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Connectedness between emerging stock markets, gold, cryptocurrencies, DeFi and NFT: Some new evidence from wavelet analysis

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ABSTRACT

This paper examines the dynamic connectedness between Gulf countries and BRICS stocks markets with a sample of cryptocurrencies, as well as two newly developed digital assets, namely NFT and DeFi, and Gold. The period under examination spans from January 2019 until September 2022. Our analysis is based on wavelet coherence, which is a suitable methodology considering the nonlinear dynamics present in data. Our empirical results clearly identify nontrivial time-varying connectedness between different assets and the stock markets. Asymmetric patterns in the interconnections of newly developed digital assets, cryptocurrencies, Gold and emerging market indices are well-documented, especially during the advent of the health and political events. Our empirical findings have relevant implications for portfolio managers, investors and researchers about portfolio allocation, investment strategies and potential diversification benefits of NFT and DeFi digital assets.

1. Introduction

Cryptocurrencies were initially proposed as an alternative to the traditional financial system, regarding peer-to-peer electronic transfers. However, they rapidly evolved into a type of (alternative) financial asset. The early literature focuses on the properties of the time series solely of cryptocurrencies, particularly in their foremost representative asset: Bitcoin. In this line, Urquhart [1] and Bariviera [2] find that in the early times of bitcoin existence daily returns failed to abide by the Efficient Market Hypothesis (EMH). However, it seems that the market is in the process of moving towards a (weakly) efficient market. Katsiampa [3] find interconnection between bitcoin and ethereum, being the latter an effective hedge against the former. The evidence reported so far is not definitive, and seems to indicate a change in dynamics, where cryptocurrencies could be more correlated with other financial assets. Crytpocurrency market seems a living entity in continuous evolution, showing that the blockchain technology has more applications than cryptocurrencies. In this sense, two recent new market emerged. One of such markets is that fore Non-Fungible Tokens (NFTs). They are rights associated to digital assets representing inter alia images, songs, or movies. These NFTs are traded, and their ownership and authenticity are validated, in the blockchain. This market segment experiences a surge since 2020, reaching over $40

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billon worth transactions [4]. The other market is that for Decentralized Finance (DeFi), term used to describe financial services (or more exactly claims on companies that offer financial services) that are implemented on public blockchains. It generally describes a distributed finance model aimed to avoid centralized institutions to do several banking activities such as borrowing or lending money, buying insurance contracts, etc. As of November 2022 NFT and DeFi market capitalization were $19bn and $54bn, respectively.

Early evidence suggested that cryptocurrencies has been substantially detached from the dynamics of traditional financial instruments such as stocks, bonds, or gold [5,6]. However, current evidence on the safe haven and hedging properties of cryptocurrencies are inconclusive and seem to vary over time. Dyhrberg [7] reports that bitcoin has similar hedging abilities as gold. In a similar vein, [8] specify that the hedging properties of bitcoin are observed at shorter investment horizons. Moreover, [9] provide evidence that bitcoin could be regarded as a diversifier, but only a safe haven against Asia Pacific stocks. Conversely, [9] finds that even in normal markets, bitcoin is more volatile, less liquid and has higher transaction costs than traditional assets. Consequently, it is probably not worth considering it as a safe haven. In a recent paper, Dowling [10] finds some co-movement between NFT and cryptocurrencies and suggests that further research on the relationship between NFT and other asset classes is needed. Precisely, this paper deepens this line of research.

The aim of this paper is to study the connectedness in the time and frequency domain of a set of cryptocurrencies, gold, NFT and DeFi with BRICS (Brazil, Russia, India, China, South Africa) and Gulf countries (Bahrain, Kuwait, Saudi Arabia, Jordan, Qatar, United Arab Emirates) stock markets during the outbreak of the health crisis and 2022 Russia–Ukraine war. For this end, we use the wavelet coherence approach in order to analyze the linkages between both time series. This method can also provide relevant information for investment decision-making in terms of short-and long-term horizons.

Our study contributes to the extant literature in threefold. First, we analyze the connectedness between cryptocurrencies and emerging stock markets (BRICS and Gulf). Indeed, the interrelationship between digital currencies in developed countries has largely received tremendous consideration over the years. As a matter of fact, [11] conduct a systematic review about the crytocurrency-stock markets nexus using 151 papers over the period 2008–2021 and find that few studies explored such linkage in emerging countries. Against this background, we investigate the lag-lead relationship between the crytocurrencies' returns and emerging stock markets' returns as analyzing the comovement of cryptocurrency-emerging stock market pairs in a dynamic framework can give further insights for investors and portfolio managers about the diversification benefits. Second, this study examines the existence of (dis)similarities of NFT and DeFi with conventional cryptocurrencies in terms of interrelationship with the emerging stock markets. As a matter of fact, new class of digital financial assets can be commonly thought to drastically differ from traditional digital currencies [12]. The connectedness between NFT, DeFi and other asset classes also remains underexplored. Third, this study contributes to the ongoing debate regarding the comovement between different asset classes with the outbreak of unprecedented and unexpected events by analyzing such association with the outbreak of Covid-19 pandemic and Russia–Ukraine war. Such analysis can give investors and portfolio managers with a better understanding of the dynamic of the new assets class-conventional assets during extreme events.

The remaining of the paper is organized as follows: Section 2 includes a brief literature review, Section 3 briefly describes the quantitative methodology used in the paper; Section 4 describes the data used in the paper and discusses the main findings. Finally, Sections 5 and 6 report lessons from empirical analysis and draws the main conclusions, respectively.

