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Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: A comparative analysis during COVID-19 and Russian-Ukraine war

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ABSTRACT

Economic and political disorders have multidimensional impacts on all economies around the world. The global world has faced out COVID-19 pandemic in 2020, and now the Russian-Ukraine geopolitical crisis. This study investigates the nexus among commodities, crypto, and G20 capital markets along with risk and returns implications. To examine the impact, we applied the TVP-VAR technique suggested by Koop and Korobilis (2014), and Antonakakis, Chatziantoniou, and Gabauer (2020) by adjusting the framework of Diebold and Yilmaz (2012). The research findings reveal that a high level of connectedness was observed during Covid-19, which was persistent for a long period and has multidimensional impacts. More particularly, EU, Canada, France Germany, and the UK were the principal supplier of spillovers to other commodities, Bitcoin, and the remaining markets. During Geopolitical Crisis (here after GPC), conclusively it is observed that of USA, Brazil, Saudi Arabia, Canada, Mexico, China, Indonesia, and Japan are the net receivers of the volatility spillovers and Russia, Germany, France, European Union, Italy, UK, Argentina, India, Australia, Turkey, Korea, and South Africa are the net transmitters of volatility spillovers. Interestingly, among net transmitters Argentina, South Africa and Turkey are suffered from high inflation and substantial budget deficits, considered as weak economies of G20. Portfolio weights has been increased dramatically during COVID-19 and Russian-Ukraine war. This research could be utilized to take investment, hedging, and diversification decisions about commodities, cryptocurrencies, and stocks, particularly in such turmoil situations with the help of connectedness and various hedging techniques.

1. Introduction

In the past two and half years, the global world has faced two major crises: the COVID-19 (a global pandemic) and the Russia-

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Ukraine war (a geopolitical emergency). Both crises caused serious financial difficulties for many economies in the world. Financial and commodities markets have seen a major downward trend worldwide during these times. Initially, the spread of COVID-19 and the high death rate led to the situation of lockdown across the world. This caused a lot of anxiety and fear among people which resulted in selloffs of safer assets like gold and the government's 10-year treasury bills (Sinha & Sawaliya, 2020). Due to the outbreak of the disease FTSE dropped by 14.3% in the year 2020 the lowest since 2008. In the United States, the number of people out of work hit 8.9%, and many workers were put into government-supported retention schemes. According to the International Monetary Fund (IMF), there is an end to a decade of job expansion, and the global economy shrunk by 4.4% in the year 2020. This decline is considered worse than the Great Depression of 1930 (BBC News, 2022).

Russia and Ukraine produce and export natural gas, crude oil, and special food products to the world in large quantities, they are among the largest producers of sunflower oil and contribute almost 60% of such global production (S&P Global Platts). Further, they also grow 28.9% of the world's wheat exports (Morgan, 2022). The present war between Russia and Ukraine not only has an adverse impact on production but its effects are multi-faceted, namely shattered supply chains, a rise in global inflation (Josephs, 2022; Cohen, 2022; Wiseman and Mchugh, 2022; Russia's war in Ukraine, 2022a), a reduction in the supply of conventional sources of energy (Economist Intelligence, 2022; Astrov, Grieveson, Kochnev, Landesmann, & Pindyuk, 2022), and low returns facing high volatility in the capital markets across the globe (Sun, Song, & Zhang, 2022; Boubaker, Goodell, Pandey, & Kumari, 2022; Meier et al., 2022).

The impact of a war in Ukraine on global Equity markets is observed instantaneously. Dow Jones fell 1.38 percent and Nasdaq lost 2.6 percent, and also a huge sell-off was seen in Asian markets. Tokyo and South Korea fell by 2%, Hong Kong and Sydney stock markets lost more than 3% (Why Russia-Ukraine crisis hit India's share market, 2022). There is weaker confidence in financial markets and higher prices for energy and its source are witnessed because of strong international sanctions against Russia (Liadze, Macchiarelli, Mortimer-Lee, & Juanino, 2022). Moreover, the impact of the Russia-Ukraine war on the world economy is observed in the commodity markets as well. These sanctions have disrupted air and sea shipments of commodities produced and exported by Russia. Brent crude prices rose 21% in the first week of the war. It is the highest since 2013. The wheat prices rose to a 14-year peak and gained around 40% since Russia's invasion. Also, Russia is a supplier of metals like aluminum which hit a record high (Financial Markets: Russia-Ukraine war, 2022). This war has further led to supply chain problems for users of commodities like a crude oil, natural gas, car, smartphones, and aircraft makers which will further affect financial markets (Balli, Billah, & Chowdhury, 2022; Liadze et al., 2022; Rueters, 2022).

Overall, the impact of the COVID-19 and Ukraine-Russia wars is huge. According to a report from *The National Institute of Economic and Social Research Britain* using the Global Econometric Model the conflict in Ukraine could reduce the level of global GDP by 1 percent by 2023, that is about $1 trillion off global GDP and add up to 3 percent additional inflation to the world in 2022 and about 2 percentage points in 2023. Considering the impact of these two events is enormous to the world economies, the present study aims to explore the comparative behavior of returns and risk spillovers during the COVID-19 and Russia-Ukraine conflict on the commodities, cryptocurrency(s), and G-20 stock markets. The purpose behind taking G-20 is very simple, it is an intergovernmental forum comprising 19 countries and the European Union (EU) and is used as proxy of world market. The G20 initially worked largely on broad macroeconomic policy, but now it includes trade, climate change, sustainable development, energy, environment, climate change, anti-corruption, etc. G20 members currently account for more than 80% of world GDP, 75% of global trade, and 60% of the global population (MEA GOI, 2012; Group of Twenty-G 20, 2012). According to World Federation of Exchanges 2019 data, the total market capitalization of G20 markets capitalization was nearly around US$ 90 trillion that is around 90% of the G20 countries' collective GDP of US$ 100 trillion (G20 Insights, 2021).

To our best of our knowledge, there is no such study conducted that has done the combined comparative analysis of how the G-20 financial markets, commodities, and cryptocurrencies respond to such turmoil events. Further, the time duration between these two global events is also less than two years, therefore it is important to understand its widespread impact. Our study will be the first one to draw comparisons between the financial crisis and geopolitical crisis on G20 stock market commodities and cryptocurrencies. This study tries to answer the following research questions and aspire to add the knowledge on following aspects to the literature. (1) Is there any difference between average return and variance of returns of G20 stocks markets, gold, oil, and crypto before and after the outbreak of the financial and geopolitical crisis? (2) Did the COVID-19 pandemic lead to more volatility in the G20 stock markets compared to the geopolitical crisis between Russia and Ukraine and vice-versa? (3) more specifically, a sub-sample analysis has also been studied during COVID-19 and Russia-Ukraine conflict to understand the dynamics of risk and return spillovers. Further, the paired portfolio weights and hedging effectiveness during COVID-19 and Russian-Ukraine war of Bitcoin, oil, gold, and EU markets are also evaluated and adding new outcomes the existing body of literature.

2. Literature review

2.1. COVID-19 impact on stock markets

Uncertain events lead to a high risk in the stock markets which creates problems in the functioning, more specifically during pandemic events (Ichev & Marinč, 2018: Liu, Manzoor, Wang, Zhang, & Manzoor, 2020; Yang et al., 2020; Mazur, Dang, & Vega, 2021; Billah, Balli, & Hoxha, 2023; Billah, Amar, & Balli, 2023). COVID-19 crisis has witnessed negative effects on stock returns in both the developed markets and emerging markets across the world (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020; Harjoto, Rossi, & Paglia, 2021; Kumar, Kaur, Tabash, Tran, & Dhankar, 2021; Uddin, Chowdhury, Anderson, & Chaudhuri, 2021). To study the COVID-19 impact (Zaremba, Kizys, Aharon, & Demir, 2020) had taken 67 countries' indices (Liu et al., 2020), took 21 countries' indices, (Anastasiou, Ballis, & Drakos, 2022), studied G20 markets, and (Chaudhary, Bakhshi, & Gupta, 2020) considered the top 10 countries' stock market indices. All these studies have found daily negative mean returns for all market indices. The stock markets fell in majorly affected countries. Even the countries in the Asia experienced more negative abnormal returns. Moreover, (Okorie & Lin, 2021) studied the fractal contagion effect of the ex-ante and ex-post COVID-19 pandemic on the stock markets of 32 of the most affected economies. The findings showed that stock markets have a fractal contagion effect of COVID-19.

Further (Nguyen, Phan, & Ming, 2021), found evidence of significant contagion effects from the U.S and China stock markets during the COVID-19. There was no change in the nature of stock index volatility; and even no strong evidence for volatility spillover effects during COVID-19. It was also seen that even both good and bad COVID-19 news have an impact on stock volatility (Baek, Mohanty, & Glambosky, 2020). Also (Mazur et al., 2021), found that some stocks such as hospitality, petroleum, real estate, and entertainment had fallen more as compared to stocks of software, natural gas, food, and healthcare (Abuzayed, Bouri, Al-Fayoumi, & Jalkh, 2021). studied systemic distress risk spillover in the most affected countries during the COVID-19. They found that bivariate systemic risk contagion exists between the global stock market and each individual stock market, and it further intensified with the spread COVID-19 across the world. Besides this (Apergis & Apergis, 2020; Kumar et al., 2021), studied daily deaths and cases, and their relationship with stock returns, and the result showed that there was a significant negative impact on the stock returns. Thus, the above-mentioned studies highlighted the positive correlation between pandemic, and stock market volatility and the negative correlation with the returns.

2.2. War impact on stock market

The previous section discusses pandemic effects on capital markets and now the current section is deliberating the geopolitical conflicts impact on capital markets. The various studies highlight that war have negative effect on capital markets (Choudhry, 2010; Hudson & Urquhart, 2015; Schneider & Troeger, 2006). Although, the effects of geopolitical may vary country to country.

Starting from World War II, (Choudhry, 2010) examines the impact of war on Dow Jones industrial average stock index. The findings showed that the wartime events resulted in structural breaks in both price movement and stock return volatility (Hudson & Urquhart, 2015). also studied world war II impact on the British stock market The result, however, showed that there was limited evidence of strong links between war events and market returns, though there was support for the 'negativity effect' (Hudson & Urquhart, 2015).

Further, (Schneider & Troeger, 2006) studied the effects of three wars i.e., Israel, and the Palestinians, the U.S.-led alliance against Iraq, and the wars fought in Ex-Yugoslavia. They focused on CAC, Dow Jones, and FTSE on Time series analyses from 1990 to 2000. The result supported the negative effect of war on the global financial markets (Kollias, Papadamou, & Stagiannis, 2010). found the effects of the Israeli military in the Gaza Strip (2008) on the return and volatility of the Tel Aviv Stock Exchange (TASE) and government bond index. The results were consistent with the studiesmentioned previously that the armed conflicts and wars had an impact on capital markets and affected asset prices though effects may not be the same across financial markets, countries, and through time.

Moreover, to explore the effect of the Russia-Ukraine war (Boungou & Yatié, 2022), analyzed stock returns of 94 countries and found a relationship between this war and the world stock market returns. Similarly (Boubaker et al., 2022), used an event study methodology to examine the impact of Russian-Ukraine war and found that the global stock market had given negative cumulative abnormal returns. The results were consistent with markets of more globalized economies being more vulnerable to international conflicts, with, some notable heterogeneities. Also (Federle, Meier, Müller, & Sehn, 2022), confirmed that countries within 1000 km of war countries have implications for returns. The war results showed dynamic conditional correlations with USD, yen, silver, Brent, WTI, and natural gas were found to be safe as compared to the ruble (Mohamad, A., 2022). Even though bonds and equities had shown war impact in the long term, cryptos had nullified it in short term, whereas, Swiss franc, gold, silver, green bonds and were the most shocking-fighting assets (Bedowska-Sojka, Demir, & Zaremba, 2022).

The above studies show that equity, commodities, and the crypto market were volatile towards wars around the world. Although the quantity of effect may vary from country to country the impact was majorly the markets showed a downward trend.

Additionally, this research employs (TVP-VAR) methodology. This framework helps in capturing all possible changes in the underlying structure of the data more flexibly and robustly and is used to predict time-varying variance-covariance structure (Antonakakis, Chatziantoniou, et al., 2020). By using the TVP-VAR methodology (Bouri, Cepni, Gabauer, & Gupta, 2021a) research showed total interconnectivity across all the five assets such as bonds, gold, currencies, world equities, and crude oil, also these were moderate, and quite stable before 2020, but during COVID-19 there were variations observed in the returns (Bouri, Lei, Jalkh, Xu, & Zhang, 2021b). applied TVP-VAR model and showed that spillover is affected by various crisis. Moreover (Umar, Aziz, & Tawil, 2021), also applied the TVP-VAR approach to analyze the connectedness between the COVID-19 induced global panic index (GPI) and precious metal returns and volatility. The results showed evidence of the positive connectedness between the GPI and precious metals with GPI except for silver. The study of (Adekoya & Oliyide, 2021) found the connectedness among the markets using TVP-VAR during COVID-19 to study the volatility spillovers among the commodity and financial assets. The results showed strong volatility across the markets, with gold and USD, being net receivers of shocks, and others being net transmitters (Jebabli, Arouri, & Teulon, 2014b). used the TVP-VAR model along with the stochastic volatility approach to study shock transmission between international food, energy, and financial markets and concluded that during 2008 there was an increase in volatility spillovers and after 2008 there was a change in the stock market. It becomes a net transmitter of volatility shocks whereas crude oil was a net receiver of the shock. Moreover, it has been seen when a portfolio is diversified with food commodities, crude oil and stocks, it highly increases its risk-adjusted performance.

Further (Singh, Dhall, Narang, & Rawat, 2020), examined the effect of COVID-19 on G-20 countries' stock markets. The empirical findings concluded that in the beginning of COVID-19 i.e., from day 0–43 cumulative average abnormal return (CAAR) varies from −0.70 percent to −42.69 percent and then from other days i.e., from 43 to 57, CAAR varies from −42.69 percent to −29.77 percent, indicating that the stock markets recovered from major correction of the COVID-19. The results of panel data analysis confirmed the

Table 1
Summary statistics daily returns of Commodities, Crypto, and G20 Markets.

