets indicate positive returns, including market returns, except for the market returns of the S&P 500 and SSEI Index. All the variables possess a significant coefficient for the Jarque-Bera test, suggesting that they are normally distributed. The ADF test reveals that all the series under examination are stationery and fit for estimation.

Wavelet coherence analysis

The study adopts the wavelet squared coherence approach to gauge the pairwise comovements between stock indices and the probable safe haven assets. The phase difference and phase arrows are included in the plots alongside the period shown on the left vertical axis, while the frequency domain is shown on the horizontal axis. The color bars show the magnitude of comovement, ranging from 0 to 1, where 0 is indicated by the deep blue color, which signifies weak comovement, while 1 indicated by a deep red color corresponds to strong comovement. The directional arrows point out to the direction of comovement. Right-pointing arrows and left-pointing arrows indicate inphase (positive comovement) and antiphase (negative comovement). The directional arrows pointing right upward and left downwards indicate that the first variable stock returns lead and the second variable gold, oil, and bitcoin returns lag, whereas right pointing downward and left pointing upward suggest that the second variables gold, oil, and bitcoin returns leading and stock returns lag. The bright red color palette within the black line pocket indicates coherence distortion at the 5% level of significance. The time scales of 5 days per week are interpreted based on Owusu Junior et al. (2019) wherein "2–4 days (intraweek scales), 4–8 days (weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (monthly to quarterly scale), 64–128 days (quarterly to biannual scale), and 128–256 days (biannual to annual scale)".