2. Literature review

Many researchers have strikingly explored the dynamic interrelatedness between cryptocurrencies and stock markets. In this regard, several scholars have increasingly focused on developed countries to explore the interrelationship between cryptocurrency and stock market (e.g. [13–15]). Nevertheless, few studies investigated such connectedness for emerging countries (e.g.[16–18]). For instance, [19] analyzes the associations between Bitcoin and major stock indices in the Asia-Pacific region over the period 2012–2019. The empirical findings display the substantial unidirectional linkage from Bitcoin to the stock markets in the long-, medium- and short-term. The association between Bitcoin and Asia-Pacific stock markets seems to be generally weak at higher frequencies whereas it increases at lower frequencies. Matkovskyy and Jalan [20] explore the contagion effect between stock indices and Bitcoin. They document crucial contagion effect from stock markets to Bitcoin. Wang et al. [21] investigate the relationship between BRICS and cryptocurrencies. They report that no digital currency can act as safe-haven asset for such markets. Mizerka et al. [22] study the association between Bitcoin and emerging/developed stock markets. They document the absence of significant relationship between them. Bhuiyan et al. [23] investigate the lag-lead relationship between Bitcoin and various asset classes (stock indices, bond indices, gold, currency and commodity) during the period 07/2014–11/2019. Using a wavelet method, they show the existence of an association between Bitcoin, crude oil and aggregate indices whereas a weak unidirectional causal relationship (resp. strong bidirectional causal relationship) is documented for the US dollar (resp. gold). The advent of unprecedented and unexpected events such as the Covid-19 pandemic have revived interest in investigating the interrelationhip structure between assets (e.g. [24,25]) given that market participants are highly worried about the direction and magnitude of net return spillover contribution(s) by different asset classe(s) in their portfolios. For example, [26] investigate the association between gold, green bonds, Dow Jones Index (DJI) and Bitcoin prices over the period 22/01/2020–03/08/2021. They show that gold, green bonds and Bitcoin are weakly related to the stock markets. This implies the possibility of using such assets as safe-haven and hedging assets during the health crisis. As well, a relationship between Bitcoin and gold seems to be strong during the sample period. Arouxet et al. [27] report that upon the outbreak of Covid-19 (around March 2020) the long memory of cryptocurrencies returns were slightly affected, but daily volatility described a strong and short-lived impact. Jeribi and Manzli [28] explore whether digital currency can hedge the Tunisian stock market with the outbreak of Covid-19 pandemic. They find that Bitcoin, Dash, Monero, and Ripple can be considered as hedges while Ethereum acts as a diversifier for the Tunisian stock market during the pre-Covid-19 crisis period. Nonetheless, Ethereum and Bitcoin cannot be considered as diversifiers and hedges during the Covid-19 pandemic. Kumah et al. [25] report the possibility of using digital currencies as safe-haven assets against the African stock market during the health crisis period. Lahiani et al. [16] explore the relationship between cryptocurrencies (Ripple, Bitcoin, Monero, Dash and Ethereum) and BRICS/developed stock markets. They show the absence of significant correlation between digital currencies and stock markets. Jeribi and Ghorbel (2022) [29] show a time-varying positive correlation between Bitcoin and South African stock market. Bitcoin cannot be considered as hedge for BRICS markets compared to developed ones whereas it is diversifier for emerging market. Using NARDL model, [30] reveal the dynamic correlation between emerging markets and cryptocurrencies (Bitcoin, Ethereum, Dash, Monero, and Ripple) has changed during the health crisis. In particular, Bitcoin, Ethereum, Dash, Monero, and Ripple can be considered as safe-haven assets for Brazil, China, and Russia with the outbreak of such event. Umar et al. [31] analyze the associations between stock markets (NYSE composite index, NASDAQ composite index, Shanghai Stock Exchange, Nikkei 225, and Euronext NV) and digital currencies (Bitcoin, Ethereum, Ripple, Bitcoin cash, and Ethereum Operating System). They document a crucial time-varying association between stock market indices and most currencies. Balcilar et al. [32] examine the volatility connectedness between cryptocurrencies and emerging markets over the period 02/10/2017–/05/2022. Based on the quantile VAR, they report that the volatility connectedness in tails is much stronger in comparison to the center of the distribution. As well, USDT and the stock markets in Thailand and Saudi Arabia seem to be the most risk transmitters during the post-Covid-19 pandemic period. They also show the crucial impact of the health crisis given the time-varying connectedness estimates. Ahmed et al. [33] analyze the connectedness between emerging stock indices and cryptocurrencies using fractional integration and cointegration technique. They reveal the disconnection between stock indices and cryptocurrency prices. Some evidence of cointegration on volatility pattern between emerging stock market indices and cryptocurrencies is well-documented. Wang et al. [34] analyze the dynamic correlation between Bitcoin and financial assets during the period 2013–2021. They show that Bitcoin is positively related to risk assets (bond, commodity and stock) whereas it is negatively linked to the U.S dollar. A positive correlation between Bitcoin and risk assets increases with the outbreak of Covid-19 pandemic. Omri [35] studies the volatility spillover effect and the directional predictability from (emerging and developed) stock market indices to Bitcoin during the period 03/2017–/2021. Using the VAR model, Granger test and impulse response function, the empirical results clearly display a substantial unidirectional volatility spillover effect from emerging markets to Bitcoin. The difference between emerging and developed markets in terms of the directional predictability is not documented. Nevertheless, there is some heterogeneity in the response of Bitcoin return to shocks in the emerging stock markets in comparison to developed ones. On the other hand, the emerging of the new class of digital financial assets have increasingly received researchers and investors' attention as it is generally thought to be significantly different from conventional cryptocurrencies [12]. In this respect, [36] analyze whether NFTs are different asset classes in terms of safe-haven features during the turbulent times. They reveal that NFTs could absorb risk during normal times. Nonetheless, they cannot be considered as distinct asset class in turbulent times as the tail connectedness NFTs and other asset classes can be increasingly high. Maouchi et al. [12] examine the behavior of 3 NFTs, 9 DeFis, Bitcoin and Ethereum with the outbreak of Covid-19 pandemic. They identify many digital financial bubbles. Nevertheless, the DeFi and NFTs bubbles seem to be less recurrent with higher magnitudes than cryptocurrencies' bubbles. Wang [37] investigates the volatility spillover connectedness between NFTs attention and financial markets. Overall, NFT markets seem to be volatility spillover receivers. Yousaf et al. [38] analyze the dynamic and static returns dynamics between four DeFi assets (Maker, Basic Token, Chainlink and Synthetix) and four currencies (RMB, JPY, EUR and GBP). They report the time-varying return spillovers between the DeFi and currency markets with the initial escalation of health crisis. Nevertheless, the spillover from Chinese Yuan to the system is not documented because of the Covid-19 pandemic. Overall, the DeFi markets seem to act as net innovation transmitters during the first Covid-19 year. Liu [39] investigates the interrelationship and spillover between NFTs and carbon markets. They report that there is a high correlation among them in the long-run. They also show that the Covid-19 pandemic inhibits carbon-NFT's spillover effect. Chu et al. [40] study the time-varying return-volume linkage of DeFi assets using the quantile-on-quantile regression and extreme value approach. They report that when trading volume increases, returns of tokens seem to be significant and positive for some cases but negative for other ones. The extreme return-volume dependence is asymmetric in the extreme positive and negative tails of the distributions. Yousaf and Yarovaya [41] investigate the dynamic and static hedging behavior for three crytocurrency classes (NFT, DeFi and classical cryptocurrencies). They suggest that the dynamic herding is detected in DeFi and conventional digital currencies for the short investment horizons. They also report that herding is not evident in NFT and conventional cryptocurrencies during high/low volatility days, up/down market and high/low trading days.