Commodities & stock markets	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF	PP	Q (1)	Q (5)	Q^2 (1)	Q^2 (5)
BITCOIN	0.254	0.043	−0.103	8.499	2415.90***	−26.01***	−25.58***	11.590**	19.379**	113.320***	206.947***
GOLD	0.069	0.022	−0.096	7.596	1688.57***	−17.34***	−17.40***	23.766***	47.480***	813.576***	1273.491***
OIL	0.072	0.032	0.606	23.814	34683.19***	−16.04***	−16.06***	9.12	17.849**	6.021	7.96***
ARGENTINA	−0.005	0.026	−3.954	78.677	461952.20***	−19.66***	−19.72***	20.155***	38.693***	1168.634***	1668.054***
AUSTRALIA	0.008	0.013	−1.015	13.013	8329.13***	−16.76***	−16.93***	22.230***	36.741***	1069.606***	1255.155***
BRAZIL	−0.009	0.022	−0.949	13.958	9868.71***	−23.75***	−24.80***	52.697***	96.595***	1300.517***	1717.412***
CANADA	0.012	0.012	−1.412	31.943	67477.27***	−17.83***	−18.98***	11.012**	25.784***	341.911***	500.119***
CHINA	−0.004	0.015	−1.013	8.909	3113.31***	−19.66***	−18.76***	11.326**	19.492**	300.873***	439.960***
EUROPEAN UNION	0.002	0.012	−1.353	20.949	26289.51***	−25.55***	−24.57***	10.544*	18.495**	213.630***	337.984***
FRANCE	0.014	0.013	−1.105	19.050	20944.01***	−13.04***	−13.03***	34.420***	60.170***	431.589***	667.383***
GERMANY	−0.003	0.013	−0.902	18.553	19560.12***	−15.27***	−16.18***	18.962***	27.460***	733.818***	1042.562***
INDIA	0.024	0.012	−1.588	22.529	31234.62***	−11.49***	−11.46***	9.977*	16.505*	124.981***	155.084***
INDONESIA	0.002	0.015	−0.119	15.572	12615.94***	−12.32***	−12.35***	25.048***	33.566***	317.489***	432.687***
ITALY	−0.002	0.015	−1.986	27.506	49178.88***	−18.93***	−18.65***	19.521***	27.983***	1421.248***	1670.008***
JAPAN	0.012	0.011	−0.121	7.519	1634.18***	−11.29***	−11.29***	34.523***	46.334***	829.980***	1189.466***
MEXICO	−0.009	0.015	−0.765	8.906	2969.95***	−15.21***	−15.22***	2.322	4.266***	229.78***	278.67***
REPUBLIC OF KOREA	0.014	0.014	−0.134	9.386	3260.19***	−12.69***	−12.45***	44.998***	59.838***	87.668***	103.388***
RUSSIA	−0.671	0.286	−43.275	1886.540	284000000***	−15.63***	−15.45***	8.558	13.794	615.099***	864.715***
SAUDI ARABIA	0.036	0.012	−2.282	37.369	95914.34***	−18.36***	−18.75***	3.487	8.131	159.847***	172.283***
SOUTH AFRICA	−0.012	0.019	−0.554	6.890	1305.67***	−17.23***	−17.63***	13.833***	30.899***	305.088***	461.487***
TURKEY	−0.055	0.022	−0.097	20.663	24897.92***	−15.33***	−15.78***	140.275***	227.283***	1699.962***	2233.589***
UK	−0.006	0.012	−1.160	21.365	27342.24***	−19.68***	−19.36***	11.277**	20.210**	223.667***	331.666***
USA	0.037	0.011	−1.034	22.488	30644.30***	−19.63***	−19.23***	8.57	15.857*	67.419***	96.877***

Note: The above table illustrates the descriptive statistics for commodities, crypto, and G20 markets (Gold, WTI Crude Oil, Bitcoin, Argentina, Australia, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Mexico, Republic of Korea, Russia, Saudi Arabia, South Africa, Turkey, USA, UK, and European Union). The period has been selected daily from January 1, 2015 to May 13, 2022. Moreover, Std. Dev., JB, ADF, and PP represents standard deviations, Jarque-Bera, Augmented Dickey & Fuller, and Phillip & Perron, autocorrelations of orders 1 and 5 (Q(1)-Q(5)), and autocorrelations of the squared time series of orders 1 and 5 ($Q^2(1)$ and $Q^2(5)$), with superiors signifying ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

recovery of stock markets from the negative impact of COVID-19. Moreover (Yousaf, Patel, & Yarovaya, 2022), studied the Russian-Ukraine war using the event study approach on the G20 and other selected stock markets. The findings led to a strong negative impact of this military action on a majority of the stock markets, especially on the Russian market. There is a significant negative impact of the Russia-Ukraine conflict on the 1st day and following other days. Even (Umar, Bossman, Choi, & Teplova, 2022) studied the Russian-Ukrainian conflict in the financial markets of Russia, and Europe and also in the commodity markets globally. TVP-VAR approaches have been used to study connectedness. The results exhibited that due to conflict relationship has changed, and both the Russian bonds and European equities become the net transmitters of shock. Besides this, the conflict affects volatility connectedness and returns.

2.3. Cryptocurrency and commodities studies

The above sections discuss the pandemic effect, geopolitical effect, and the use of TVP-VAR methodology. The current section highlights the past research done in the new growing asset that is cryptocurrency and commodities. It has been seen the pandemic crisis and geopolitical crisis have an effect on corresponding financial markets.

Naeem, Lucey, Karim, and Ghafoor (2022) studied whether financial volatilities able to mitigate the risk of cryptocurrency indexes using time-varying parameters vector autoregression approach and the result shows that there are distinct spillover patterns between financial volatilities and cryptocurrency indexes. Also, there is extreme risk spillovers during turmoil periods. Katsiampa, Yarovaya, and Zięba (2022) collected high-frequency data from January 2019 to December 2020 to study the co-movements and the correlations of Bitcoin and thirty-one tradable cryptocurrencies. The findings disclosed that the assets which can be categorized as Apps and have protocols become attractive for investors as compared to pure cryptocurrencies. Liu (2019) guided that by including more (ten) cryptocurrencies in the portfolio useful to generate better risk-adjusted return. Moreover, some researcher also proposed that cryptocurrencies are not useful for investors to manage their systematic risk significantly. Conlon and McGee (2020) verified that bitcoin was not a haven asset during the COVID-19 crisis time. Similarly, Susilo, Wahyudi, Pangestuti, Nugroho, and Robiyanto (2020) also proved that the equities/cryptocurrencies focused investment has a better performance than risk mitigation. In the words of Billah, Elsayed, and Hadhri (2023) sukuk and green bond markets show limited vulnerability to global risk factors across different quantiles, making Sukuk an effective hedge for both green bonds and global risks.

Additionally, Hasan, Naeem, Arif, and Yarovaya (2021) studied higher-moment connectedness among three dominant cryptocurrencies. It is found that in COVID-19 pandemic connectedness among Bitcoin and Litecoin (Ripple and Binance Coin) emerged as the leading spillover receivers (transmitters). Similarly, Ghorbel, Loukil, and Bahloul (2022) analyzed the connectedness among major cryptocurrencies, the G7 stock indexes, and the gold price during the coronavirus disease 2019 (COVID-19) pandemic period, in 2020. The result presented the connectedness which could be existed due to economic and financial uncertainties on account of coronavirus. Moreover, Grobys and Sapkota (2019) have studied the set of 143 cryptocurrencies from 2014 to 2018. In contrast to earlier studies, the findings did not indicate any evidence of significant momentum payoffs suggested in earlier studies.

Further, Wang, Bouri, Fareed, and Dai (2022) studied the volatility in commodities around the Russia-Ukraine war. The volatility spillover is seen more in the war than in pandemic i.e., ranges from 35% to 85%. It was observed that commodities like aluminum, platinum, silver, gold, copper, and sugar became net transmitters of volatility. In terms of return spillovers, crude oil was a net transmitter whereas, soybeans and wheat became net receivers. Also, Kyriazis (2020) reviewed the empirical literature concerning the impacts of geopolitical uncertainty. The focus is mainly on cryptocurrencies, oil, gold, and stock markets. The findings showed that the GPR index is negatively related to returns and volatility of oil prices. Similarly, Iqbal, Bouri, Grebinevych, and Roubaud (2022), studied the spillovers among the energy, metals, and agricultural commodities from the period of September 23, 2008, to June 1, 2020. The results indicate that the connectedness is higher in lower and upper quantiles than the median. It implies that there are volatility shocks during extreme events like COVID 19. Even (Mensi, Riaz, Ali, Vinh, & Hoon, 2022), examined the precious metals such as silver, gold, palladium platinum, and foreign exchange of US, Canada, Australia, China, Japan, Eurozone, UK, and Switzerland in terms of quantile dependence, volatility spillovers, and connectedness. Patel, Kumar, Bouri, and Iqbal (2023) analyzed the return and volatility connected behaviour amongst green and dirty cryptocurrencies with SRIs and strong linkages are observed during war comparative to pre-war. Interestingly, Babar, Ahmad, and Yousaf (2023) also confirmed higher degree of connected amongst agriculture commodities and emerging markets during COVID-19 and Russian-Ukrainian military conflict. While weak associations are observed amongst sample assets for full sample period.

By applying Asymmetric DCC (ADCC) and GO-GARCH models Basher and Sadorsky (2016) proposed that oil is the best asset to hedge emerging market stock prices compared to gold prices, and bond prices. Ewing and Malik (2016) utilized the hedging approach of Chang, McAleer, and Tansuchat (2011) found that participants of stock and oil markets share the common information to take portfolio decisions and also confirmed the presence of cross-market hedging. Wang and Liu (2016) also utilize the percentage reduction in variance to measure the hedging effectiveness (Chang et al., 2011). They also concluded that investment is made in stocks of oil-exporting countries rather that oil-importing countries is helpful to better hedge the investment. Outcome of Antonakakis, Cunado, Filis, Gabauer, and De Gracia (2018) from pre-, during and post-financial crisis periods proposed that the average hedge ratios in the oil price volatility shown marginal change. Khalfaoui, Boutahar, and Boubaker (2015) followed the hedge ratio and hedge effectiveness and concluded that hedge ratios are changing as scales changes and advise to investors and financial markets participant that they should hold less stocks than crude oil. Antonakakis, Cunado, Filis, Gabauer, and de Gracia (2020b), concluded that VIX is the least useful implied volatility index to hedge against oil implied volatility, investors can utilize the findings of dynamic weights and hedge ratios to get benefit substantially by adjusting their portfolios. As per Nugroho (2021), COVID-19 causes increases in dynamic connectedness of gold and gold-backed cryptocurrencies and confirmed a contagion effect. The results show that gold is the net volatility receiver during the COVID-19 pandemic. Moreover, gold and gold backed cryptocurrencies portfolio shown high profitability performance along with zero hedge effectiveness under optimal weights strategy.

3. Data and methodology

3.1. Data

To navigate the spillover effects of the full period (January 1, 2015 to May 15, 2022), pre and during COVID-19, and Russian invasion of Ukraine. We have used the data of two major commodities spot prices, namely crude oil (OIL), and gold (XAUUSD), Bitcoin as a proxy of crypto markets, and G20 (European Union, UK, USA, Turkey, South Africa, Saudi Arabia, Russia, Republic of Korea, Mexico, Japan, Italy, Indonesia, India, Germany, France, China, Canada, Brazil, Australia, Argentina) MSCI market indices, for the above-mentioned period.[1] The total 1863 trading days are being taken; daily log returns are being used for further analysis. These markets represent the global world as they hold two-thirds of the world population and contribute 85% and 75% of the world GDP and trade respectively. They also have strong trade and economic ties with each other (Vieito, Bhanu Murthy, & Tripathi, 2013; Amin & Naseer, 2017; Ibrahim & Ajide, 2021). These countries have consisted of participants from different continents/part of the global world. These markets have the largest consumer base, trade, and cross-border investments among themselves and in the rest of the world. Further, they have the potential to swing global development with their high degree of commodity consumption, GDP, and trade contribution. Moreover, the data has been extracted from Bloomberg database system.

As per the summary statistics table, both the commodities and Bitcoin (highest) are yielding positive average returns, while European Union (EU) and nine other markets have generated positive returns in the given time, whereas the remaining markets failed to add any value to the investors. Here, important to note that the USA is the best performing market followed by Saudi Arabia and India, while Russian market depleted a huge wealth of the investors and similar negative returns are produced by Turkey but with a huge difference to Russia. A high degree of volatility is being observed among the commodities and Crypto markets. It is due to COVID-19 and Russian-Ukraine geopolitical crisis in the last three years. Amongst the markets, Russia has shown the highest volatility shadowed by Argentina, Turkey, and Brazil. We may perceive the direct impact of the Russian invasion on commodities as well as stock markets (Boungou & Yatié, 2022; Federle et al., 2022; Liadze et al., 2022; Morgan, 2022).[2] Further, skewness has been tested and except for oil, all have depicted as negative skewness, which infers that the tail of the left side of the distribution is longer or fatter than the tail on the right side. If we talk about kurtosis, it is found to be extreme excess (leptokurtic), i.e., needs to be a wider tail compared to a normal distribution, hence observations are extremely situated. The last two columns of Table 1 provide portmanteau test statistics Q and Q^2 (for quadratic data) by Ljung and Box (1978) to examine the dependencies of the first and second moments in the distribution of financial market indices. For most of the Q indices, the Q statistic is significant, indicating that these indices correlate sequentially. The second-quarter statistics (Q^2) are meaningful/significant for all markets and show a solid second-moment dependence (conditional heteroscedasticity) in the distribution of market indices, which exhibit ARCH/GARCH type effects.

Additionally, volatility clustering can be observed among all the markets (including crypto and commodity markets) not only during COVID-19 but also during the Russian invasion of Ukraine in 2022. Comparatively, large spikes are being seen during COVID-19, as it was a worldwide crisis and had strong contagious effects (Corbet, Larkin, & Lucey, 2020; Fry-McKibbin, Greenwood-Nimmo, Hsiao, & Qi, 2022; Gharib, Mefteh-Wali, & Jabeur, 2021; Okorie & Lin, 2021). Since, the invasion is a geopolitical crisis, therefore it has lesser impact on other continents of the world (Le Billon, 2004). Here, worth noting is that Russia, its neighbors, and trade partners reflected greater volatility during wartime as compared to the other markets. During Covid-19, gold and oil displayed high sensitivity compared with cryptocurrency (bitcoin), while during wartime gold has shown a large amount of volatility clustering.