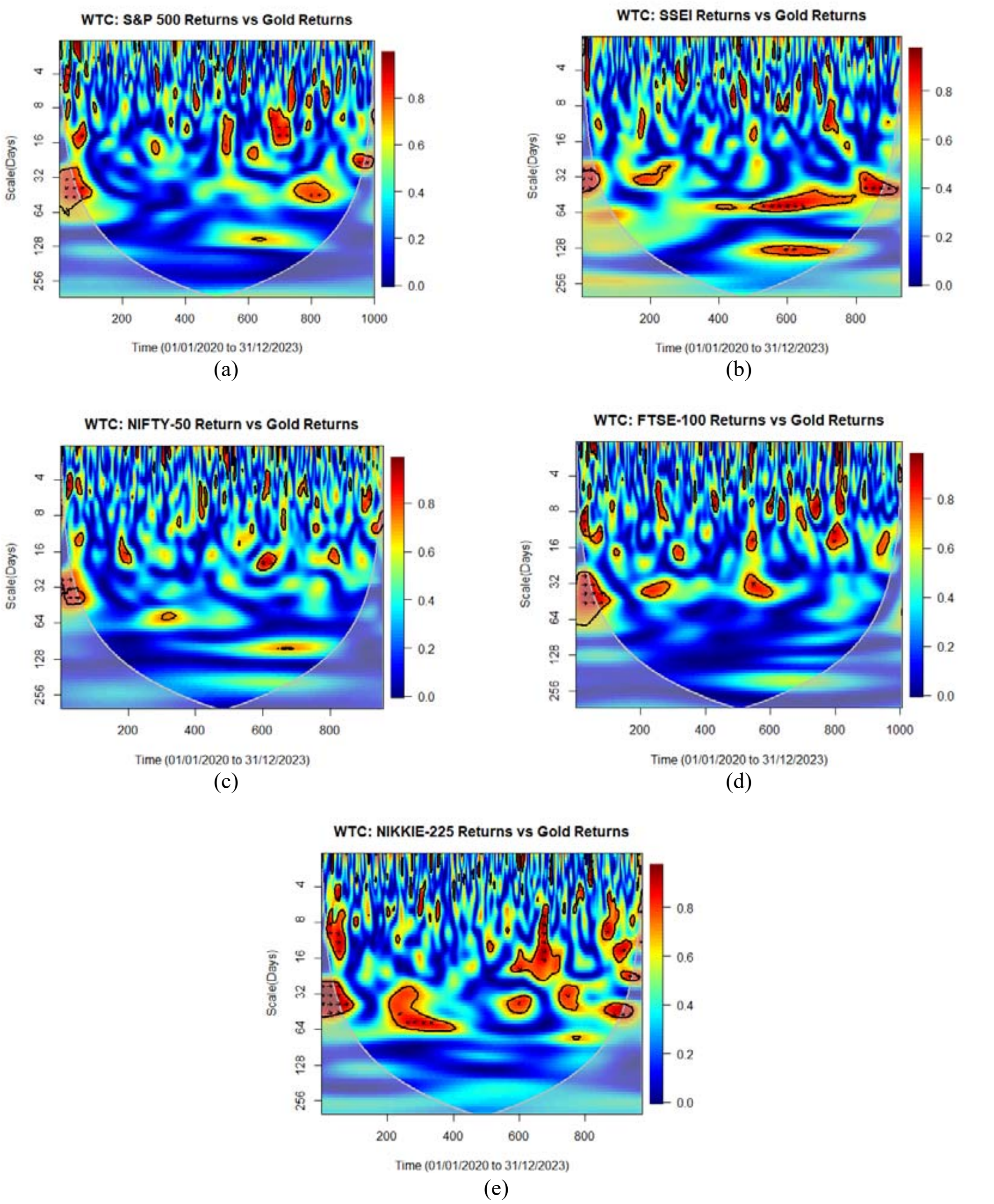
Table 1. *Descriptive Statistics*

	Mean	Std. dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	ADF test	Obs.
United States									
S&P-500	-0.0004	0.0145	-0.0896	0.1276	0.7813	12.6097	6766.9[a]	-09.22[a]	1001
Gold	0.0003	0.0099	-0.0526	0.0513	-0.3354	3.4749	526.25[a]	-10.52[a]	1001
Oil	0.0009	0.0407	-0.2813	0.4258	1.1458	29.7500	3729.7[a]	-09.24[a]	1001
BTC	0.0017	0.0433	-0.4972	0.1918	-1.7320	20.0228	1730.1[a]	-09.77[a]	1001
China									
SSEI	-0.0001	0.1007	-0.0800	0.0754	-0.4681	7.2557	2093.2[a]	-10.35[a]	933
Gold	0.0035	0.0094	-0.0548	0.0473	-0.4369	3.8863	621.42[a]	-10.28[a]	933
Oil	0.0009	0.0427	-0.2813	0.4258	1.0545	26.9725	2859.1[a]	-8.78[a]	933
BTC	0.0016	0.0438	-0.4972	0.1918	-1.7926	20.4610	1685.7[a]	-9.35[a]	933
India									
NIFTY-50	0.0006	0.0130	-0.1390	0.0840	-1.7413	20.4049	1718.5[a]	-8.57[a]	958
Gold	0.0004	0.0099	-0.0568	0.0484	-0.3757	3.5328	535.66[a]	-10.28[a]	958
Oil	0.0009	0.0426	-0.2813	0.4258	1.3333	29.1499	3435.9[a]	-8.15[a]	958
BTC	0.0019	0.0435	-0.4972	0.1918	-1.7551	20.3618	1712.3[a]	-9.03[a]	958
Europe									
FTSE-100	0.0001	0.0119	-0.1151	0.0866	-1.1437	14.3032	8845.6[a]	-9.13[a]	1007
Gold	0.0003	0.0095	-0.0562	0.0508	-0.2709	4.5576	525.66[a]	-10.28[a]	1007
Oil	0.0008	0.0406	-0.2813	0.4258	1.1399	29.9714	3435.9[a]	-8.15[a]	1007
BTC	0.0017	0.0440	-0.1918	0.4972	1.6582	18.8033	1712.3[a]	-9.03[a]	1007
Japan									
NIKKEI-225	0.0004	0.0129	-0.0627	0.0773	0.0452	3.0579	382.93[a]	-10.33[a]	974
Gold	0.0005	0.0107	-0.0653	0.0535	-0.3769	4.8773	994.97[a]	-11.11[a]	974
Oil	0.0007	0.0416	-0.2813	0.4387	2.1517	37.7927	589.76[a]	-8.89[a]	974
BTC	0.0021	0.0446	-0.4772	0.1918	-1.6739	18.6434	146.30[a]	-9.48[a]	974

Notes: The Jarque-Bera test statistics represent normality test; ADF denotes Augmented Dickey Fuller test; [a] means indicates a Rejection of the null hypothesis at the 1% significance level.