3. Methods

Following [42,43], we adopt the Wavelet Coherence approach in order to produce the linkages between both time series ($x(t)$ and $y(t)$) across the time–frequency domain. They also allow to detect the lead/lag relationships and phase differences among time series. In this contrast to classical time series modeling, the wavelet technique enables to identify the comovement between both time series in the frequency and time domains [44]. In general, the wavelet technique employs a bivariate framework on a continuous wavelet transform, using the Morlet wavelet.[1] Such method provides many scaled localizations [47]. One might detect comovement across time series in both frequency and time domains using the wavelet coherence approach. In this context, one might apply the Wavelet coherence analyses (Wavelet Coherence (WTC), Cross Wavelet Transform (XWT) and Continuous Wavelet Transform (CWT)) on many time series. In particular, the CWT technique offers the XWT plots that display regions in both frequency and time spaces. In these regions, each time series show common power and its related phase relationship. The Continuous Wavelet Transform $W_x(\mu, s)$ is given as follows:

$$W_x(\mu, s) = \int_{-\infty}^{+\infty} \frac{x(t)\psi'\left(\frac{t-\mu}{s}\right)}{\sqrt{s}} \tag{1}$$

Where $\psi'(\cdot)$ refers to the complex conjugate of $\psi(\cdot)$. The Cross Wavelet Transform (XWT) can be generalized by CWT to investigate the dynamic connectdness between both time series. One express the XWT function as follows:

$$W_{xy}(\mu, s) = W_x(\mu, s).W_y^*(\mu, s) \tag{2}$$

where $W_{xy}(\mu, s)$ calculates the linkages between both time series; μ and s refer to time and scale, respectively; W corresponds to the wavelet; $*$ is a complex conjugate.

Overwhelmingly, the Cross Wavelet Transform (XWT) refers to the covariance between two variables. It can detect regions at each time and scale when the linkage between two time series is well-pronounced. Nevertheless, the empirical findings of the Cross Wavelet Transform (XWT) are restricted given the lack of bounds. That is why the wavelet coherence technique is preferred by taking into account a smoothing operator S [47]. The Continuous Wavelet Transform can be calculated as follows:

$$R_{xy}^2(\mu, s) = \frac{\left|S\left(\frac{1}{s}W_{xy}(\mu, s)\right)\right|^2}{S\left(\frac{1}{s}\left|W_x(\mu, s)\right|^2\right)S\left(\frac{1}{s}\left|W_y(\mu, s)\right|^2\right)} \tag{3}$$

with $R_{xy}^2(\mu, s)$ the squared correlation between time series across frequency and time. It ranges from 0 (no correlation) to 1 (high correlation). For a more detailed discussion on this methodology we refer also to [48,49].

4. Data and descriptive statistics

In this paper, we use the adjusted closing values of stock market indices from two different regions for our empirical analysis. We collect Gulf stock markets indices comprising BAX (Bahrain), FTGP (Kuwait), TASI (Saudi Arabia), MSM30 (Jordan), QEAS (Qatar) and ADI (United Arab Emirates) and BRICS stock markets indices including SSE (China), RTSI (Russia), BSE30 (India), Bovespa (Brazil) and South Africa (JSE40). We also gather the prices of Bitcoin (BTC), Monero, Gold, True and Tether. We thereafter employ the NFT and DeFi indices. We extract the chosen daily Gulf and BRICS market indices and Gold prices from DataStream. We source the data from Bitcoin, Ethereum and Monero as well as NFT and DeFi from the website https://coinmarketcap.com/. The selectioin of coimarketcap as source for data on cryptoassets is that, as found recently in [50], results produces for such data is consistent with main exchange platforms. Following [51,52], we used the daily frequency to have quite high number of observations which allows for deeper and insightful information.

The time span ranges from January 02, 2019 to September 05, 2022. Such time period includes the outbreak of the Covid-19 pandemic and Russia–Ukraine war. These political and health crisis events are unprecedented events which are expected to potentially influence the pairwise coherence levels of the asset classes. In this case, our data is segregated in three different sub-periods: The pre-Covid-19 period (02/01/2018-1/12/2019), the Covid-19 period (02/01/2020–3/02/2022) and the Ukraine–Russia war (24/02/2022–5/09/2022). We calculate the continuously compounded daily returns as the first difference of the logarithm of stock market indices. Table 1 reports the descriptive statistics for the assets under study before (02/01/2018–1/12/2019) and during the Covid-19 pandemic (02/01/2020–3/02/2022) and the Ukraine–Russia war (24/02/2022–5/09/2022). It is worth noting that some interesting facts according to the sample sub-period under study. Before the Covid-19 pandemic, the mean index return of each asset seems to be positive, except for JSE and MSM. As well, the mean return of Ethereum and Monero are negative. Nevertheless, the average return of all these aforementioned stock markets and assets becomes positive with the outbreak of Covid-19 pandemic. However, the mean return of RTSI, Bovespa and True presents negative values. With the advent of the Russia–Ukraine war, only RTSI,

[1] In our paper, the frequency of the Morlet wavelet is set to 6, $\omega_0 = 6$, as it specifies the best localization between time and frequency. The higher ω_0, the better frequency localization yet poorer time localization, and vice versa. Following many researchers e.g. [45–47], we fix $\omega_0 = 6$ which meets the admissibility condition of the wavelet transform.

Table 1
A snapshot of descriptive statistics for different assets.