3.2. Methodology

This study uses the total and frequency connectedness approach to examine the relationship among commodities, crypto and G20 markets. For valuation purposes, the price set is converted to the return of the first difference as follows:

$$R_t = \ln(P_t/P_{t-1}) \times 100 \tag{1}$$

3.2.1. Volatility estimation

Using a vector from the return series $r_t = [r_{1,t}, \ldots.., r_{n,t}]$, the following mean equation is calculated:

$$r_t = \mu + \gamma r_{t-1} + \varepsilon_t. \tag{2}$$

In Equation (2), the constant term vector is denoted by μ, while $\varepsilon_t = [\varepsilon_{1,t}, \ldots.., \varepsilon_{n,t}]$ is the error term vector. Then the calculated conditional variable $h_{i,t}^2$ from the GARCH (1,1) process with one variance is as follows:

$$h_{i,t}^2 = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1}^2. \tag{3}$$

[1] We have checked the correlation between these variables and found the range between −0.02 and 0.48. Therefore, we may say there is no multicollinearity exists.

[2] Read more at https://www.jpmorgan.com/insights/research/russia-ukraine-crisis-market-impact.

In Eq. (3), $\omega > 0, \alpha \geq 0, and\ \beta \geq 0, and\ \alpha + \beta < 1$.

3.2.2. TVP-VAR connectedness approach

This part explains the TVP-VAR connection technique and Diebold and Yilmaz's (2012) initial method. This method based-index predict the performance of systematic risk caused by turmoil events which is proved Korobilis and Yilmaz (2018). Utilizing the Bayesian information standard (BIC), we approximate a TVP-VAR design with a lag period of order one:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N\left(0, \sum_t\right) \tag{4}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t \quad \nu_t \sim N(0, R_t) \tag{5}$$

where Y_t as well as Y_{t-1} are vectors of $N \times 1$ dimension endogenous variables; ε_t is a dimensional decay term $N \times 1$ with a time varying variance-covariance matrix $N \times N$, $\sum_t$; β_t is the $N \times N$ matrix of VAR coefficients; ν_t is an $N^2 \times 1$ intercept vector with $N^2 \times N^2$ dimensions of the time varying variance-covariance matrix, R_t; $vec(\beta_t)$ is a vectorization of β_t.

Then the TVP-VIMA model is written as follows: $y_t = \sum_{h=0} N_{h,t}\varepsilon_{t-1}$ where $N_0 = I_Z$ and ε_t denotes symmetric white noise, where $Z \times Z$ varies Matrix time covariance $E(\varepsilon_t \varepsilon_t^{'}) = \sum_t$ varies with time. Therefore, the L-step prediction error is as follows:

$$\varphi_t(L) = y_{t+L} - E(|) = \sum_{l=0}^{L-1} N_{l,t}\varepsilon_{t+L-l} \tag{6}$$

A matrix of forecast error covariance be able to be recorded as below:

$$E\left(\varphi_t(L)\varphi_t^{'}(L) = N_{l,t}\Sigma_t N_{h,t}^{'}\right), \tag{7}$$

The suggested structure counts on Pesaran and Shin's (1998) L-step in advance generalized forecast error variance decomposition (GFEVD). The GFEVD, $gST_{ij,t}$, stands for an effect of a shock originating from variable j on variable i and also can be written as follows:

$$\varphi_{ij,t}^{gen}(L) = \frac{E\left(\varphi_{i,t}^2(L)\right) - E\left[\varphi_{i,t}(L) - E\left(\varphi_{i,t}(L)\right)|\varepsilon_{j,t+1,\ldots,}\varepsilon_{j,t+1}\right]^2}{E(\varphi_{it}^2(L))} \tag{8}$$

$$= \frac{\sum_{l=0}^{L-1}\left(e_i^{'}N_{lt}\Sigma_t e_j\right)^2}{(e^{'}\Sigma_t e_j)\cdot\sum_{l=0}^{L-1}\left(e_i^{'}N_{lt}\sum_t N_{lt}^{'}e_i\right)} \tag{9}$$

$$gST_{ij,t} = \frac{\varphi_{ij,t}^{gen}(L)}{\sum_{j=1}^{L}\varphi_{ij,t}^{gen}(L)} \tag{10}$$

where e_i represents the $Z \times 1$ unselected vector that has one in the $i - th$ position, and $\varphi_{ij,t}^{gen}(L), (L)$, which is a symmetric reduction in Variance from denotes the forecast error of variable i due to the shock state of variable j in the future.

$\sum_{j=1}^{Z}\varphi_{ij,t}^{gen}(L) \neq 1$ normalizes to one, which gives the value $gST_{ij,t}$. We collect these metrics as follows:

$$X_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}, \tag{11}$$

$$X_{i\rightarrow\bullet,t}^{gen,to} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}. \tag{12}$$

We then present the total net directional connectivity: $X_{i,t}^{gen,net} = X_{i\rightarrow\bullet,t}^{gen,to} - X_{i\leftarrow\bullet,t}^{gen.\ from}$. If $X_{i,t}^{gen,net} < 0(X_{i,t}^{gen,net} > 0)$, variable i implies a net receiving (sending) shock. In other words, variable i is controlled by other variables in the network.

In addition, we present the Total Connectivity Index (TCI), which clarifies the network within the network. TCI can be defined as:

$$gST_t = \frac{1}{z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{gen,from} = \frac{1}{z}\sum_{i=1}^{Z} X_{i\rightarrow\bullet,t}^{gen,to} \tag{13}$$

where higher level network overflow has greater value.

Finally, the spillovers of the net pairwise directions can be represented as:

$X_{i,t}^{gen,net} = gST_{ij,t}^{gen,to} - gST_{ij,t}^{gen,from}$. If $X_{ij,t}^{gen,net} > 0$, which implies that row i has a stronger influence over row j.

3.2.3. Extended joint connectedness approach

The $gST_{ij,t}$ and $jST_{ij,t}$ are assumed:

$$X_{i\leftarrow\bullet,t}^{jnt,from} = \sum_{j=1,i\neq j}^{Z} jST_{ij,t}, \quad (14)$$

$$X_{\bullet\leftarrow i,t}^{jnt,to} = \sum_{j=1,i\neq j}^{Z} jSTji, t, \quad (15)$$

$$jSI_i = \frac{1}{z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{jnt,from} = \frac{1}{z}\sum_{i=1}^{Z} X_{i\rightarrow\bullet}^{jnt,to}.$$

To generalize a scaling approach, we used Lastrapes and Wiesen (2021) approach where the scaling factor η differs for each order as follows:

$$\eta_i = \frac{X_{i\leftarrow\bullet,t}^{jnt,from}}{X_{i\leftarrow\bullet,t}^{gen,from}} \quad (16)$$

$$\eta = \frac{1}{z}\sum_{i=1}^{Z} \eta_i \quad (17)$$

Our scaling and the one derived from the joint connectivity method are the same; the method that we have chosen which offers greater suppleness since each row has its very own scaling element. Ultimately, the complying with activities need to be coded:

Lastly, we can obtain:

(1) $jST_{ij,t} - \eta_i gST_{ij,t}$,
(2) $jST_{ii,t} = 1 - X_Z^{j\,jnt,from}$
(3) $X_{i\rightarrow\bullet,t}^{jnt,to} = \sum_{j=1,j\neq i}^{Z} jST_{ij,t}$.

At last, permitting the scaling parameter to differ by row enables to calculate the net total and pairwise directional connectedness steps as follows:

$$X_{i,t}^{jnt,net} = X_{i\rightarrow\bullet,t}^{jnt,to} - X_{i\leftarrow\bullet,t}^{jnt,from}, \quad (18)$$

$$X_{ij,t}^{jnt,net} = gST_{ji,t} - gST_{ij,t}. \quad (19)$$

Even if the interpretations are identical to the initial connectivity method, the results are much more accurate since the shortcomings of the row count normalization method have been overcome (Caloia, Cipollini, & Muzzioli, 2019).

This strategy is much less distortion-sensitive, does not call for differing window sizes, and also spots criterion changes extra precisely (Antonakakis, Chatziantoniou, et al., 2020). On top of that, we have not just made use of the joint connectivity technique suggested by Lastrapes and Wiesen (2021) also applied by Balcilar et al. (2021), which gives much more precise results because of different normalization strategies of Diebold and Yilmaz (2009, 2012, 2014), however we have additionally extended this structure. This proposed standard permit boosted adaptability and also even enables the calculation of metrics for paired connectivity networks, which was formerly unattainable.

3.2.4. TVP-VAR frequency connectedness

Chatziantoniou, Gabauer, and Gupta (2021) introduces the TVP-VAR based frequency connectedness framework which combines the work of Baruník and Křehlík (2018) and Antonakakis, Chatziantoniou, et al. (2020) whereas the latter already unifies the connectedness approach of Diebold and Yılmaz (2012), (2014) with the TVP-VAR framework of Koop and Korobilis (2014). To uncover return and volatility connectivity among commodities, crypto and G20 markets, we employ a contemporary connectedness methodology that is grounded on Generalized Forecast Error Variance Decomposition (GFEVD), processed from a Time-varying Parameter Generalized Vector Autoregressive (TVP-VAR) aspect (Antonakakis, Chatziantoniou, et al., 2020). The TVP-VAR (1) implied by the Bayesian Information Criterion (BIC) is presented as:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t; \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \quad (20)$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \nu_t; \; \nu_t | F_{t-1} \sim N(0, \Xi_t) \quad (21)$$

where Y_t and Y_{t-1} are $N \times 1$ dimensional endogenous variable vectors; ε_t is the $N \times 1$ dimensional disturbance term with an $N\times N$ dimensional time-varying variance-covariance matrix, S_t; β_t is the $N \times N$ dimensional VAR coefficient matrix; ν_t is an $N^2\times 1$ disturbance vector with an $N^2 \times N^2$ dimensional time-varying variance-covariance matrix, Ξ_t; $vec(\beta_t)$ is the vectorization of β_t.

In order to extract the GFEVD, the TVP-VAR is transformed into Vector Moving Average (VMA) representation as:

$$Y_t = \sum_{j=0}^{\infty} A_{jt}\varepsilon_{t-j} \tag{22}$$

where A_{jt} is an $N \times N$ dimensional matrix through the customary Wold Representation Theorem.

The unscaled GFEVD ($\theta^{g}_{ij,t}(H)$) is expressed as:

$$\theta^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}\left(e'_i A_t S_t e_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}\left(e_i A_t S_t A'_t e_i\right)} \tag{23}$$

To ensure that each row sums up to unity, implying that selected variables explain 100% of variable i's forecast error variance, we compute the scaled GFEVD ($\widetilde{\theta}^{g}_{ij,t}(H)$) as:

$$\widetilde{\theta}^{g}_{ij,t}(H) = \frac{\theta^{g}_{ij,t}(H)}{\sum_{j=1}^{N}\theta^{g}_{ij,t}(H)} \tag{24}$$

where, $\sum_{j=1}^{k}\theta^{g}_{ij,t}(H) = 1,\ \sum_{i,j=1}^{k}\widetilde{\theta}^{g}_{ij,t}(H) = k,$ and e_i is a vector with one on the i^{th} element and zero otherwise; $\widetilde{\theta}^{g}_{ij,t}(H)$ represents a measure of the bidirectional connectedness from index j to index i at horizon H.

The GFEVD is applied to compute various connectedness measures within the context of Diebold and Yılmaz (2014) - the total directional connectedness of index i to all indexes ($C_{\blacksquare\leftarrow i,t}(H)$) in Eq. (25), the total directional connectedness of all indexes to index i ($C_{i\leftarrow\blacksquare,t}(H)$) in Eq. (26), the net total directional connectedness ($C_{i,t}(H)$) in Eq. (27), and the net bidirectional connectedness ($C_{ij,t}$) in Eq. (28).

$$C_{\blacksquare\leftarrow i,t}(H) = \frac{\sum_{j=1, j\neq i}^{N}\widetilde{\theta}^{g}_{ji,t}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}^{g}_{ji,t}(H)} \times 100 \tag{25}$$

$$C_{i\leftarrow\blacksquare,t}(H) = \frac{\sum_{j=1, i\neq j}^{N}\widetilde{\theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}^{g}_{ij,t}(H)} \times 100 \tag{26}$$

$$C_{i,t}(H) = C_{\blacksquare\leftarrow i,t}(H) - C_{i\leftarrow\blacksquare,t}(H) \tag{27}$$

$$C_{ij,t} = C_{i\leftarrow j,t}(H) - C_{j\leftarrow i,t}(H) \tag{28}$$

If $C_{ij,t} > 0$ ($C_{ij,t} < 0$), index i dominates (is dominated by) index j implying that index i influences (is influenced by) index j more than being influenced by (influencing) it.

The total connectedness index (TCI) is another relevant metric highlighting the degree of network interconnectedness and hence market risk. Considering that the TCI can be calculated as the average total directional connectedness to (from) others, it is equal to the average amount of spillovers one index transmits (receives) from all others. Chatziantoniou, Gabauer, and Stenfors (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares the

TCI is within [0, $\frac{K-1}{K}$]. To obtain a TCI which is within [0,1], the adjusted TCI is:

$$C^{g}_{t}(H) = \frac{\sum_{i,j=1, i\neq j}^{K}\widetilde{\theta}^{g}_{ij,t}(H)}{\sum_{i,j=1}^{K}\widetilde{\theta}^{g}_{ij,t}(H)} = \frac{\sum_{i,j=1, i\neq j}^{K}\widetilde{\theta}^{g}_{ij,t}(H)}{K} \tag{29}$$

Table 2
Total Spillover index between commodities, crypto, and G20 markets.