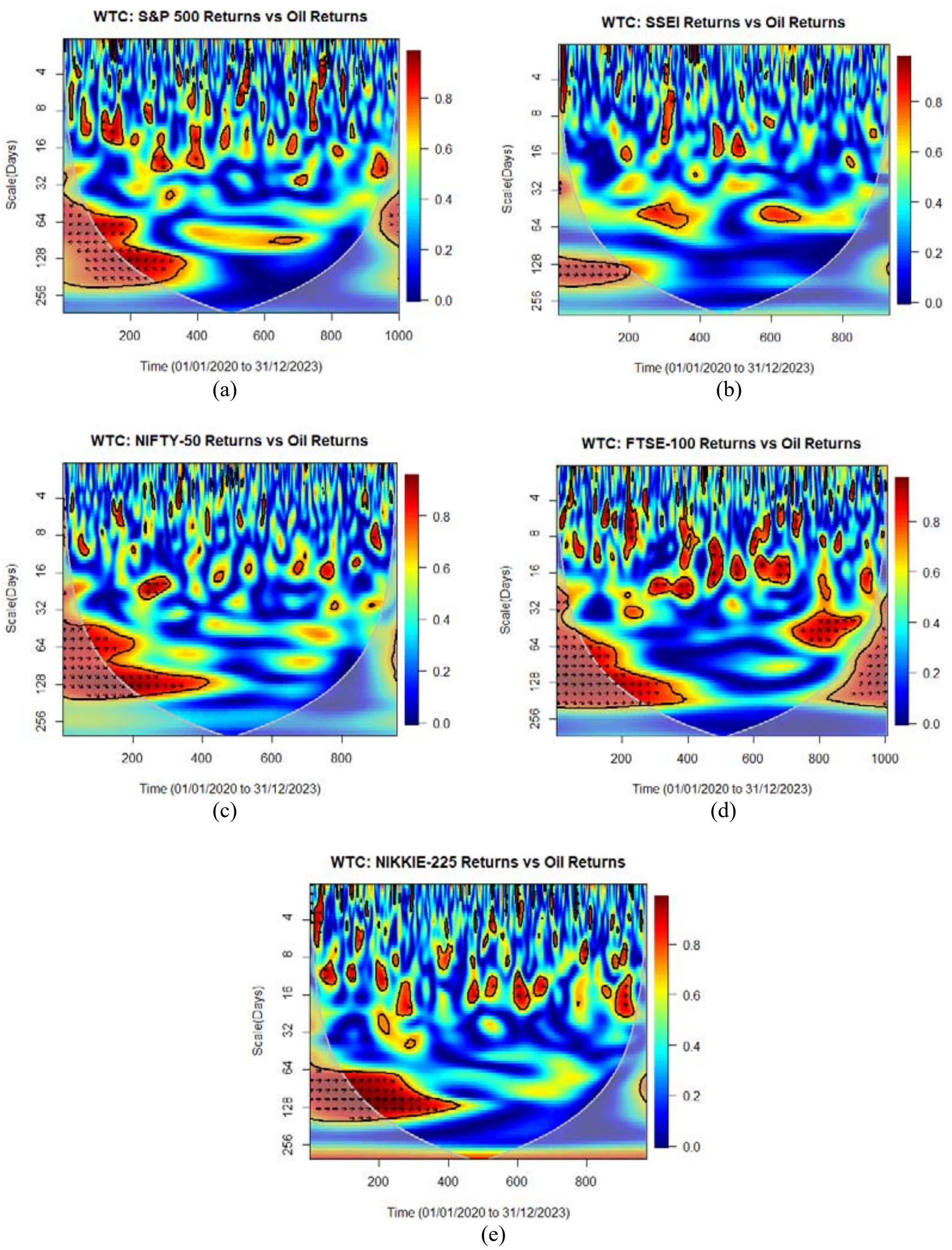
The classification of an asset as a hedge, diversifier, or safe haven is based on (Baur and Lucey, 2010; Bouri *et al.*, 2017, 2020), wherein an asset is a diversifier having a weak positive correlation with another asset in the portfolio, while a hedge can be weak (strong) having no correlation (negative correlation) with other assets on average. However, assets that are uncorrelated (negatively correlated) with other assets during crises or turmoil's, such as the period of COVID-19 and the Russia-Ukraine War, are considered safe havens.

Figure 1. *Wavelet Coherence – Gold*



(a) USA - WTC: S&P 500 and Gold. (b) China-WTC: SSEI and Gold. (c) India-WTC: Nifty-50 and Gold (d) Europe-WTC: FTSE-100 and Gold (e) WTC: WTC: NIKKEI-100 and Gold.