	BTC	ETHER	MONERO	GOLD	SSE	RTSI	BSE	BOVESPA	JSE	BAX	KUINDEX	MSM	QEAS	TASI	ADI	TETHER	TRUE	DeFi	NFT
Before Covid-19 Pandemic																			
Mean	0.000	−0.002	−0.002	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA
Median	0.000	−0.003	0.002	0.001	0.000	0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	NA	NA
Maximum	0.201	0.298	0.176	0.032	0.054	0.028	0.052	0.045	0.035	0.234	0.022	0.019	0.034	0.042	0.036	0.021	0.033	NA	NA
Minimum	−0.156	−0.224	−0.205	−0.021	−0.054	−0.04	−0.023	−0.038	−0.031	−0.232	−0.035	−0.019	−0.042	−0.04	−0.034	−0.026	−0.022	NA	NA
Std. Dev.	0.044	0.057	0.055	0.007	0.011	0.01	0.009	0.012	0.01	0.018	0.006	0.005	0.008	0.01	0.008	0.004	0.005	NA	NA
Skewness	0.08	0.145	−0.402	0.451	0.052	−0.338	0.748	−0.149	−0.166	0.114	−0.494	0.163	−0.05	−0.265	0.176	−0.474	0.893	NA	NA
Kurtosis	6.646	7.024	4.954	4.777	6.391	3.854	7.172	3.989	3.947	156.985	7.743	5.157	6.848	6.146	6.307	14.757	14.376	NA	NA
Jarque–Bera	190.864	233.348	64.004	56.92	164.998	17.028	281.532	15.279	14.425	339863	336.445	68.232	212.333	145.865	158.494	1994.015	1900.516	NA	NA
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA
Observations	344	344	344	344	344	344	344	344	344	344	344	344	344	344	344	344	344	NA	NA
During Covid-19 Pandemic																			
Mean	0.003	0.006	0.002	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.006
Median	0.003	0.007	0.007	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000	0.000	0.002	0.001
Maximum	0.194	0.35	0.325	0.043	0.061	0.088	0.067	0.13	0.079	0.024	0.041	0.022	0.04	0.068	0.081	0.005	0.008	0.212	0.337
Minimum	−0.497	−0.58	−0.52	−0.059	−0.08	−0.142	−0.141	−0.16	−0.105	−0.06	−0.192	−0.057	−0.1	−0.087	−0.084	−0.008	−0.005	−0.386	−0.429
Std. Dev.	0.049	0.068	0.065	0.01	0.011	0.022	0.015	0.021	0.015	0.006	0.012	0.006	0.009	0.011	0.013	0.001	0.001	0.072	0.087
Skewness	−1.958	−1.701	−2.016	−0.763	−0.503	−1.384	−2.048	−1.595	−1.039	−2.519	−8.071	−2.267	−2.835	−2.2	−0.542	−0.464	0.903	−0.583	0.085
Kurtosis	23.676	18.565	19.229	7.145	11.102	10.809	20.971	19.709	12.214	23.642	128.383	24.025	36.727	21.761	19.096	22.266	23.293	5.475	5.915
Jarque–Bera	10240	5870.375	6466.367	451.156	1541.363	1587.405	7856.568	6691.624	2063.177	10440.39	369569.3	10698.23	27047.7	8587.409	6018.669	8603.576	9598.784	116.373	89.887
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	555	555	555	555	555	555	555	555	555	555	555	555	555	555	555	555	555	373	253
During the Russia–Ukraine War																			
Mean	−0.004	−0.007	0	−0.001	0	0	0	0	−0.001	0	0	0.001	0	0	0.001	0	0	−0.004	−0.008
Median	−0.002	0	0.002	0	0.001	0.001	−0.001	0	−0.001	0	0	0	0	0	0	0	0	−0.003	−0.007
Maximum	0.102	0.247	0.259	0.025	0.034	0.232	0.034	0.027	0.041	0.034	2.396	0.028	0.065	0.026	0.029	0.002	0.004	0.276	0.217
Minimum	−0.287	−0.477	−0.275	−0.028	−0.053	−0.483	−0.048	−0.028	−0.039	−0.026	−2.405	−0.019	−0.073	−0.045	−0.06	−0.004	−0.002	−0.325	−0.3
Std. Dev.	0.047	0.074	0.065	0.009	0.012	0.052	0.012	0.012	0.015	0.008	0.283	0.006	0.013	0.011	0.011	0	0	0.07	0.071
Skewness	−1.789	−2.54	−0.434	−0.321	−1.1	−5.018	−0.278	−0.187	0.15	0.31	−0.051	0.969	−0.324	−0.748	−1.03	−6.167	6.181	−0.749	−0.758
Kurtosis	12.211	18.215	6.514	3.498	6.676	55.601	4.789	2.646	3.017	6.84	72.4	6.315	11.86	5.115	9.43	70.92	71.496	8.032	6.307
Jarque–Bera	589.892	1554.667	79.159	3.99	110.892	17324.99	21.2	1.601	0.546	91.394	29098.61	89.073	476.808	40.574	275.45	28790.02	29269.41	166.56	79.957
Probability	0.000	0.000	0.000	0.136	0.000	0.000	0.000	0.449	0.761	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	145	145	145	145	145	145	145	145	145	145	145	145	145	145	145	145	145	145	145

Note: BTC, ETHER, BSE, JSE, KUINDEX and MSM refer to Bitcoin, Ethereum, BSE30, FTGP and MSM30, respectively.

BSE, KUWAITI, MSM, QEAS and ADI indices and True has positive values compared to other analyzed asset classes. This clearly shows the heterogeneous reaction of different markets to the outbreak of unexpected and unprecedented events. As a matter of fact both NFT and DeFi become negative values during the 2022 Russian invasion of Ukraine compared to the outbreak of Covid-19 pandemic. The daily returns of the analyzed asset classes seem to be negatively skewed during turbulent periods, except for True and NFT (resp. JSE, BAX, MSM and True) with the advent of Covid-19 pandemic (resp. the 2022 Russian invasion of Ukraine). The leptokurtic feature of the return distribution of time series is well-pronounced for different sub-periods given the value of kurtosis. The daily returns are not normally distributed given that the Jarque–Bera statistics are significant at 1% level.