	GOLD	OIL	ARG	AUS	BR	CND	CHI	FR	GER	IND	INDO	ITL	JPN	KOREA	MEX	RUS	SA	SAF	TUR	UK	USA	EU	BIT	FROM
GOLD	68.04	1.72	1.08	0.95	2.56	3.64	0.51	1.08	1.32	0.55	0.57	0.93	1.2	0.38	1.52	3.51	0.97	2.31	1.31	1.57	1.76	1.36	1.15	31.96
OIL	0.93	56.9	1.7	1.57	2.73	6.39	0.73	2.11	1.77	0.88	0.69	2.1	0.3	0.53	2.37	5.73	1.24	2.03	0.89	2.68	2.66	2.39	0.68	43.1
ARG	0.58	1.24	52.58	1.37	3.98	4.54	0.59	3.05	3.05	1.35	0.86	2.27	0.55	1.08	3.38	2.31	0.76	2.94	1.31	2.49	5.44	3.38	0.87	47.42
AUS	0.69	1.54	1.73	35.84	2.65	5.74	1.04	4.26	4.06	2.12	1.51	3.33	2.61	2.83	3.5	4.13	0.93	4.09	1.55	5.07	5.07	4.92	0.78	64.16
BR	1.16	1.82	3.53	2.35	44.55	4.79	0.62	3.4	2.93	1.41	1.27	2.7	0.8	1.36	5.91	2.8	0.72	4.58	2	3.39	3.61	3.67	0.64	55.45
CND	1.35	3.33	3.43	4.07	4.11	20.64	0.76	6.22	5.76	1.8	1.18	5.07	0.86	1.64	4.92	5.6	0.93	4.51	1.75	6.44	8.09	6.84	0.7	79.36
CHI	0.61	0.83	1.43	1.88	1.45	1.99	61.83	1.72	1.76	1.8	1.66	1.2	1.17	3.65	1.47	4.58	0.81	2.48	0.59	1.83	2.38	1.98	0.91	38.17
FR	0.65	1.25	2.5	3.24	3.12	6.36	0.75	3.16	13.16	2.3	1.07	11.24	0.87	2.07	4.33	4.14	1.04	5.26	2.38	10.63	5.47	14.4	0.6	96.84
GER	0.69	1.1	2.49	3.21	2.79	6.12	0.8	13.8	4.28	2.41	1.06	11.01	0.85	2.12	4.05	3.94	1.02	5.35	2.4	9.99	5.37	14.43	0.68	95.72
IND	0.71	0.72	1.92	2.6	2.11	2.95	1.09	3.37	3.41	48.82	3.03	2.55	0.96	3.34	2.88	2.39	1.1	3.41	1.54	3.48	3.16	3.78	0.68	51.18
INDO	0.89	0.87	1.93	2.2	2.44	2.75	1.17	2.51	2.17	3.49	52.48	1.67	0.91	3.24	3.29	3.16	0.83	3.96	1.68	2.26	2.95	2.57	0.57	47.52
ITL	0.48	1.34	2.02	2.72	2.7	5.56	0.5	12.21	11.41	1.96	0.8	12.6	0.66	1.51	3.59	5.75	1.03	4	1.96	9.24	4.45	12.8	0.7	87.4
JPN	0.82	1.04	2.35	3.57	1.87	4.56	0.8	4.18	4.01	1.66	1.02	3.62	43.91	2.6	2.25	3.16	0.73	1.91	1.23	3.59	5.9	4.48	0.72	56.09
KOREA	0.69	0.89	1.89	3.57	2.61	3.72	2.06	4.14	4.02	3.14	2.53	3	2.36	41.07	3.04	2.41	0.7	4.21	1.47	3.77	3.76	4.42	0.55	58.93
MEX	0.71	1.41	2.78	2.82	5.17	5.12	0.65	4.41	3.96	1.88	1.47	3.42	0.82	1.82	38.13	3.21	0.75	5.56	2.34	4.24	4.12	4.65	0.56	61.87
RUS	0.48	1.77	1.25	1.48	2.33	3.25	0.54	2.86	2.72	0.96	0.62	2.42	0.31	0.97	2.52	62.13	0.49	3.08	1.32	2.93	2.15	3.07	0.34	37.87
SA	0.54	1.8	1.21	1.73	1.21	2.33	0.84	2.08	1.91	1.37	0.97	1.76	0.72	0.98	1.72	6.18	63.35	1.7	1.14	1.75	1.84	2.09	0.76	36.65
SAF	1.33	1.27	2.44	3.56	4.16	4.66	1.27	5.34	5.2	2.33	2	3.77	0.85	2.76	5.52	3.41	0.81	31.13	3.03	5.49	3.07	5.99	0.61	68.87
TUR	0.7	0.7	1.27	1.75	2.18	2.23	0.34	3.14	3.05	1.52	1.02	2.41	0.69	1.17	2.95	2.24	0.81	3.95	59.21	2.88	1.59	3.43	0.74	40.79
UK	0.85	1.69	2.24	4.07	3.29	7.23	0.91	11.29	10.1	2.67	1.18	9.07	0.87	2.21	4.47	3.48	0.87	5.72	2.33	5.9	5.56	13.48	0.51	94.1
USA	0.79	1.66	4.56	2.39	3.46	9.27	0.77	5.54	5.24	1.82	1.16	4.39	0.73	1.42	4.26	2.42	0.82	2.99	1.35	4.8	33.54	5.92	0.69	66.46
EU	0.72	1.37	2.6	3.57	3.21	6.71	0.8	13.61	13.01	2.48	1.12	11.15	0.89	2.08	4.39	4.07	1	5.62	2.47	11.98	5.71	0.79	0.65	99.21
BIT	0.78	0.62	1.19	1.09	0.9	1.25	0.84	1	1.16	0.67	0.68	1.06	0.91	0.61	0.9	1.3	1.12	0.87	1.23	0.92	1.4	1.15	78.35	21.65
TO	17.15	30	47.55	55.74	61.02	101.18	18.39	111.35	105.19	40.58	27.47	90.15	20.94	40.38	73.25	79.93	19.49	80.54	37.29	101.41	85.5	121.21	15.09	**TCI**
NET	−14.81	−13.1	0.13	−8.41	5.57	21.82	−19.78	14.51	9.46	−10.61	−20.05	2.74	−35.15	−18.56	11.38	42.06	−17.16	11.67	−3.5	7.31	19.04	22	−6.56	**60.03**

Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

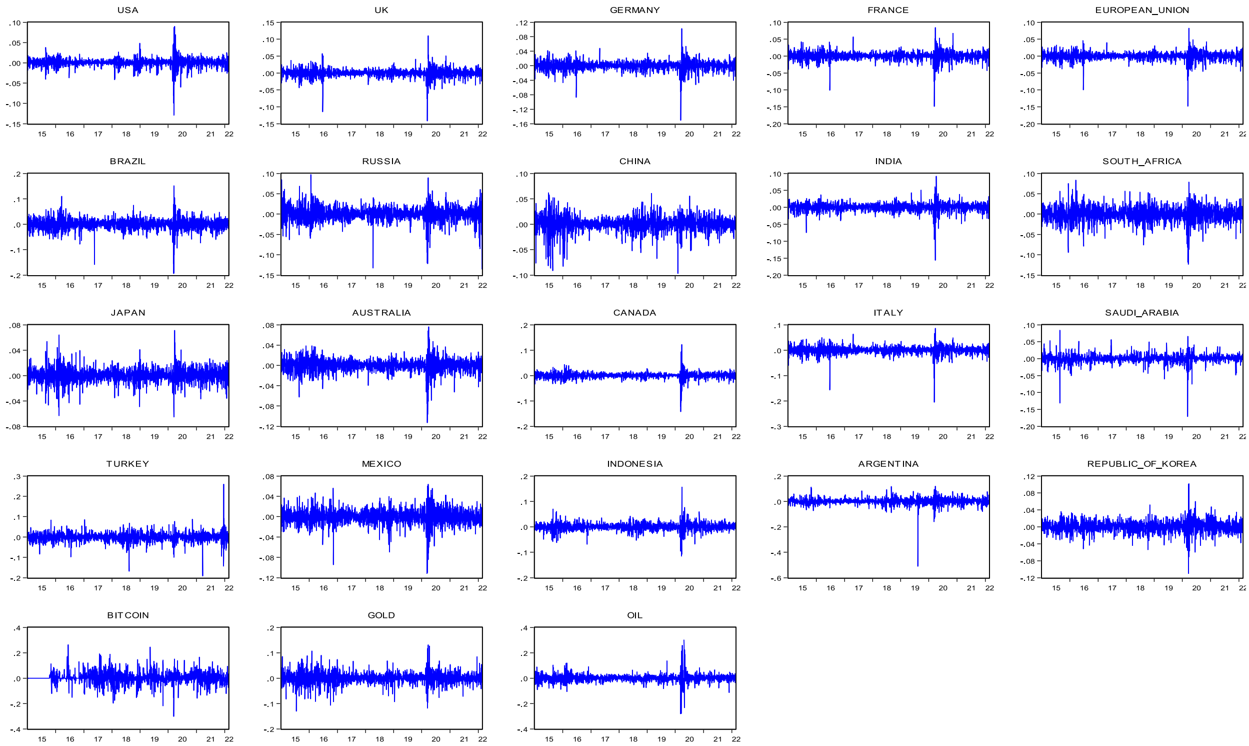


Fig. 1. Evolution of Returns of Bitcoin, Commodities, and G20 indices from January 01, 2015 to May 15, 2022.

$$C_t^g(H) = \left(\frac{K}{K-1}\right)\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{K} \tilde{\theta}^g_{ij,t}(H)}{K} \tag{30}$$

$$C_t^g(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{K} \tilde{\theta}^g_{ij,t}(H)}{K-1} \quad 0 \leq C_t^g(H) \leq 1. \tag{31}$$

So far, we have focused on the connectedness assessment in the time domain. Analogously, we continue with the connectedness assessment in the frequency domain. Following spectral decomposition method of Stiassny (1996), we can derive the frequency response function, $\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where $i = \sqrt{-1}$. Hence, at a given frequency ω, we can define the spectral density of x_t as the Fourier Transform for $TVP - VMA(\infty)$ filtered series, this can be expressed as follows:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x'_{t-h}\right)e^{-i\omega h} = \Psi\left(e^{-i\omega h}\right)\sum_t \Psi'\left(e^{+i\omega h}\right) \tag{32}$$

Significantly, the frequency GFEVD is the combination of spectral density and the GFEVD. As in the time domain, we need to stabilize the frequency GFEVD which can be created as follows,

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}(\Psi(\tau)(e^{-i\omega h})\Sigma(\tau))_{ij}\right|^2}{\sum_{h=0}^{\infty}(\Psi(e^{-i\omega h})\Sigma(\tau)\Psi(\tau)(e^{i\omega h}))_{ii}} \tag{33}$$

$$\tilde{\theta_{ij}}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N}\theta_{ij}(\omega)} \tag{34}$$

where $\theta_{ij}(\omega)$ is the percentage of the variable *ith* spectrum at frequency ω that is caused by variable *jth* shock. It can be interpreted as a within-frequency indicator.

To evaluate short-term as well as long-term connectedness as opposed to connectedness at a single frequency, we accumulate all frequencies within a details range, $d = (a, b)$:

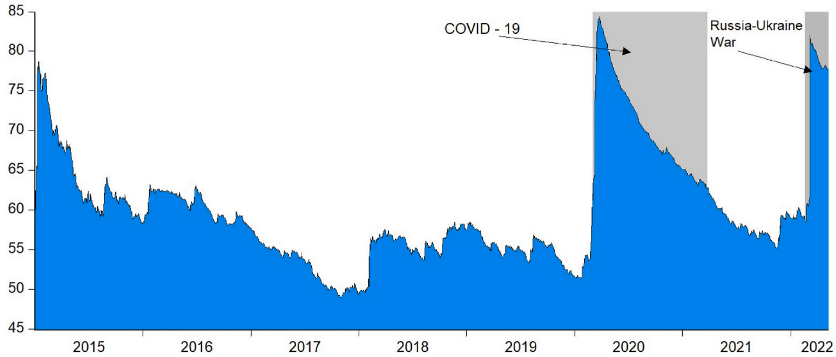


Fig. 2. Total time-varying connectedness between commodities, crypto and G20 markets. *Notes*: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

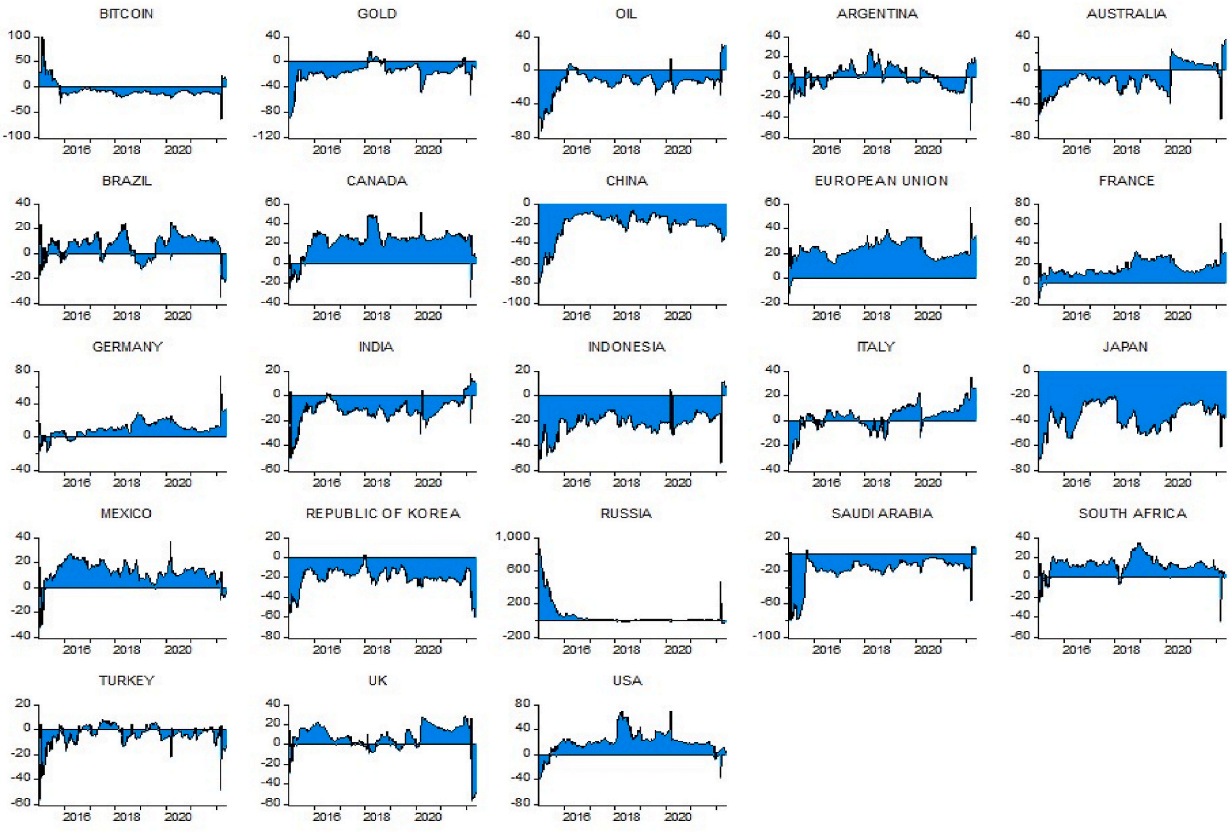


Fig. 3. Net total return spillovers. Notes: See Fig. 2.