Figure 2. *Wavelet Coherence – Oil*

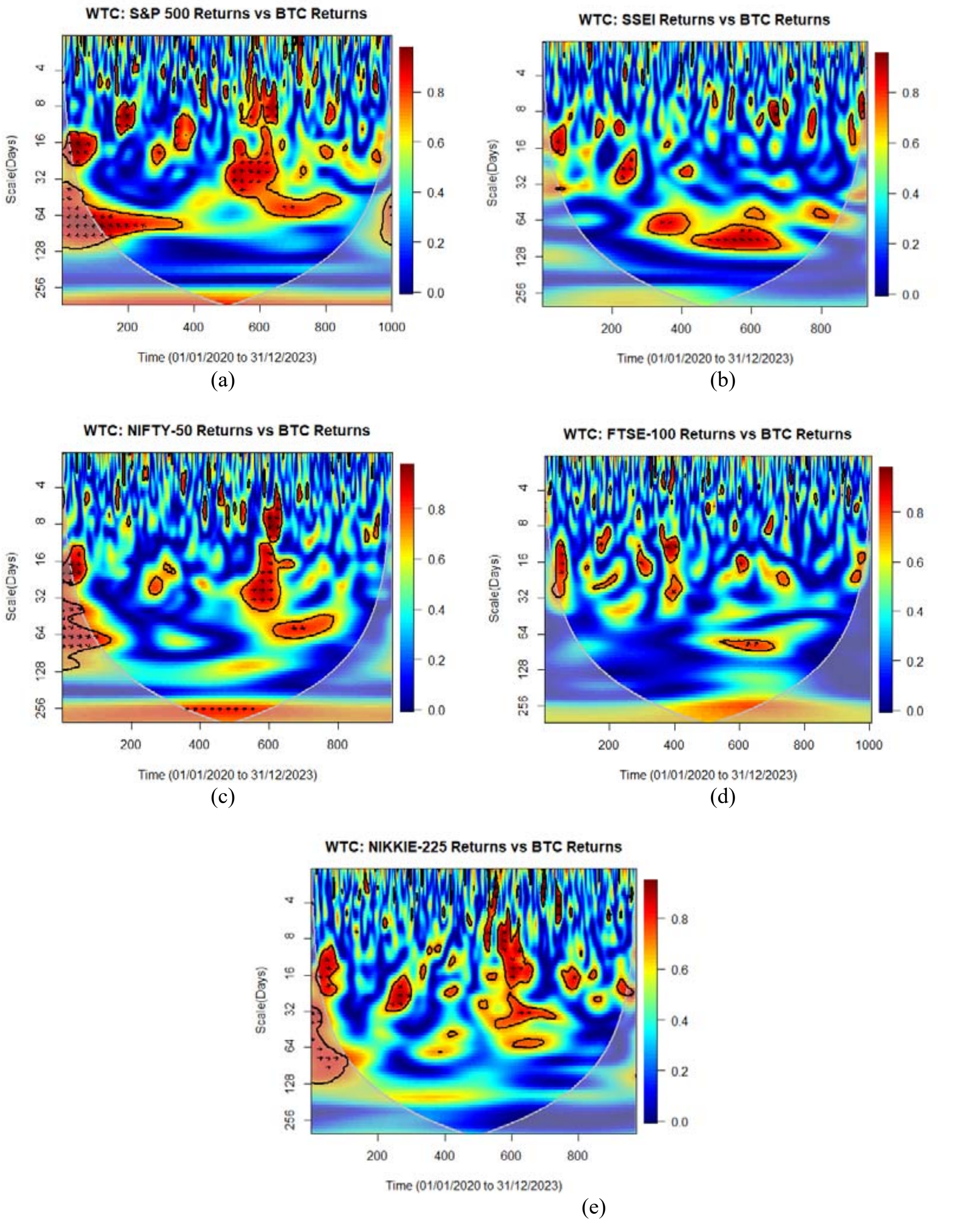


(a) USA - WTC: S&P 500 and Oil. (b) China-WTC: SSEI and Oil. (c) India-WTC: Nifty-50 and Oil (d) Europe-WTC: FTSE-100 and Oil (e) WTC: WTC: NIKKEI-100 and Oil.

Figure 1 depicts the coherency results for gold and stock market indices across time and frequency domains, which do not appear to vary considerably between markets, with a deep blue colour dominating the majority of the plot region. However, in the short-term investment horizon (up to 16 days), there are a number of black contours across the crisis period, indicating a robust correlation between gold and stock market returns. The medium-term and long-term investment horizons, on the other hand, have different consequences. For both crisis periods, the US, India, and European markets exhibit less volatility than Japan and China. During the medium-term horizon, all markets except the US show an in-phase direction of arrows facing rightward during the crisis, indicating a positive dependency between stocks and gold, whereas US markets show left-ward arrows, indicating a negative correlation, demonstrating the presence of safe haven characteristics for gold in US markets (Baur and Lucey, 2010). The long-term horizon for all markets is dominated by a deep blue colour, indicating no association, especially during times of crisis. We can suitably conclude that gold exhibits safe haven features only over a long-term investment horizon, while primarily acting as a portfolio diversifier against stock market risk. This findings corroborate the pervious findings of (Paramati, Abedi Shamsabadi and Reddy Kummitha, 2023; Velip, Jambotkar and Velip, 2023).

The representations in Figure 2 reveal strong comovements and dependency between stock returns and oil returns across markets. The presence of large red contours in the short, medium, and long-term investment horizons with right-facing arrows during the COVID-19 period (2020–2021) for China, India, Europe, and Japan strongly suggests the existence of high dependency, suggesting that oil can be used as a diversifier in turmoil and for the short run as a hedge but does not act as a safe haven for stock market risk. Interestingly, the US stock market reveals a negative correlation with oil, which points to the safe haven phenomenon of oil with equities in the COVID-19 period but not during the war period. Besides the prevalence of a strong association during the COVID-19 period, such a trend was not evident during the Russia-Ukraine war, except for Europe. This indicates that market volatility was not as persistent during the Russia-Ukraine war as compared to the period of COVID-19, and markets regained momentum in the short term.

Figure 3. *Wavelet Coherence – Bitcoin*



(a) USA - WTC: S&P 500 and Bitcoin. (b) China-WTC: SSEI and Bitcoin. (c) India-WTC: Nifty-50 and Bitcoin (d) Europe-WTC: FTSE-100 and Bitcoin (e) WTC: WTC: NIKKEI-100 and Bitcoin.

Figure 3 depicts the presence of strong safe haven attributes for bitcoin in the United States and China during both crisis periods, with the effects being stronger during the Covid-19 pandemic, whereas the safe haven phenomenon is only visible for medium-term and long investment horizons during the Russia-Ukraine war. Furthermore, biotin is viewed as a diversifier or hedge in the markets of India, Europe, and Japan, rather than a safe haven during both crisis eras. This finding is consistent with(Bouri *et al.*, 2017; Kliber *et al.*, 2019), who found cryptocurrency as a hedge or diversification tool rather than a safe haven.