Using the wavelet coherence analysis, we attempt to disentangle and better highlight the multi-scale connectedness between DeFi (Fig. 1), and NFT (Fig. 2), Bitcoin (Figure 1A), Ethereum (Figure 2A), Gold (Figure 3A), Monero (Figure 4A), Tether (Figure 5A) and True (Figure 6A) and major indices in BRICS and Gulf regions. Figures 1A–6A are all reported in Appendix[2]

The wavelet coherence heatmap allows us to display the pairwise relationship between two time series coupled with their lag/lead patterns. In this regard, arrows in the wavelet coherence heatmaps can inform about phase difference between two selected variables. More precisely, the $\leftarrow$ (resp. $\rightarrow$) arrows indicate that both variables behave in anti-phase (resp. phase). The $\downarrow$ (resp. $\uparrow$) arrows show that the first variable leads (resp. lags) the second one. The color-wise regions in each plot interpret the coherence wavelet heatmap more easily. In this context, white (resp. black) regions refer to high (resp. low) correlation. The right down (resp. left up) pointing arrows imply that Bitcoin, Ethereum, Gold, Monero, Tether, DeFi or NFT is leading (resp. lagging) stock index in BRICS/Gulf region. The left down (resp. left up) pointing arrows indicate that such asset is lagging (resp. leading) stock index in BRICS/Gulf region. Needless to say, the horizontal axis refers to time whereas the vertical axis indicates the frequency or investment horizon length (days).

Fig. 1 presents the eleven pairwise wavelet coherence charts revealing between DeFi and stock market indices. All in all, DeFi is lagging ADI, QEAS and FTGPCST during the two years 2021–2022 at different frequency bands. Nevertheless, DeFi is leading TASI, MSM30, RTSI, JSE40, Bovespa, BSE and BAX during the same period. The ongoing global uncertainties due to the outbreak of the Covid-19 pandemic seem to significantly affect the behavior of stock index-DeFi. The lack of

[2] For a better reading and clarity of our study, we only report Figures related to the NFT/DeFi-emerging stock market nexus to better understand the potential comovement of emerging markets with the new digital assets. For the other couples, all figures are available in Appendix 1 (Figure 1A to Figure 6A). Nevertheless, we interpret all the comovements of pairs in order to detect potential (dis)similarities of conventional and new asset classes in terms of interrelationships with emerging stock markets.

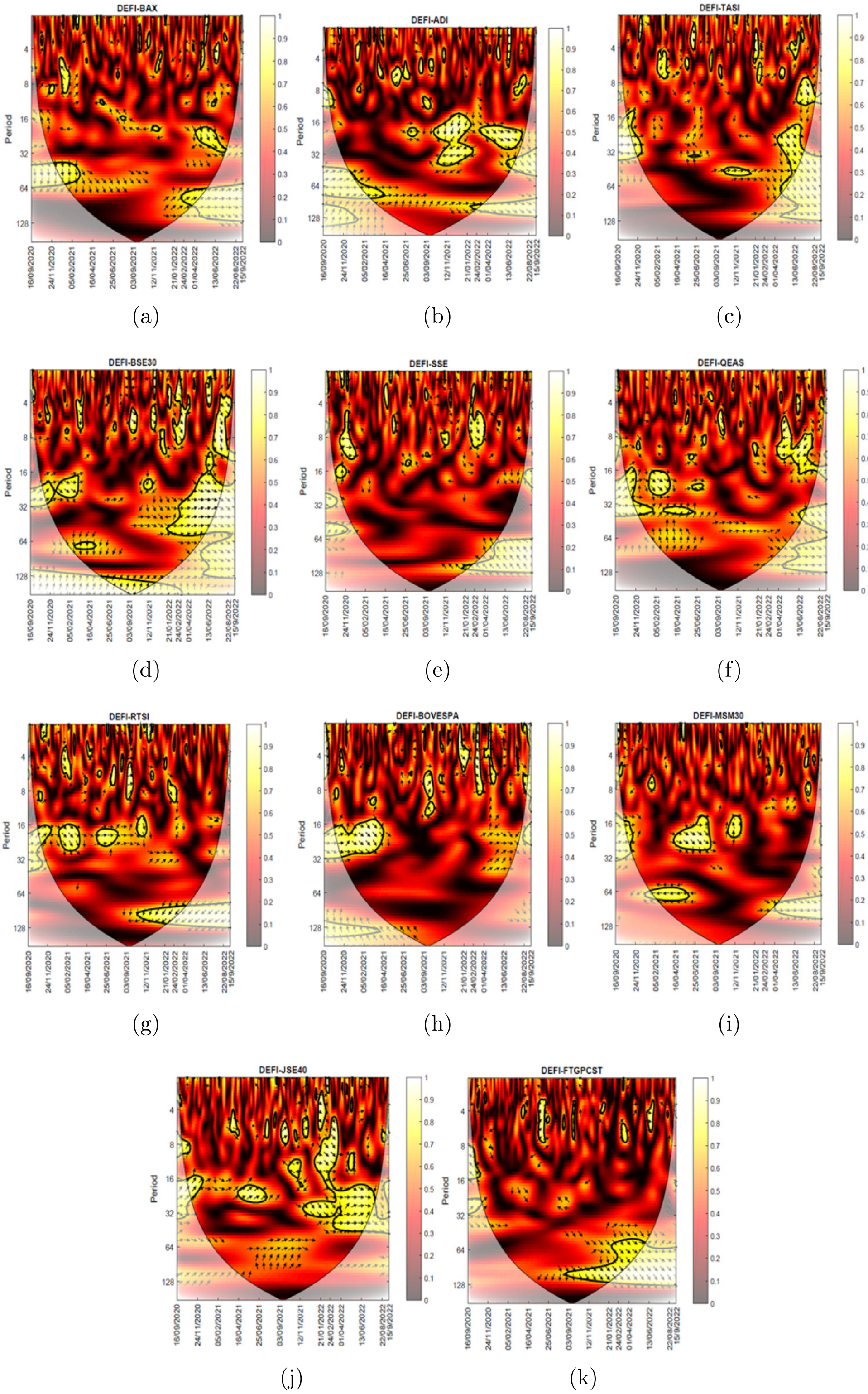

Fig. 1. Wavelet coherence of DeFi and stock returns pairs.