$$a, b \in (-\pi, \pi), a < b$$

$$\theta_{ij}(d) = \int_a^b \theta_{ij}(\omega) d\omega \tag{35}$$

From here, we can determine exactly the same connectedness procedures as in Diebold and also Yılmaz, 2012, Diebold and also Yılmaz, 2014 which can be analyzed identically, nonetheless, in this case they refer to frequency connectedness steps that offer info about spillovers in a particular frequency range d:

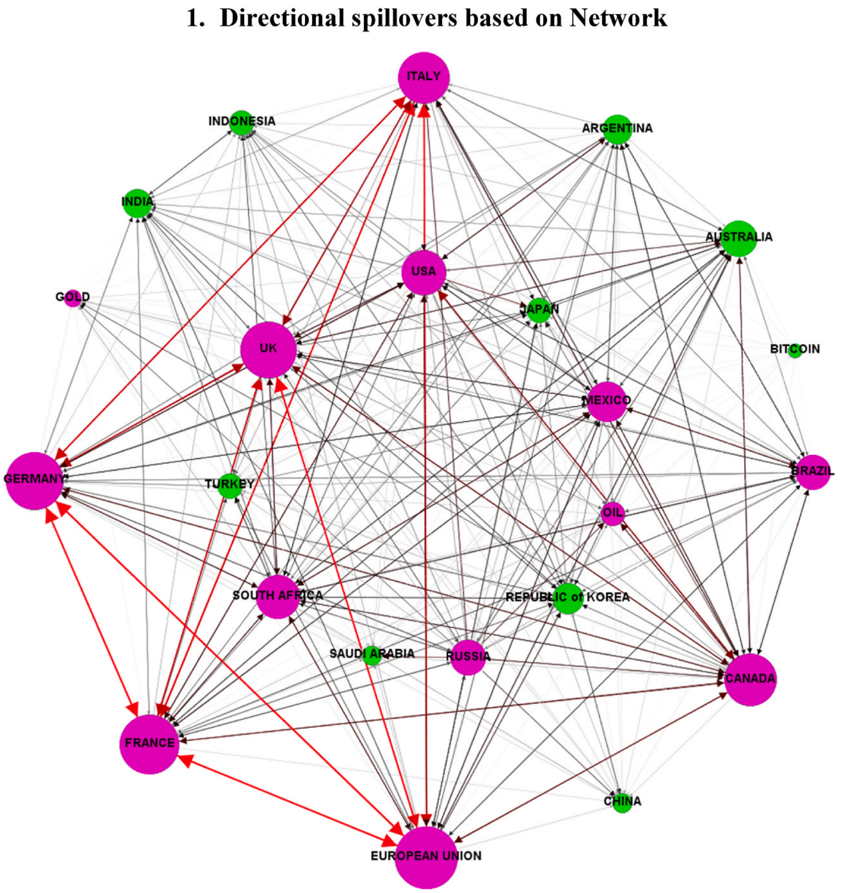


Fig. 4. Total Connectivity table network of returns between commodities, crypto and G20 markets. Notes: See Fig. 2.

$$TO_i(d) = \sum_{i=1, i \neq j}^{N} \theta_{ji}(d) \tag{36}$$

$$FROM_i(d) = \sum\nolimits_{i=1, i \neq j}^{N} \theta_{ij}(d) \tag{37}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{38}$$

$$TCI(d) = N^{-1} \sum\nolimits_{i=1}^{N} TO_i(d) = N^{-1} \sum\nolimits_{i=1}^{N} FROM_i(d) \tag{39}$$

In this paper, there are three frequency bands demonstrating short-term and long-term dynamics ranging from 1 to 5 days $d_1 = (\pi/5, \pi)$, from 6 to 22 days,], and from 23 to infinite days, $d_3 = (0, \pi/22]$. Thus, $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ demonstrate the short-term total directional connectedness TO others, short-term total directional connectedness FROM others, short-term NET total directional connectedness, and short-term total connectedness index, additionally $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ demonstrate the medium-term total directional connectedness TO others, medium-term total directional connectedness FROM others, medium-term NET total directional connectedness, and medium-term total connectedness index, finally $TO_i(d)$, $FROM_i(d)$, $NET_i(d)$, and $TCI(d)$ illustrate the long-term total directional connectedness TO others, long-term total directional connectedness FROM others, long-term NET total directional connectedness, and long-term total connectedness index.

Lastly, the relationship between the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Yılmaz, 2012, Diebold & Yılmaz, 2014 time-domain measures:

$$TO_i(H) = \sum_{d} TO_i(d) \tag{40}$$

$$FROM_i(H) = \sum_{d} FROM_i(d) \tag{41}$$

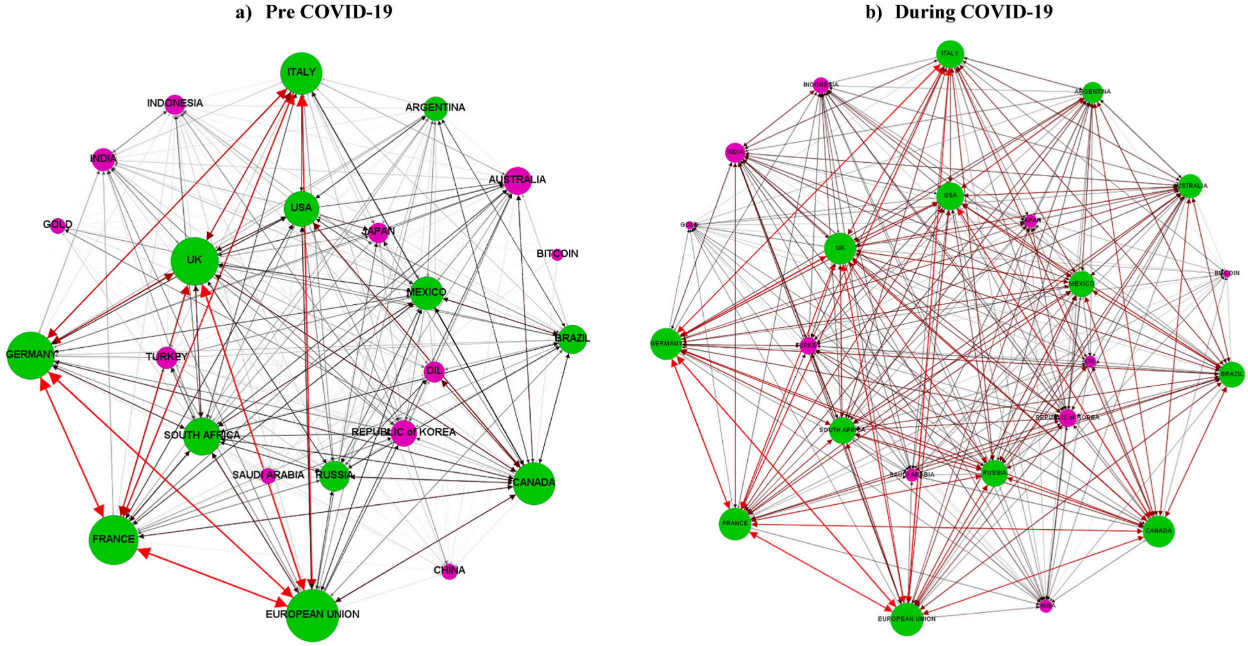


Fig. 5. Connectivity table network of returns pre and during COVID-19 between commodities, crypto and G20 markets. Notes: See Fig. 2.

$$NET_i(H) = \sum_d NET_i(d) \tag{42}$$

$$TCI(H) = \sum_d TCI(d) \tag{43}$$

3.3. DCC-GARCH t-Copula

By adopting Antonakakis, Chatziantoniou, and Gabauer (2018), & Antonakakis, Cunado, et al. (2020), we have estimated mixed DCC-GARCH t-Copula.[3] Also, dynamic variance-covariance and correlations can be estimated with the given equation

$$X_t = V_t^{1/2} z_t \quad z_t t_\eta^{\sim}, \tag{44}$$

here, V_t is the dynamic variance-covariance matrix, t_η is N – dimensional student's t distribution and z_t are the standardized residuals.

Patton (2006) described in his research that conditional distributions could be computed based on DCC–GARCH t –Copula as given below:

$$C(u_1, \ldots, u_N | R_t, \eta) = t_\eta \left(F_{x_1}^{-1}(u_1 | \blacksquare_1), \ldots, F_{X_N}^{-1}(u_N | \blacksquare_N) \right) \tag{45}$$

$$= \int_{-\infty}^{F_1^{-1}(u_1)} \cdots \int_{-\infty}^{F_1^{-1} u_N} \frac{\Gamma\left(\frac{\eta+N}{2}\right)}{\Gamma\left(\frac{\eta}{2}\right)(\eta\pi)^{N/2} |R_t|^{1/2}} \left(1 + \frac{1}{\eta} z_t, R_t^{-1} Z_t \right)^{(\eta+N)/2} dz_1, \ldots, dz_N, \tag{46}$$

Here, $F_{X_N}^{-1}(u_1 | \blacksquare_1)$ denotes the conditional distribution and $\blacksquare_1$ represents the estimated parameters of the GARCH model. The model can have different marginal distributions unlike the original DCC-GARCH model. In the following step, the underlying DCC-GARCH model of Engle (2002) is used to estimate dynamics variance – covariances and correlations, R_t. Hereby, the time-varying variance-covariances are constructed as follows:

[3] Multivariate GARCH models, for example, the DCC-GARCH model, have been widely used in the literature to study dynamic portfolio optimization such as (Liu et al., 2020; and Billah, Amar, et al., 2023). In addition, the DCC-GARCH model, which is more economical and flexible than other GARCH models, such as the BEKK-GARCH model, often provides better adaptation and forecasting performance (Huang, Su, & Li, 2010). This model is a tool for predicting and analyzing time series volatility when volatility varies from time to time. The DCC-GARCH model has an advantage over the BEKK-GARCH model in forecasting because the DCC-GARCH model is more economical than the BEKK-GARCH model. With this in mind, it is essential to balance economy and flexibility when modelling a multivariate GARCH model.

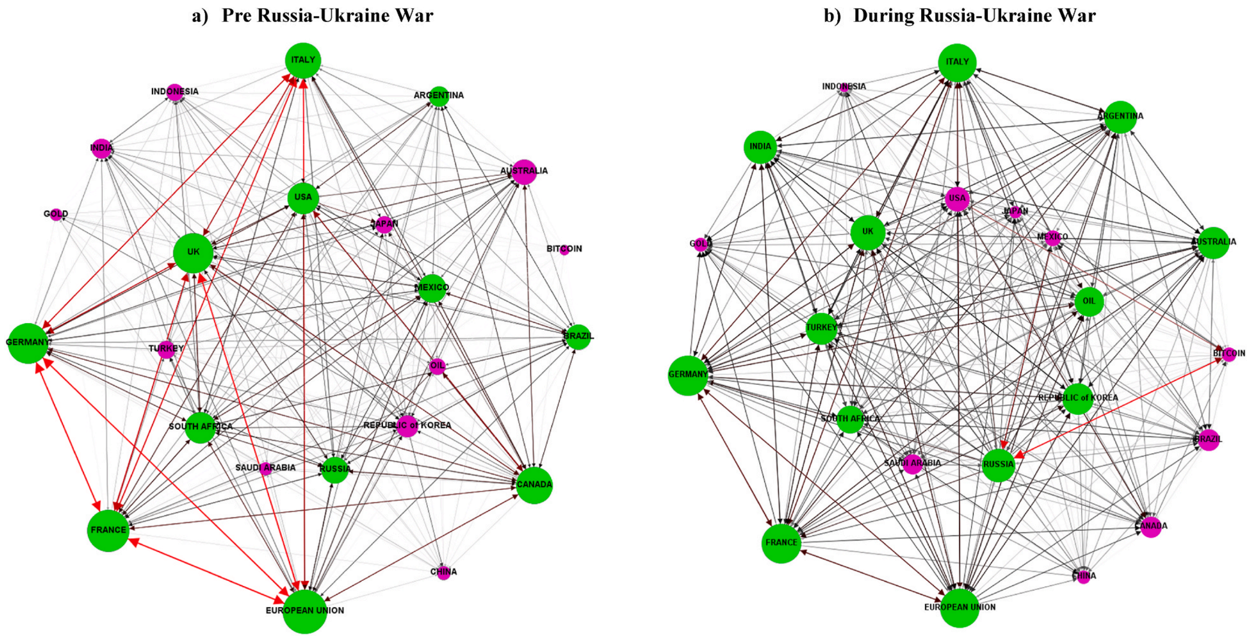


Fig. 6. Connectivity table network of returns pre and during Russia-Ukraine war between commodities, crypto and G20 markets. Notes: See Fig. 2.

$$H_t = D_t R_t R, \tag{47}$$

where $D_t = diag\,(h_{11t},\ldots,h_{NNt})$, which follow a univariate GARCH process. To find the most appropriate univariate GARCH model, we estimate all restricted family GARCH models (Hentschel, 1995).[4] The family GARCH model can be formulated by:

$$h_{iit}^{\lambda i} = \omega_i + \alpha_i h_{iit-1}^{\lambda i}\left(|z_{it-1} - \zeta_i| - \gamma_i(z_{it-1} - \zeta_i)\right)^{\delta_i} + \beta h_{iit-1}^{\lambda i}. \tag{48}$$

After calculating the time-varying variance-covariances, we compute the dynamic conditional correlations, R_t, which are based on the standardized residuals' conditional variance-covariances, Q_t, that are assumed to follow a GARCH (1,1) model Engle (2002):

$$Q_t = (1 - a - b)\overline{Q} + a z_{t-1} z_{t-1} + b Q_{t-1} \tag{49}$$

$$R_t = diag(Q_t)^{-1}\ diag(Q_t)^{-1/2} Qt \tag{50}$$

where $\overline{Q}$ is the unconditional variance-covariance matrix of the standardized residuals, a is the shock parameter and b is the persistency parameter. A stationary process requires that $a > 0, b > 0\ and\ a + b < 1$.