Pair-wise connectedness analysis

The robustness of the estimates from the wavelet coherence is established using the TVP-VAR-based directional pairwise connectedness approach proposed by (Antonakakis, Chatziantoniou and Gabauer, 2020; Gabauer, 2021). Figure A1 – A3 (see Appendix) presents the graphical representation of the connectedness, which ranges from 0 to 100, where a higher value indicates strong interconnectedness between two variables across the time domain plotted on the horizontal x-axis. The bilateral connectedness across stock market indices and gold, oil, and bitcoins demonstrates similar patterns. There is strong evidence to suggest a strong connectedness and the beginning of 2020, which is the onset of the COVID-19 pandemic, and a spike in the onset of the Russia-Ukraine war in 2022. This finding yields similar results as the wavelets measure and support the hedge, diversifier, and safe haven characteristics of gold, oil, and bitcoin returns.

4. Conclusion

The aim of the present study is to evaluate the existence of safe haven attributes of gold, oil, and cryptocurrency against equities from five major countries, trailing two important global events, i.e., the health crisis arising from the COVID-19 pandemic and the geopolitical tension resulting from the Russia-Ukraine war. The study relies heavily on the novel wavelet coherence methodology and revealed persistent and strong correlations between gold, oil, and bitcoin returns vis-à-vis stock returns during periods of tranquility and turmoil. Gold exhibits safe haven features only over a long-term investment horizon, acting as a portfolio diversifier against stock market risk in short-term and medium-term periods. Both oil and bitcoins, on the contrary, are highly correlated with equities, suggesting they are viable diversifiers in turmoil and as hedges, but not as safe havens for stock market risk. The presence of all the assets as safe havens is found to be true only for the US, while bitcoins are for China. Nevertheless, under normal circumstances, all examined assets possess the capacity to function as hedging assets and diversifiers against equities across different investing horizons. The findings of this study will help to enhance the knowledge of the investor community, policymakers, and portfolio managers worldwide over safe haven assets and portfolio construction across various economic scenarios and investment horizons. The present study is limited and focused on selective assets; future research can be carried out on digital assets, exotic assets, and green assets alongside different economic events and time horizons.

References

Ali, S.R.M. et al., 2022. The impacts of COVID-19 crisis on spillovers between the oil and stock markets: Evidence from the largest oil importers and exporters, *Economic Analysis and Policy*, 73, pp. 345-372. Available at: <https://doi.org/10.1016/J.EAP.2021.11.009>

Antonakakis, N., Chatziantoniou, I. and Gabauer, D., 2020. Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions, *Journal of Risk and Financial Management 2020, Vol. 13, Page 84*, 13(4), p. 84. Available at: <https://doi.org/10.3390/JRFM13040084>

Baur, D.G. and Lucey, B.M., 2010. Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, *Financial Review*, 45(2), pp. 217-229. Available at: <https://doi.org/10.1111/J.1540-6288.2010.00244.X>

Boubaker, H. and Larbi, O.B., 2022. Dynamic dependence and hedging strategies in BRICS stock markets with oil during crises, *Economic Analysis and Policy*, 76, pp. 263-279. Available at: <https://doi.org/10.1016/J.EAP.2022.08.011>

Bouri, E. et al., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?, *Finance Research Letters*, 20, pp. 192-198. Available at: <https://doi.org/10.1016/J.FRL.2016.09.025>

Bouri, E. et al., 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis, *The Quarterly Review of Economics and Finance*, 77, pp. 156-164. Available at: <https://doi.org/10.1016/J.QREF.2020.03.004>

Conlon, T. and McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the Covid-19 bear market, *Finance Research Letters*, 35, p. 101607. Available at: <https://doi.org/10.1016/J.FRL.2020.101607>

Diebold, F.X. and Yılmaz, K. (Economist), 2015. Financial and macroeconomic connectedness: a network approach to measurement and monitoring, *Choice Reviews Online*, 53(03), pp. 53-1378-53–1378. Available at: <https://doi.org/10.5860/choice.193144>

Gabauer, D., 2021. Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the ERM I system, *Journal of Multinational Financial Management*, 60, p. 100680. Available at: <https://doi.org/10.1016/J.MULFIN.2021.100680>

Hussain Shahzad, S.J. et al., 2020. Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin, *Economic Modelling*, 87, pp. 212-224. Available at: <https://doi.org/10.1016/J.ECONMOD.2019.07.023>

Kliber, A. et al., 2019. Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation – A stochastic volatility approach, *Physica A: Statistical Mechanics and its Applications*, 524, pp. 246-257. Available at: <https://doi.org/10.1016/J.PHYSA.2019.04.145>

Mensi, W. et al., 2023. Extreme dependencies and spillovers between gold and stock markets: evidence from MENA countries, *Financial Innovation*, 9(1), pp. 1-27. Available at: <https://doi.org/10.1186/S40854-023-00451-Z/TABLES/5>