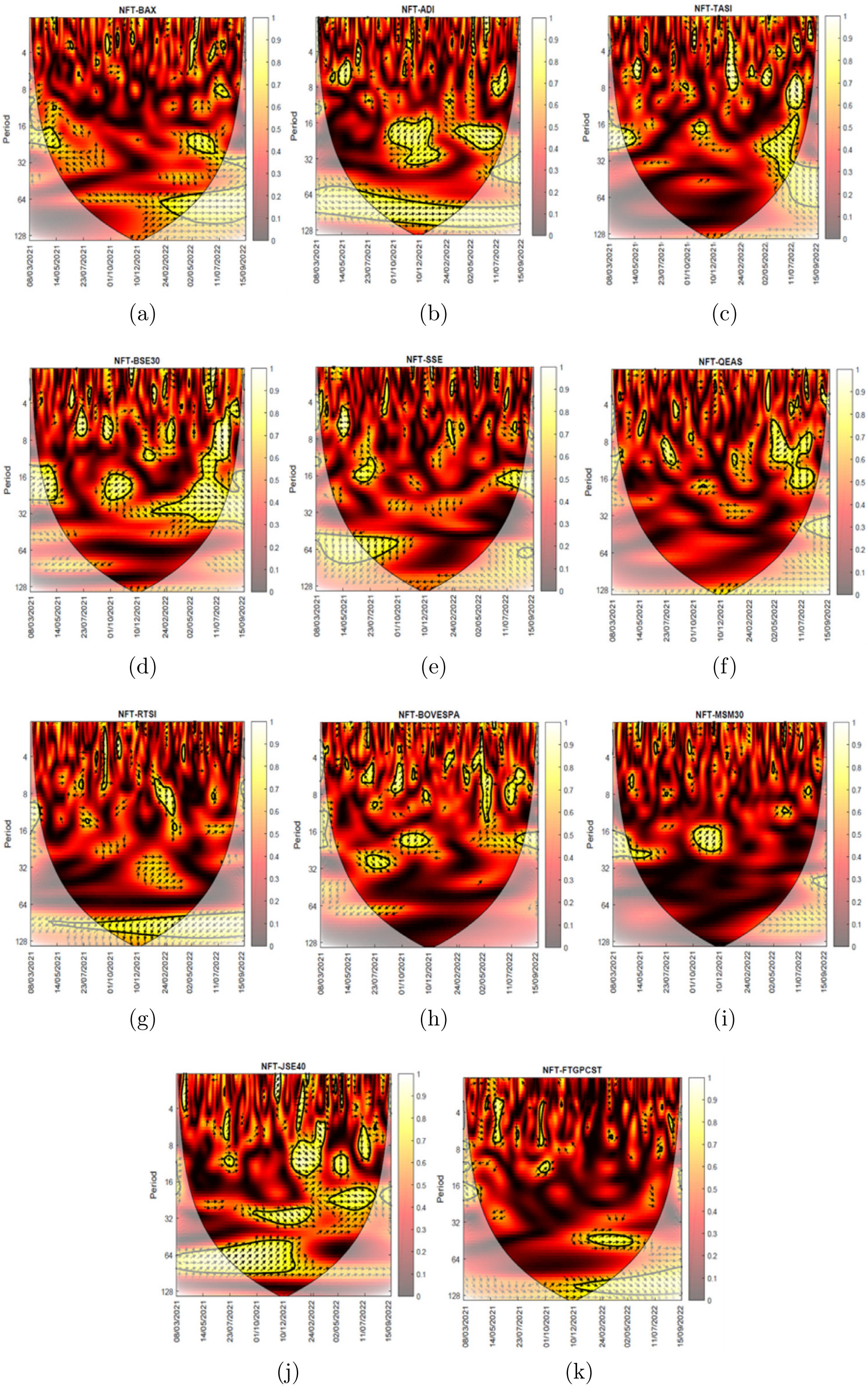

Fig. 2. Wavelet coherence of NFT and stock returns pairs.

significant comovement between SSE and DeFi is well-documented during the period 16/09/2020–5/09/2022. With the advent of the Russia–Ukraine war, some significant correlations between DeFi and some stock market indices with DeFi leading TASI, QEAS, FTGPCST, BSE30 and BAX at different frequency bands are well documented.

From Fig. 2, the substantial islands between the stock market and NFT seem to exist during the period 08/03/2021–5/09/2022. The lack of significant associations between MSM30 and NFT (Bovespa and NFT) is well-documented during the period 16/09/2020–5/09/2022. During the Covid-19 years and the 2022 Russian invasion of Ukraine, NFT is leading ADI, SSE, TASI, BAX, JSE40 and BSE30 at 32-64-day frequency bands while it is lagging RTSI and Bovespa at 64-128-day and 16-32-day frequencies. Like DeFi, significant correlations between NFT and other stock market indices exist during the advent of the Russia–Ukraine war.

Compared to Bitcoin, Ethereum, Gold, Bitcoin, Monero, Tether and DeFi, the substantial islands between the emerging stock market and NFT seem to be larger during the period 08/03/2021–5/09/2022. All without losing sight of the fact that each conventional asset class is characterized by distinct connection patterns, particularly with two different unprecedented and unexpected events. For instance, Bitcoin lags BAX, TASI, RTSI and BSE30 during the period 02/01/2020-12/05/2020 at 64-128-day frequency bands. Bitcoin is also lagging BSE30 and JSE40 during 24/02/2022–8/04/2022 at 16-31-day frequency scale. Nevertheless, Bitcoin is leading QEAS during 24/02/2022–8/04/2022 (at 64- 128-day frequency bands), Bovespa during 02/07/2019–2/05/2020 (at 64- 128-day frequency bands) and JSE40 during 02/01/2020–2/05/2020 (at 8- 32-day frequency bands). As well, Bitcoin is leading TASI during the period 24/02/2022–8/02/2022 at 32-64-day frequency scale. Overwhelmingly, Bitcoin-stock index comovements display high variability in different investment horizons and time periods including during the outbreak of the Covid-19 pandemic and the Russia–Ukraine war. Nonetheless, the dynamic interdependency between these different assets seems to be generally significant (but low) and more pronounced during the first waves of coronavirus. The same findings seem to be overwhelmingly shown for Ethereum and stock index pairwise. A similar pattern might be generally detected in Ethereum-stock index pair during the first few months of the pandemic. The high comovement seems to be more pronounced with JSE40, BSE30 and Bovespa. Only the comovements between Ethereum and ADI, BAX, SSE, JSE40 seem to be statistically significant at 16–32 and 64–28-day frequency bands during the Russia–Ukraine war with different lead–lag patterns. Such findings confirm those of [53,54] that cryptocurrencies tend to move with the stock markets amid increasing global uncertainty caused by the health crisis.