Since R_t [Equation (17)] is very restrictive and cannot capture tail distribution, this research uses Kendall's t measure (Kruskal, 1958) as follows:

$$\tau\left(\varepsilon_i, \varepsilon_j\right) = \frac{2}{\pi}\left[1 - \sum_{\varepsilon \in \mathbb{R}} P(X_i = x)^2\right] arcsin\left(R_{ijt}\right). \tag{51}$$

3.3.1. Optimal hedge ratios

In order to calculate the optimum hedging costs, we calculate hedge ratios a la Kroner and Sultan (1993) and optimal portfolio weights a la Kroner and Ng (1998). Hedge ratios determine the costs of hedging a 1 USD long position in variable i with a β_{ijt} USD short position in variable j. This can be calculated by

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}}, \tag{52}$$

[4] Antonakakis, Cunado, et al. (2020) used the GARCH selection criterion introduced by Antonakakis, Gabauer, Gupta, and Plakandaras (2018) and extend their approach by taking under consideration even more models. This can be done conveniently by using the family GARCH model which is an omnibus model including the GARCH (Bollerslev, 1986), IGARCH (Engle & Bollerslev, 1986), EGARCH (Nelson, 1991), AVGARCH (Schwert, 1990), TGARCH (Zakoian, 1994), GJRGARCH (GLOSTEN, JAGANNATHAN, & RUNKLE, 1993), NGARCH (Higgins & Bera, 1992), NAGARCH (ENGLE & NG, 1993), and APARCH (Ding, Granger, & Engle, 1993) as special cases.

Table 3
Total Volatility Spillover index between commodities, crypto, and G20 markets.

	GOLD	OIL	ARG	AUS	BR	CND	CHI	FR	GER	IND	INDO	ITL	JPN	KOREA	MEX	RUS	SA	SAF	TUR	UK	USA	EU	BIT	FROM
GOLD	21.97	1.31	0.63	3.29	2.52	4.21	0.5	3.18	3.88	1.99	1.72	3.66	1.53	1.51	2.97	28.18	1.68	1.43	1.06	2.97	4.65	3.3	1.87	78.03
OIL	1.28	36.24	0.51	3.53	1.81	3.36	0.42	2.3	2.7	2.25	2.39	1.47	1.29	1.12	1.84	25.7	1.4	2.13	0.57	1.74	2.46	2.37	1.1	63.76
ARG	0.42	0.6	46.89	0.74	1.57	1.42	0.41	1.77	1.97	0.92	0.53	1.33	0.82	0.59	1.14	30.39	1.21	1.17	0.38	1.23	2.26	1.73	0.51	53.11
AUS	1.68	1.16	0.68	13.01	3.37	4.96	0.49	4.13	4.7	2.27	1.5	3.72	2.67	2.2	2.48	29.18	1.12	3.02	0.81	4.16	6.58	4.32	1.78	86.99
BR	1.49	1.83	1.04	3.18	30.17	5.55	0.67	4.3	4.57	2.18	2.09	4.97	1.29	1.5	3.44	12.31	0.96	2.67	1.04	3.81	4.82	4.52	1.6	69.83
CND	1.53	1.51	0.78	3.71	4.04	8.93	0.33	5.73	6.72	2.17	1.68	5.16	1.4	2.1	3.11	25.61	0.77	3.58	0.72	4.9	7.87	6.12	1.54	91.07
CHI	1.91	1.47	0.59	2.45	2.03	2.07	27.2	2.38	2.58	3.85	1.16	1.82	2	2.51	1.42	31.61	1.46	1.43	0.84	1.92	3.65	2.3	1.36	72.8
FR	0.77	1.03	0.6	3.07	3.3	6.1	0.38	7.72	12.45	1.87	1.2	9.95	0.87	1.26	2.97	12	0.68	4.13	0.87	9.39	5.29	13.08	1.03	92.28
GER	1.04	0.87	0.58	3.43	3.12	7.01	0.44	10.89	6.82	1.92	1.45	8.36	1.06	1.49	2.83	16.81	0.7	4.12	0.82	8.31	5.68	11.12	1.14	93.18
IND	1.22	2.58	0.72	3.8	3.07	3.72	0.71	3.46	3.51	28.23	3.34	2.15	1.76	3.24	2.21	20.66	1.8	3.04	0.89	2.68	2.98	3.4	0.86	71.77
INDO	1.39	1.85	1.35	3.35	2.73	4.24	0.83	3.63	4.04	2.4	20.49	2.92	1.45	2.24	2.75	24.4	1.54	3.88	1.38	3.72	4.27	3.84	1.31	79.51
ITL	0.94	0.71	0.52	3.32	3.85	5.08	0.54	10.79	10.33	1.45	1.25	13.62	0.94	1.24	3.42	11.46	0.83	3.02	1.1	8.42	4.84	10.67	1.66	86.38
JPN	2.39	1.2	0.84	3.8	1.62	4.55	0.75	3.62	4.84	1.63	1.22	3.96	20.36	3.24	1.99	23.4	1.39	1.54	0.93	3.74	7.03	4.16	1.79	79.64
KOREA	1.49	1.42	0.86	3.37	2.06	5.24	1.53	3.58	4.27	2.13	1.54	2.42	2.99	24.26	1.48	23.74	1.46	2.73	0.69	3.02	5.16	3.74	0.83	75.74
MEX	1.36	1.35	1.07	2.73	4.02	4.48	0.87	4.74	4.99	1.52	1.89	3.93	1.55	1.68	23.61	20.14	1.49	3.53	0.93	3.42	4.89	4.64	1.17	76.39
RUS	2.68	2.01	0.18	1.56	0.56	1.2	1.1	2.31	4.31	1.35	1.02	2.58	2.43	0.74	1.12	62.38	3.16	0.86	1.7	1.32	1.07	2.7	1.65	37.62
SA	1.51	2.69	1.48	3.04	3.43	4.93	1.44	2.91	3.13	2.04	2.13	2.45	1.87	2.3	3.49	20.71	25.92	2.27	0.85	2.27	4.68	2.84	1.62	74.08
SAF	1.56	1.09	1.09	2.79	3.47	4.77	0.66	5.42	5.83	1.54	1.49	4.87	1.98	2.45	3.11	20.45	1.07	19.41	1.03	4.91	4.6	5.56	0.87	80.59
TUR	1.81	1.02	0.92	1.41	1.81	1.99	0.48	2.82	3.38	1.08	1.54	2.99	1.43	0.95	2.42	23.33	0.87	1.27	39.34	2.48	2.04	2.96	1.69	60.66
UK	1.02	1.23	0.57	3.69	2.6	5.6	0.4	10.22	9.79	1.87	1.11	7.65	1.26	1.9	2.61	15.72	0.78	3.79	0.62	9.12	5.47	12.06	0.93	90.88
USA	1.41	1.16	0.88	3.18	3.95	8.68	0.44	4.46	4.88	1.47	1.03	4.47	1.45	1.78	2.82	27.12	1.06	2.13	0.67	3.38	17.38	4.48	1.72	82.62
EU	0.74	0.96	0.62	3.37	3.1	5.95	0.36	12.66	12.17	1.77	1.15	9.75	1.07	1.45	2.92	14.13	0.69	4.07	0.68	11.1	5.62	4.53	1.12	95.47
BIT	1.34	2.76	0.93	2.88	2.08	2.24	0.94	2.14	2.76	1.78	1.62	2.33	2.17	1.64	3.37	24.86	2.14	1.57	2.1	1.67	2.74	2.33	31.63	68.37
TO	30.97	31.84	17.44	65.69	60.09	97.34	14.69	107.46	117.79	41.45	34.06	92.93	35.27	39.12	55.88	481.92	28.26	57.39	20.66	90.56	98.62	112.23	29.13	**TCI**
NET	−47.06	−31.92	−35.67	−21.3	−9.74	6.27	−58.11	15.18	24.61	−30.32	−45.45	6.55	−44.37	−36.62	−20.51	444.3	−45.82	−23.21	−40	−0.32	16	16.76	−39.24	**76.56**

Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

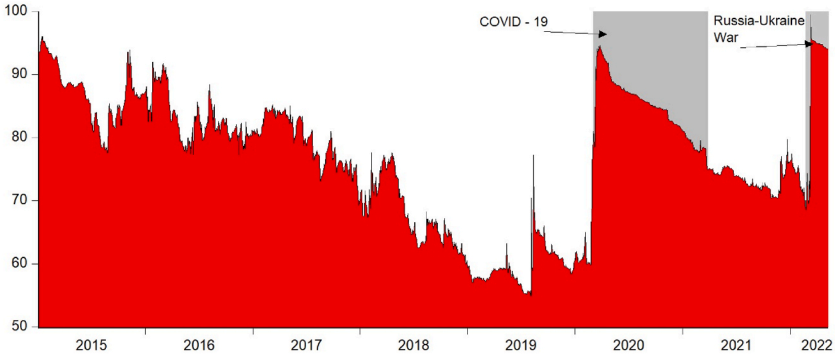


Fig. 7. Total time-varying Volatility connectedness between commodities, crypto and G20 markets. *Notes*: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

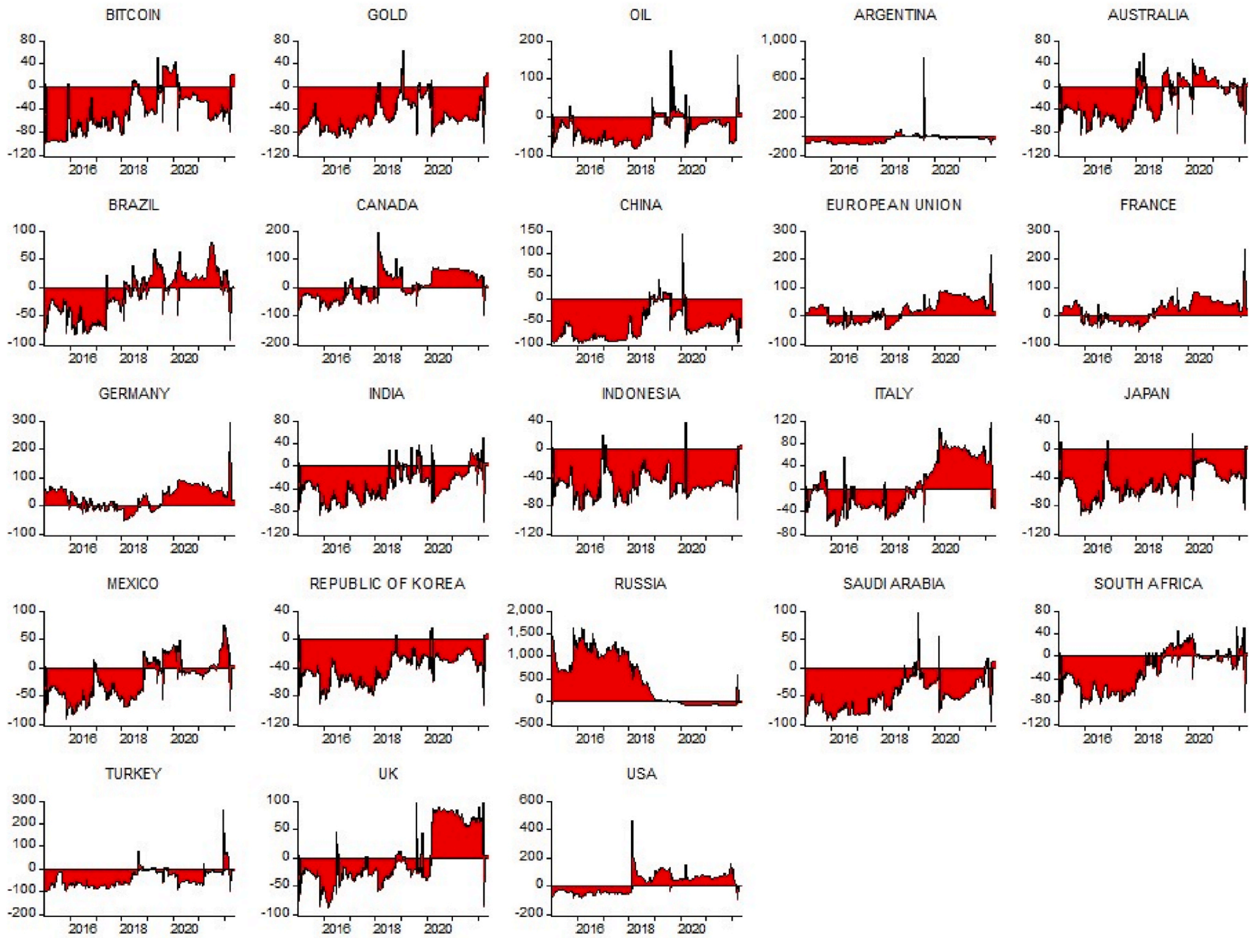


Fig. 8. Net total volatility spillovers. Notes: See Fig. 2.

where h_{ijt} is the conditional covariance of variable *i* and *j*. This implies that higher conditional variances lead to lower long position hedging costs whereas an increase in the conditional covariances will increase the long position hedging costs.