Pandey, D.K. and Kumari, V., 2021. Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak, *International Review of Economics & Finance*, 71, pp. 467-483. Available at: <https://doi.org/10.1016/J.IREF.2020.09.014>

Paramati, S.R., Abedi Shamsabadi, H. and Reddy Kummitha, H., 2023. How did gold prices respond to the COVID-19 pandemic?, *Applied Economics Letters*, 30(20), pp. 2987-2993. Available at: <https://doi.org/10.1080/13504851.2022.2117773>

Selmi, R. et al., 2018. Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold, *Energy Economics*, 74, pp. 787-801. Available at: <https://doi.org/10.1016/J.ENECO.2018.07.007>

Shahzad, S.J.H. et al., 2019. Is Bitcoin a better safe-haven investment than gold and commodities?, *International Review of Financial Analysis*, 63, pp. 322-330. Available at: <https://doi.org/10.1016/J.IRFA.2019.01.002>

Smales, L.A., 2019. Bitcoin as a safe haven: Is it even worth considering?, *Finance Research Letters*, 30, pp. 385-393. Available at: https://doi.org/10.1016/J.FRL.2018.11.002>

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

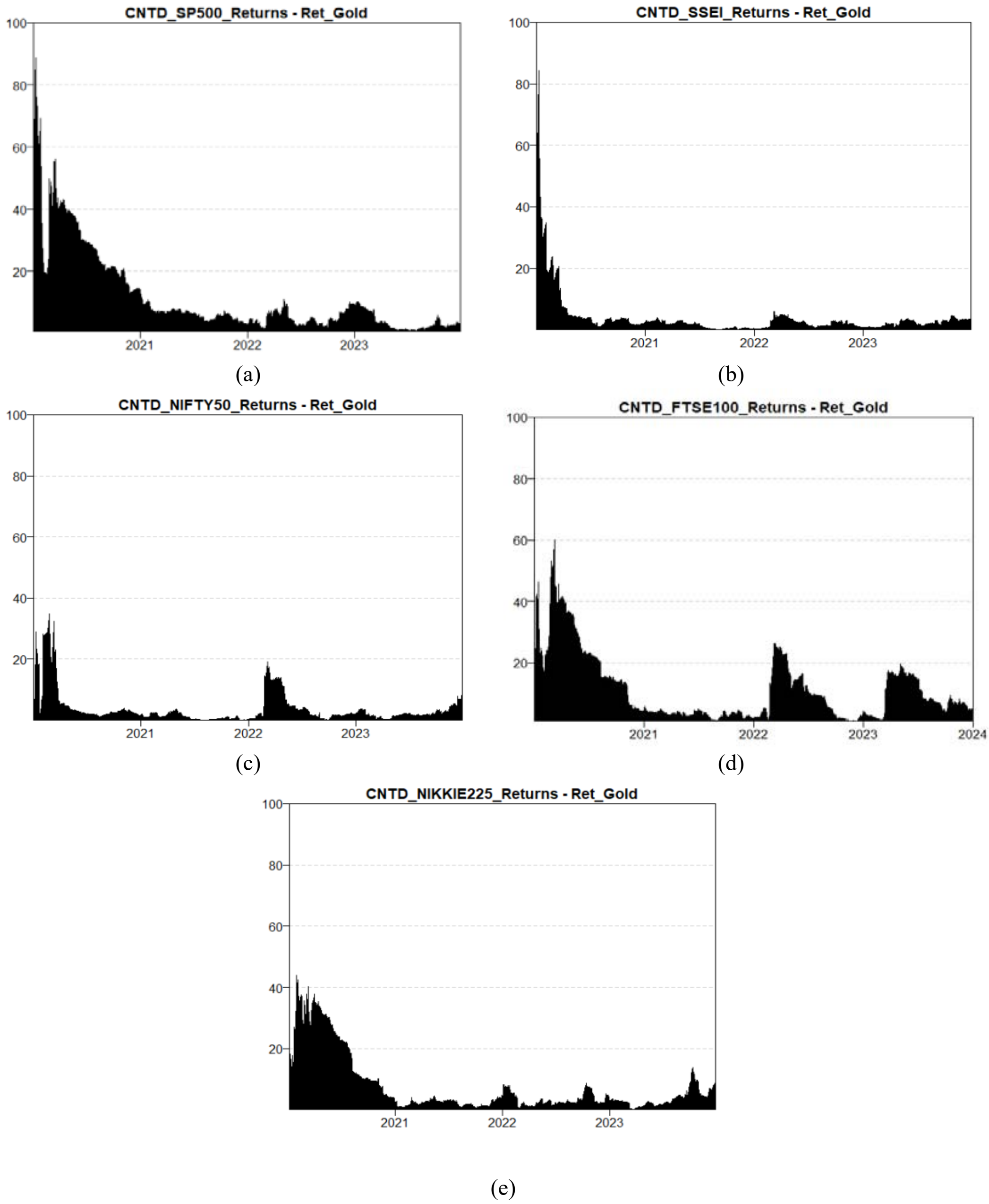
Torrence, C. and Webster, P.J., 1999. Interdecadal changes in the ENSO-monsoon system, *Journal of Climate*, 12(8 PART 2), pp. 2679-2690. Available at: <https://doi.org/10.1175/1520-0442(1999)012<2679:icitem>2.0.co;2>