As far as the Gold-stock index comovements are concerned, significant islands between stock market indices in BRICS and Gulf regions during the first few months of the Covid-19 pandemic are detected, but they seem to be smaller. The right down pointing arrows reveal generally that Gold is leading BSE30, Bovespa, MSM30, JSE40 and RTSI at different frequency scales (particularly at 64–28-day frequency bands). However, Gold is lagging QEAS, SSE and ADI during the first waves of the Covid-19 pandemic.

Two salient and interesting facts can emerge from the Monero-stock index. First, Monero tends to generally lead stock indices during the first waves of the health crisis at medium- and long-term investment horizons. Second, a significant correlation between Monero and BSE30, JSE40, FTGPCST, TASI and BAX at the end of our sample period which is characterized by the outbreak of the Russia–Ukraine war at different frequency scales. Again, the comovement between the aforementioned assets and stock indices is rather documented during the Covid-19 pandemic compared to the Russian invasion of Ukraine.

Surprisingly enough, significant association between Tether and only FTGPCST, TASI and BAX is well-pronounced during two years 2020–2021. More precisely, the right down or left up pointing arrows show that Tether is leading such assets at 64–28- day frequency bands during the pandemic. The similar pattern is observed for BAX during the period 26/11/2021–8/04/2022.

By and large, stock market indices in BRICS and Gulf regions seem to commove significantly (but with very small magnitude) with True. Most of time, they are in phase during the first waves of Covid-19 pandemic, indicating that the stock markets are positively and significantly correlated at 64-128-day bands. The right down pointing arrows indicate that True is generally leading TASI, QEAS, FTGPCST and BAX. Some insignificant dynamic correlations are documented for ADI, SSE, JSE40, BSE30 and Bovespa.

To sum up, it is understood that there is a causal and dynamic relationship among new class of digital financial assets (NFT and DeFi), conventional assets (Bitcoin, Ethereum, Gold, Monero, Tether and True) and emerging stock markets. Nevertheless, the dynamic correlation between NFT/DeFi and emerging stock markets seems to be somewhat different compared to other conventional assets. Such findings confirm the fact that such assets can be different from traditional ones. Such discrepancy is even more pronounced with the varying levels of the war and pandemic's intensity. The aforementioned results show that the Covid-19 pandemic has dissimilar effects on the comovements between different asset classes. In this regard, the high comovements between different asset classes can be highly affected by systemic health/war-related risk factors. In some cases, a changing behavior in leading/lagging the interdependencies among digital and conventional asset classes can be detected with the type of unexpected event. Not only that, the interdependencies between the new/conventional assets diverge across investment horizons.

Further, we use the VAR model-based Granger Causality test for different sub-periods in order to not only offer additional support to our connectedness findings but also deepen and strengthen our findings about lead–lag patterns and phase difference among different asset classes. Needless to say, the Granger Causality test within the scope of VAR analysis and the compatibility of the chosen model with the sample data was checked. The model and the empirical

Table 2
Summary of granger causality test results during different sub-periods.

Summary of Granger Causality Test Results during the Pre-Covid-19 Period (02/01/2018-31/12/2019)											
VAR model Exogenous	SSE	RTSI	BSE	BVSP	JSE	BAX	KuwIndex	MSM	QEAS	TASI	ADI
BTC→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
ETHE→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	Cause	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
Monero→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Gold→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
Tether→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
True→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Summary of Granger Causality Test Results during the Covid-19 Period (02/01/2020-23/02/2022)											
VAR model Exogenous	SSE	RTSI	BSE	BVSP	JSE	BAX	KuwIndex	MSM	QEAS	TASI	ADI
BTC→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
ETHE→ALL	Cause	*Not Cause*	*Not Cause*	*Not Cause*	Cause	Cause	*Not Cause*	*Not Cause*	*Not Cause*	Cause	Cause
Monero→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Gold→ALL	Cause	Cause	Cause	*Not Cause*	*Not Cause*	Cause	*Not Cause*	Cause	Cause	Cause	Cause
Tether→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
True→ALL	*Not Cause*	*Not Cause*	*Not Cause*	Cause	Cause	*Not Cause*	Cause	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
NFT→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Defi→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Stock return→ALL			*BSE Cause ALL*		*JSE Cause ALL*					*TASI Cause ALL*	
Summary of Granger Causality Test Results during the Russia–Ukraine War Period (24/02/2022-15/09/2022)											
VAR model Exogenous	SSE	RTSI	BSE	BVSP	JSE	BAX	KuwIndex	MSM	QEAS	TASI	ADI
BTC→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
ETHE→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Monero→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause	Cause
Gold→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	Cause	*Not Cause*	*Not Cause*	*Not Cause*
Tether→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	*Not Cause*	Cause	Cause	Cause
True→ALL	Cause	Cause	Cause	Cause	Cause	Cause	Cause	*Not Cause*	Cause	Cause	Cause
NFT→ALL	*Not Cause*	Cause	Cause	Cause	Cause	*Not Cause*	Cause	Cause	*Not Cause*	Cause	Cause
Defi→ALL	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*	*Not Cause*
Stock return→ALL		*RTSI Cause ALL*	*BSE Cause ALL*		*JSE Cause ALL*	*BAX Cause ALL*	*KuwIndex Cause ALL*			*TASI Cause ALL*	*ADI Cause ALL*

results are reported in Appendix 2. For reasons of clarity and better understanding of our empirical findings, we sum up them in Table 2. Recall that the Granger Causality test examines whether a one-time series causes the other one or if a time series could be served to predict the other(s). Overall, the findings of Granger Causality test indicate the discrepancy among different asset classes in terms of causal relationship with emerging stock market in BRICS and Gulf regions. For instance, there is unidirectional relationship between Monero and emerging stock markets whereas Gold has no causal relationship with emerging stock markets during the pre-Covid-19 pandemic period. Afterwards, the causal connectedness estimates between time series confirm the substantial impact of Covid-19 pandemic. For instance, there is unidirectional relationship from NFT and DeFi to all emerging stock markets over the Covid-19 pandemic period, implying that they are the leading risk transmitters to emerging stock markets. Nevertheless, with the advent of the Russia–Ukraine war, no causal relationship between DeFi and emerging stock markets is documented. Therefore, the worst effect of the Covid-19 pandemic and Russia–Ukraine war news changes the pattern of new/conventional asset class-emerging stock markets nexus.