3.3.2. *Optimal portfolio weights*

The conditional covariances from DCC-t-Copula is used to create the optimal portfolio weights with the following formula (Kroner & Ng, 1998):

1. Directional spillovers based on Network

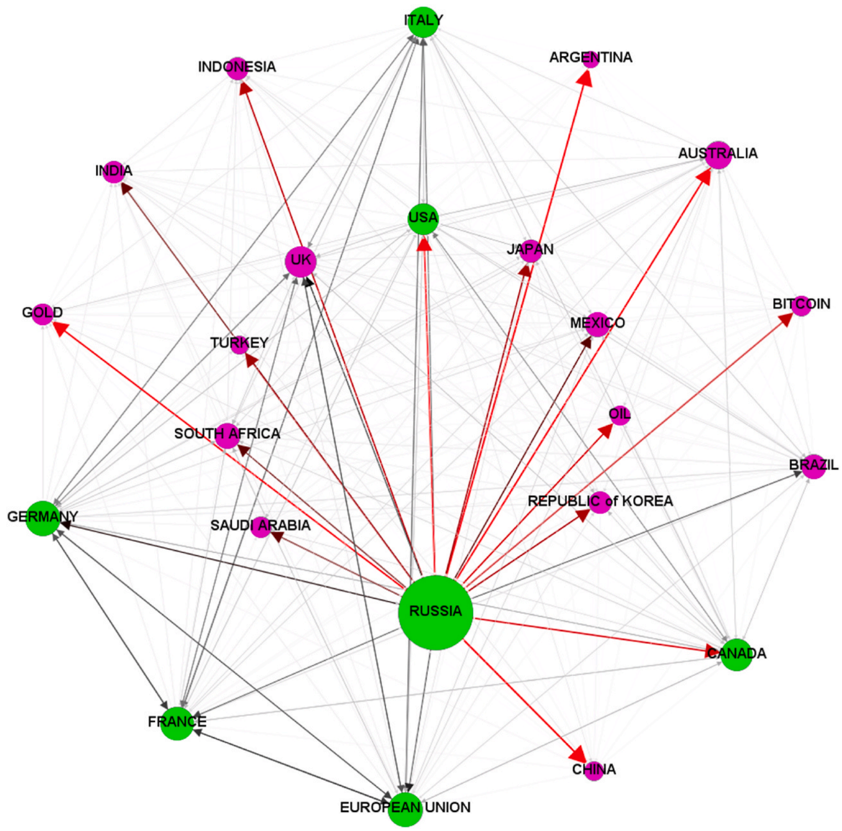


Fig. 9. Total Connectivity table network of volatilities between commodities, crypto and G20 markets. Notes: See Fig. 2.

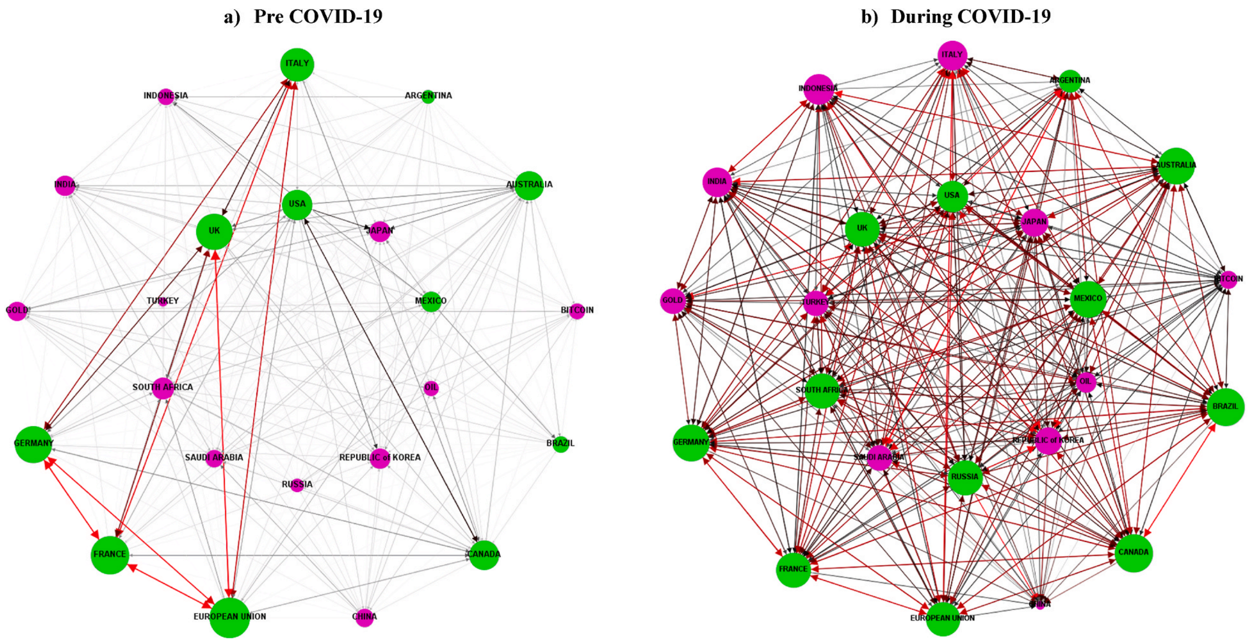


Fig. 10. Connectivity table network of volatilities pre and during COVID-19 between commodities, crypto and G20 markets. Notes: See Fig. 2.

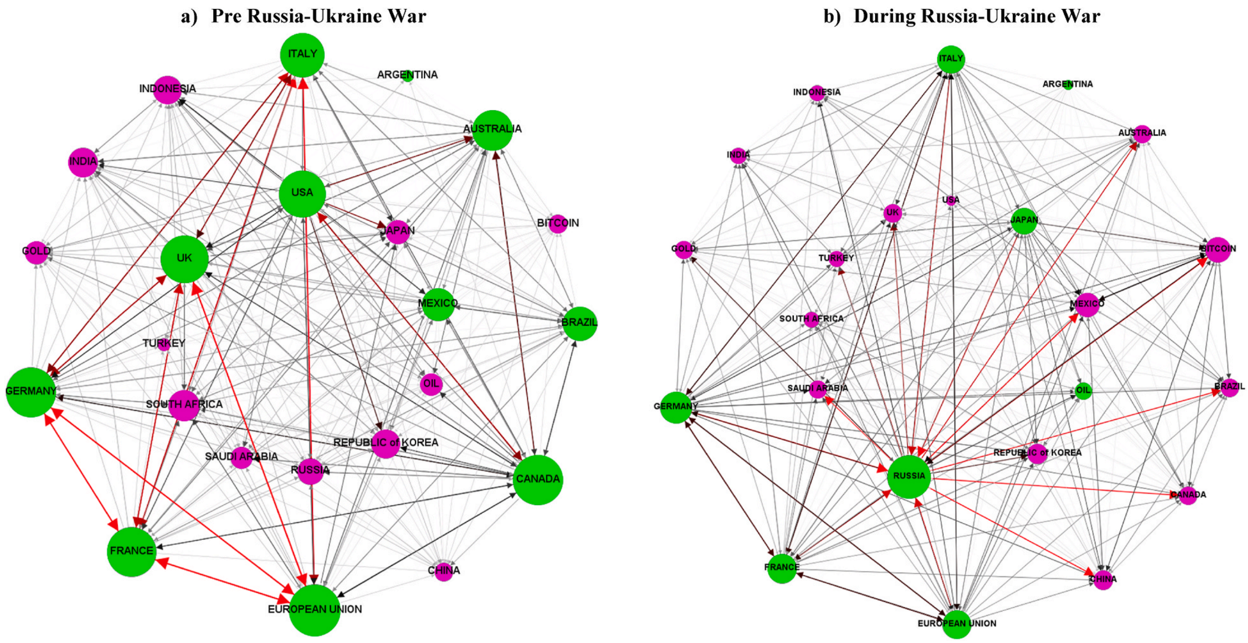


Fig. 11. Connectivity table network of volatilities pre and during Russia-Ukraine war between commodities, crypto and G20 markets. Notes: See Fig. 2.

$$w_{xn,t} = \frac{h_{nn,t} - h_{xn,t}}{h_{xx,t} - 2h_{xn,t} + h_{nn,t}}, \text{with} w_{xn,t} = \begin{cases} 0 \; if \; w_{xn,t} < 0 \\ w_{xn,t} \; if \; 0 \leq w_{xn,t} \leq \#1 \\ 1; \; if \; w_{xn,t} > 1 \end{cases} \tag{53}$$

where $w_{xn,t}$ is the proportion of asset x at time t. The weight of asset n is calculated as $1 - w_{xn,t}$.

The formula for the hedge effectiveness is stated below:

$$\text{Hedge Effectiveness} = \frac{\sigma^2\text{unhedged} - \sigma^2_{\text{hedged}}}{\sigma^2\text{unhedged}} \tag{54}$$

where $\sigma^2_{\text{unhedged}}$ is the variance of individual assets and σ^2_{hedged} is the portfolio variance of two-asset portfolio. Moreover, as per the Antonakakis, Cunado, et al. (2020), under this paper they also calculated the significance of hedge effectiveness. To deal with non-normality of the data of hedge effectiveness, the researchers applied Fligner and Killeen (1976)'s methodology.

4. Empirical findings

4.1. The dynamic return connectedness network spillovers

We have employed Antonakakis, Chatziantoniou, et al. (2020)'s network connectedness of a first order TVP-VAR model, a newer version of the traditional Diebold and Yilmaz (2012) method. The model is estimated for the return spillovers amongst the commodities, Crypto markets, and G20 markets for the period from January 1, 2015 to May 15, 2022. The results are clearly display the impact of COVID-19 and invasion crisis on the returns connectedness on crypto, commodities, and all sample markets.

The dynamic connectedness network spillovers results have been plotted in Table 2 system-wide total dynamic connectedness index results are based on a 1st-order TVP-VAR with a 1st-order delay length, and a 28-level GFEVD, the outcomes of volatility spillovers are aligned with returns spillovers. The overall average volatility contribution across variables was 60.03%, which showed a high degree of spillovers. In pre-COVID-19 era, gold and oil (commodities), bitcoin, and Australia, China, India, Indonesia, Japan, Korea, South Africa, and Turkey markets were net recipients of volatility spillovers from other markets, while all other markets are net transmitters. Amongst the markets, Japan (−35.15%) was the largest recipient of volatility spillovers, followed by Indonesia (−20.05%) and China (−19.78%), while Russia (42.06%), EU (22.00%), Canada (21.82%), and USA (19.04%) are greatest transmitters. On the other hand, oil, gold, and Bitcoin are the receivers of 14.81%, 13.10%, and 6.56% of spillovers respectively. Bitcoin (78.35%), Gold (68.04%), and Oil (56.9%) volatility could be explained by their lags while markets were highly associated and predicted by other markets as well. Interestingly, EU is more sensitive towards variation in Germany and UK rather than its own previous lag (see Fig. 1).

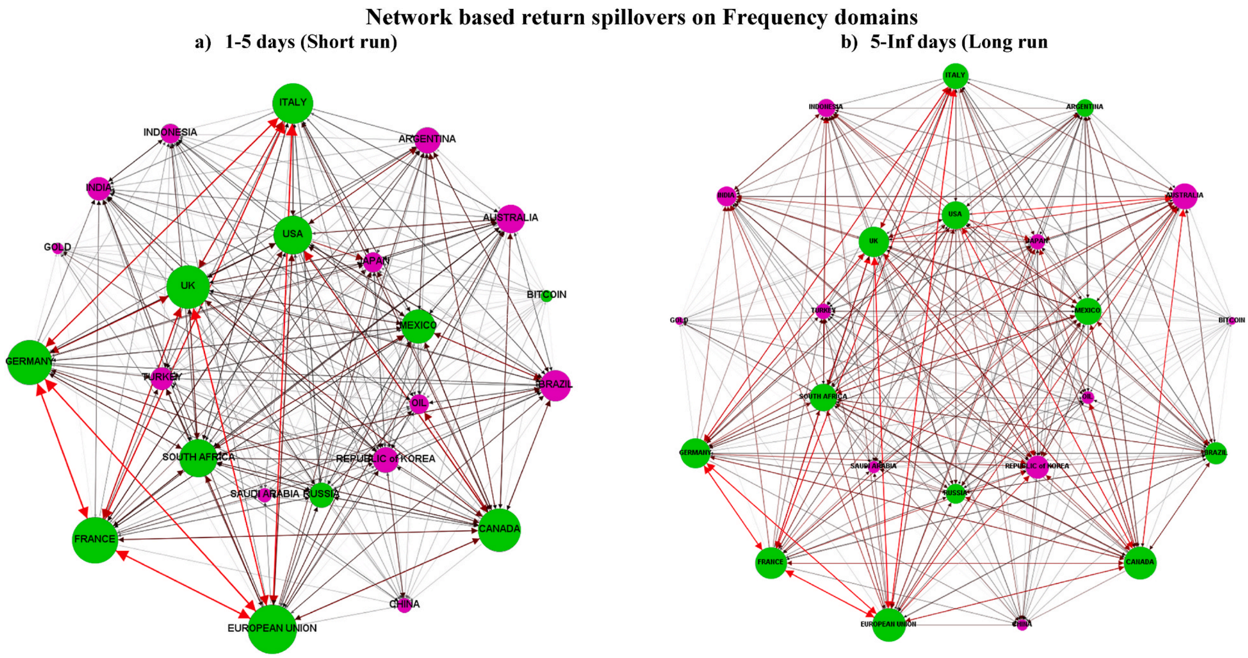


Fig. 12. Total Connectivity table network of returns at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

4.2. Averaged total time varying return spillovers & net return spillovers

For further deep insights, averaged total time-varying (averaged total returns) spillovers among the G20 markets, commodities, and crypto are examined and results shown in Fig. 2. It is depicting the time-varying volatility from January 1, 2015 to May 15, 2022. The volatility caused by European Debt Crisis reached nearly to 50% in the mid of 2017. In March 2020, a huge spike can be seen where the return volatility level almost reached 85%, due to the COVID-19 break out on March 11, 2020, when World Health Organization (WHO) announced the novel coronavirus COVID-19 outbreak was a global pandemic (Kumar et al., 2021). This volatility persisted for a long time, started settling in 2021, and reached below to 55%. But Russian invasion of Ukraine further triggered the return spillover level, and again it crossed the 80% mark. Fig. 2 undoubtedly shows the effects of these two different types of crises on sample markets, which is supported by (Corbet et al., 2020; Okorie & Lin, 2021; Gharib et al., 2021; Kumar et al., 2021, Boungou & Yatié, 2022; Fry-McKibbin et al., 2022; Boubaker et al., 2022; Liadze et al., 2022; Federle et al., 2022). As capital markets, commodities, and cryptos all are highly sensitive to such uncertain events and provide limited scope of diversification opportunities as articulated by (Aromi & Clements, 2019; Deng, Leippold, Wagner, & Wang, 2022, pp. 22–29; Hetkamp et al., 2020; Jiang, Tian, & Mo, 2020; Mazur et al., 2021; Naeem, Pham, Senthilkumar, & Karim, 2022; Sun et al., 2022; Umar, Bossman, et al., 2022).