Velip, Suraj, Jambotkar, M. and Velip, Savita, 2023. A wavelet-based time-frequency dependency and safe haven attributes of gold: evidence from the Russia–Ukraine war, *Applied Economics Letters* [Preprint]. Available at: <https://doi.org/10.1080/13504851.2023.2275644>

Yousfi, M., Farhani, R. and Bouzgarrou, H., 2024. From the pandemic to the Russia–Ukraine crisis: Dynamic behavior of connectedness between financial markets and implications for portfolio management, *Economic Analysis and Policy*, 81, pp. 1178-1197. Available at: <https://doi.org/10.1016/J.EAP.2024.02.001>

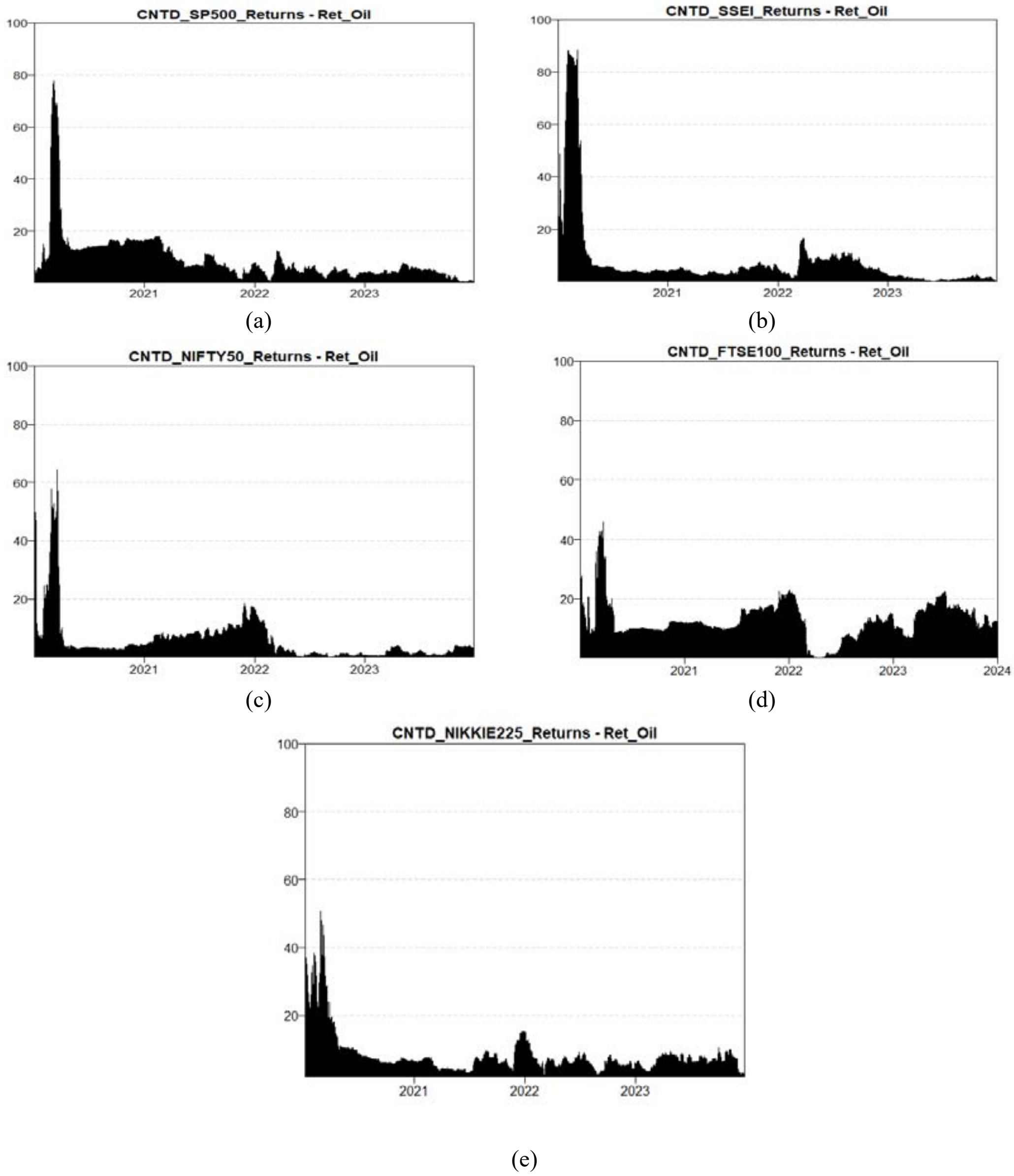
Appendix

Figure A1. *Dynamic pairwise connectedness plot– Gold*