5. Discussion

Our paper attempts to analyze the dynamic frequency–time connectedness of two newly developed digital assets (NFT and DeFi) and classical and well-known assets (Bitcoin, Ethereum, Gold, Monero, Tether and True) and stock indices in BRICS and Gulf regions. For this end, we apply the wavelvet coherence method on returns of different asset classes over the period 02/01/2018–5/09/2022. Using such method allows us to investigate and better understand the nature of correlation structure, phase difference, lag lead patterns and different time periods of various variables under consideration, particularly with the advent of extremely stressful and unpredictable events (the Covid-19 pandemic and the Russia–Ukraine war). Our empirical results display the existence of relationships between newly developed digital assets (NFT and DeFi) and index returns of emerging stock markets. Such connectedness tends to change in both short- and long-run. As well, the NFT/emerging asset class and DeFi/emerging asset class pairwise frequency–time connectedness seems to be somewhat different compared to the couples of Bitcoin, Ethereum, Gold, Monero, Tether and True and other asset classes. Such differences among assets' couples seem to be in their response to the changing levels of the war and pandemic's intensity. In particular, there is asymmetric dynamics of linkages depending of the nature of stressful and unexpected events. An abrupt hike in correlation between NFT, DeFi and other stock market indices exist during the advent of the Russia–Ukraine war. Such significant patterns in connectedness can be attributed to systemic health/war-related risk factors which underline the significance of market-specific risk drivers during the initial escalation of the pandemic and war. Overall, our outcomes are in line with similar patterns shown by some researchers (e.g. [10,31]). Umar et al. [31] show that the health crisis significantly affects both the return and volatility spillovers. The time-varying interdependence between different assets depends on the different waves of the pandemic. Zhang et al. [55] indicate that NFT can act as hedge for US dollar, bonds and gold during the period 01/01/2018–1/03/2022. In particular, NFT is hedge for US dollar and stocks (resp. US dollar) before (resp. during) the Covid-19 pandemic. Yousaf and Yarovaya [41] show weak but significant static return and volatility spillovers between NFT, DeFi and other markets. From dynamic perspective, the return and volatility connectedness seems to be greater during the first wave of the Covid-19 pandemic.

Using more advanced econometric techniques such as the wavelet method, a network-VAR method and networks technique attempts to be understand the correlation structure between assets' prices, the markets' interconnectedness and really how price information and shocks attributed to systemic health/war-related risk factors can be transmitted among assets' prices in the same or between market(s). As a matter, Giudici and Polinesi [56] profess that apprehending price interconnectedness is a crucial factor to depict the cross-linkages between markets and if prices in different markets quickly react to each other and assess the market efficiency. Therefore, such techniques can help to approach the complex reality of markets, particularly with the outbreak of unprecedented and unexpected events. Not only that, the empirical results based on such techniques can changed the pattern of investor thinking by implementing more risk-mitigating tactics during crises and offer straightforward insights for regulators and policymakers. In this regard, and for instance, Giudici and Abu-Hashish [57] use a network VAR approach to apprehend the dynamics of cryptocurrency prices. They find that such model can successfully depict the correlation structured between Bitcoin prices in various markets. Giudici and Polinesi [56] rather use correlation networks and document Bitcoin prices seem to positively relate with each other. By constructing a network volatility index, Ahelegbey and Giudici [58] show that during crisis periods (e.g. the Covid-19 pandemic and the tech bubble), the stock market interconnectedness contributes to global market turmoil.

6. Conclusions

Our paper applies the wavelet coherence method to study the comovements between the newly developed digital assets (NFT and DeFi), traditional well-known assets (Bitcoin, Ethereum, Gold, Monero, Tether and True) and stock indices of Gulf and BRICS stock markets. Our results clearly show the existence of relationships between NFT, DeFi and other assets. Such connectedness tends to change in both short- and long- run, in particular with the outbreak of health and political crisis. Our empirical findings also display the asymmetric patterns in the dynamics of Bitcoin/emerging market index, Ethereum/emerging market index, Gold/emerging market index, Monero/emerging market index, Tether/emerging market index and True/emerging market index pairwises. The comovements between emerging stock markets and the aforementioned assets tend to be different and in some cases weak or insignificant against an extremely stressful and unexpected events. Therefore, there are discrepancies between pairwises in their reactions to the changing levels of the war and pandemic's intensity.

Our empirical findings could have insightful implications to different market participants and researchers, especially during episodes of slowdown such as the 2022 Russian invasion of Ukraine and the Covid-19 pandemic or any other systemic risk event. Based on these empirical findings, investors and portfolio managers could develop cross-asset hedging strategies by taking into consideration the diversification benefits of adding NFT and DeFi assets. Our outcomes can motivate researchers to investigate the interconnections of NFT and DeFi digital assets and major asset classes which still not sufficiently investigated.

Nevertheless, this study presents some limitations which can be considered in future studies. These limitations include increasing the analysis period to better explore the effect of the Russia–Ukraine war on the comovements between different asset classes. As well, including potential drivers of the connection between NFT/DeFi and emerging stock markets such as investor sentiment/attention, media coverage indicators and fake news index could be useful for investors to understand such association. Similarly, further extensions of our work may comprise performing the volatility spillover analysis and computing dynamic optimal ratios.

CRediT authorship contribution statement

Azza Bejaoui: Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Wajdi Frikha:** Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Ahmed Jeribi:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Aurelio F. Bariviera:** Conceptualization, Writing – original draft, Writing – review & editing , Supervision.

Declaration of competing interest

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

Data availability

Data will be made available on request

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.physa.2023.128720.

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