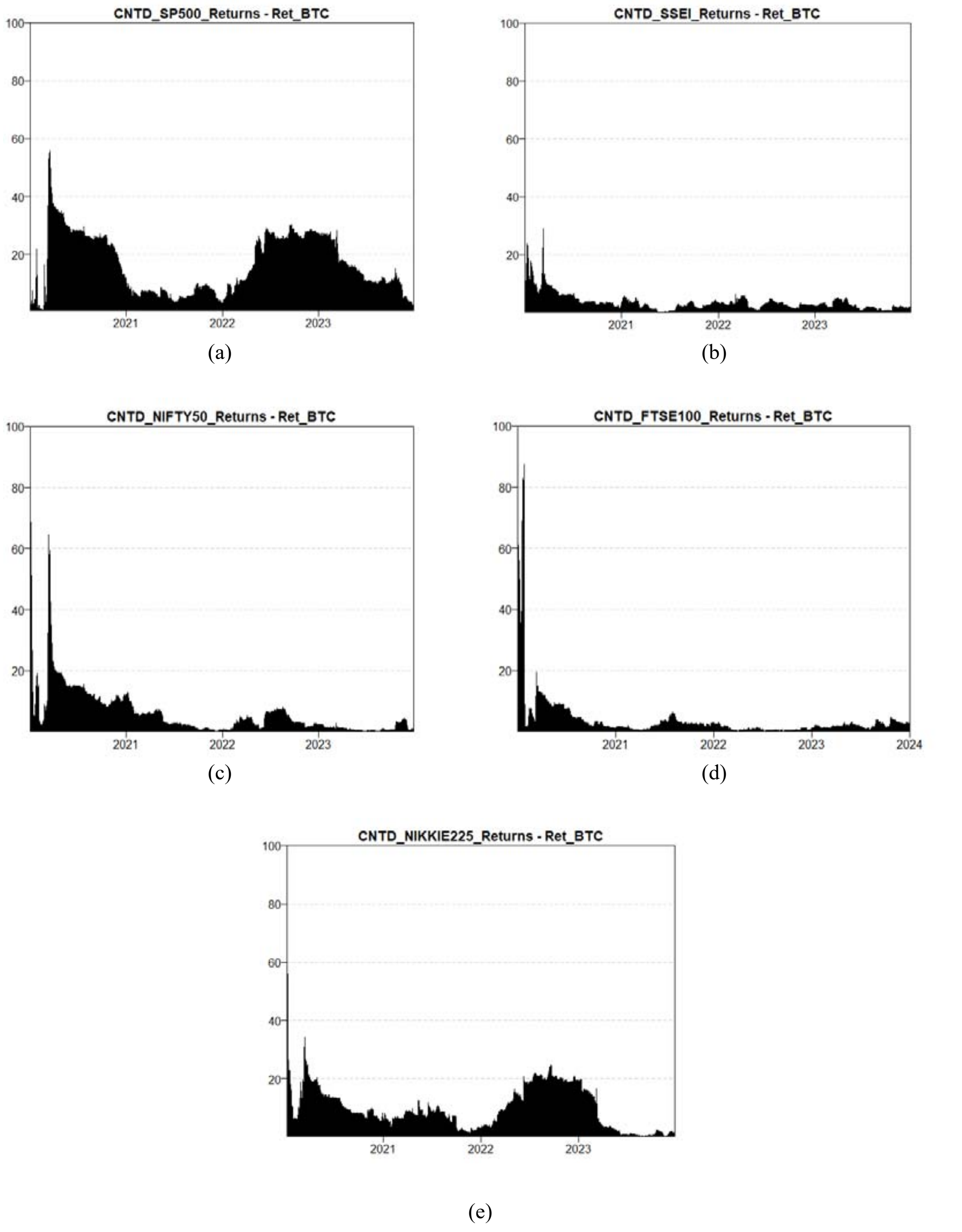
(a) USA - CNTD: S&P 500 and Gold. (b) China - CNTD: SSEI and Gold. (c) India - CNTD: Nifty-50 and Gold (d) Europe - CNTD: FTSE-100 and Gold (e) Japan - CNTD: NIKKEI-100 and Gold.

Figure A2. *Dynamic pairwise connectedness plot– Oil*



(a) USA - CNTD: S&P 500 and Oil. (b) China- CNTD: SSEI and Oil. (c) India - CNTD: Nifty-50 and Oil (d) Europe - CNTD: FTSE-100 and Oil (e) Japan - CNTD: NIKKEI-100 and Oil.

Figure 21. *Dynamic pairwise connectedness plot– Bitcoin*



(a) USA - CNTD: S&P 500 and Gold. (b) China - CNTD: SSEI and Bitcoin. (c) India - CNTD: Nifty-50 and Bitcoin (d) Europe- CNTD: FTSE-100 and Bitcoin (e) Japan - CNTD: NIKKEI-100 and Bitcoin.