For a robust understanding of the spillovers and more so specifically during critical periods, we have analyzed the time-varying behavior of interconnectedness among commodities, cryptocurrencies, and stock markets. Subsequently, we used total net return

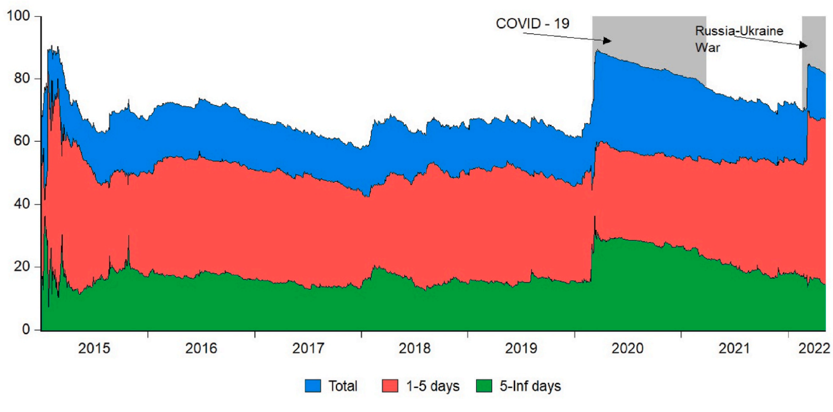


Fig. 13. Total time-varying return connectedness between commodities, crypto and G20 markets at the short and long runs. Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

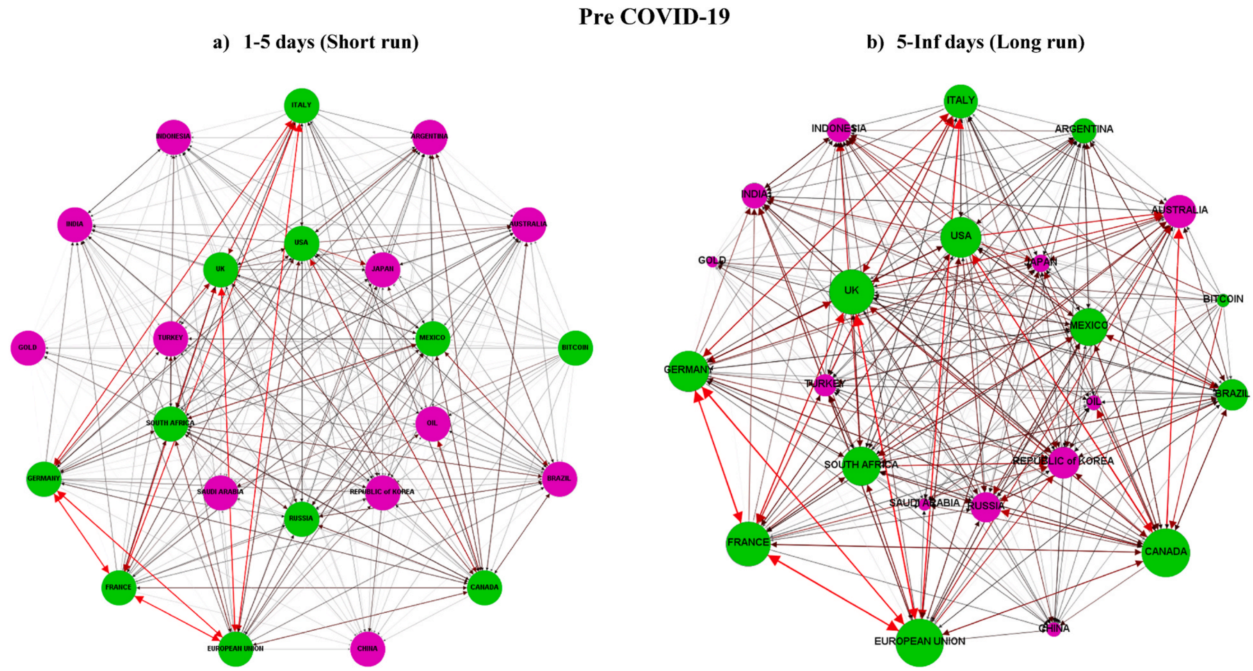


Fig. 14. Total Connectivity table network of returns pre COVID-19 at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

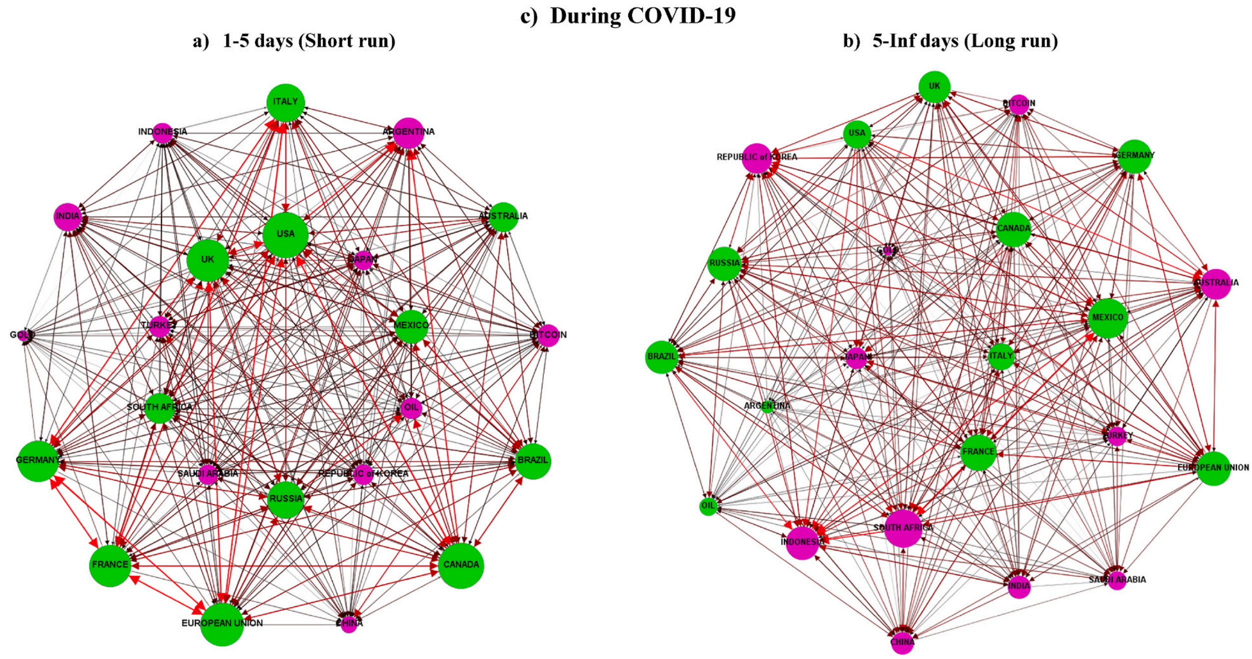


Fig. 15. Total Connectivity table network of returns during COVID-19 at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

spillovers as exhibited in Fig. 3. It is observed from Fig. 3, that gold, China, Indonesia, Japan, and Saudi Arabia are the consistent net recipients of return spillovers with huge quantum, while USA, UK, South Africa, Mexico, Germany, Franc, EU, and Canada are the net transmitter of spillovers with a large and consistent spike. During this invasion crisis gold, bitcoin, crude oil and almost each markets are highly impacted, it was supporting the outcomes from past studies of (Adekoya, Oliyide, Yaya, & Al-Faryan, 2022; Bedowska-Sojka et al., 2022; Mohamad, A., 2022; Ayed et al., 2022). Undoubtedly, Russia is the largest net transmitter of spillover followed by the US,

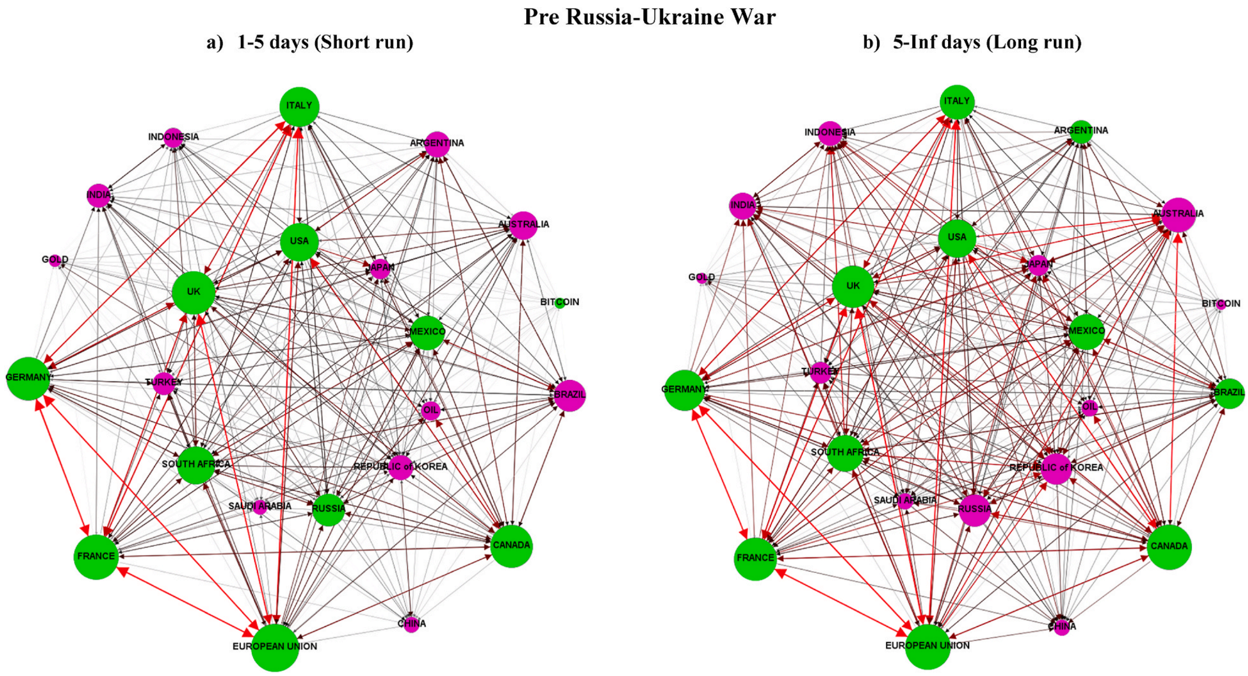


Fig. 16. Total Connectivity table network of returns pre-Russia-Ukraine war at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

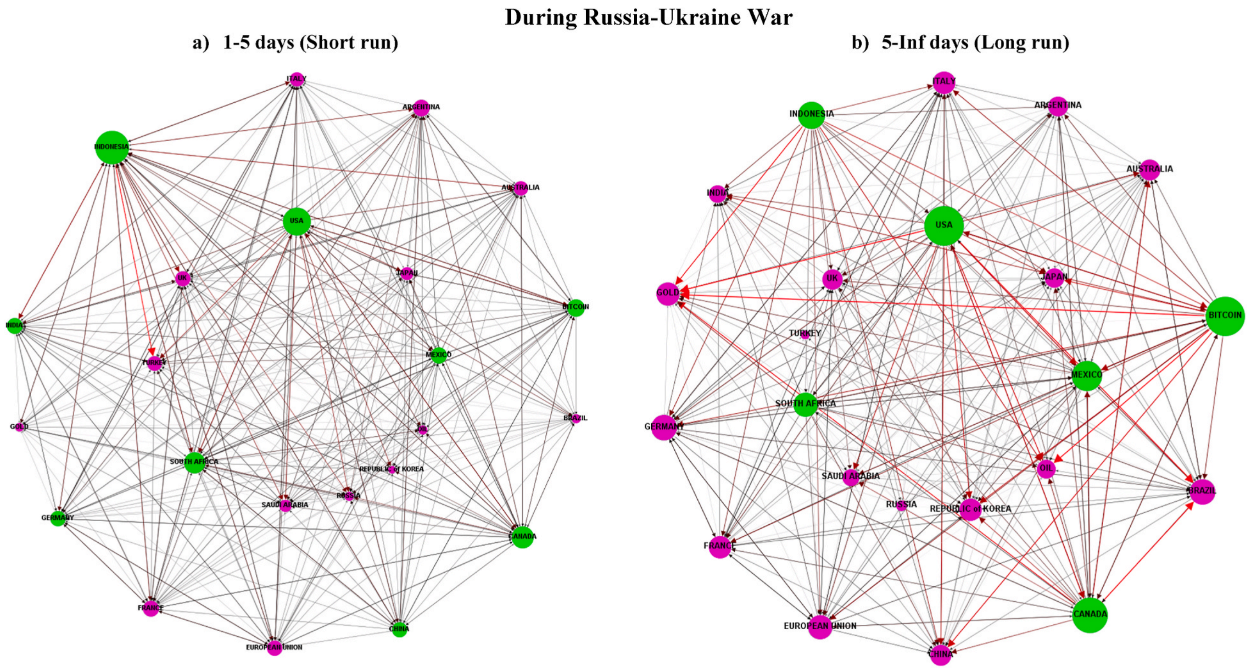


Fig. 17. Total Connectivity table network of returns during-Russia-Ukraine war at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

India, Australia, EU, France, Germany, and Italy. Argentina and SAF are two exceptional transmitters of shocks with their fragile economic and market conditions (Bianchi, 2022; Sheefeni, 2022). Contrariwise, all remaining sample markets have shown as net recipients of the shock. Here, except for Mexico, all other sample variables are showing rocket spikes. Similar findings were proved by (Adekoya et al., 2022; Bedowska-Sojka et al., 2022; Mohamad, A., 2022; Boungou & Yatié, 2022; Yousaf et al., 2022; Deng et al., 2022,

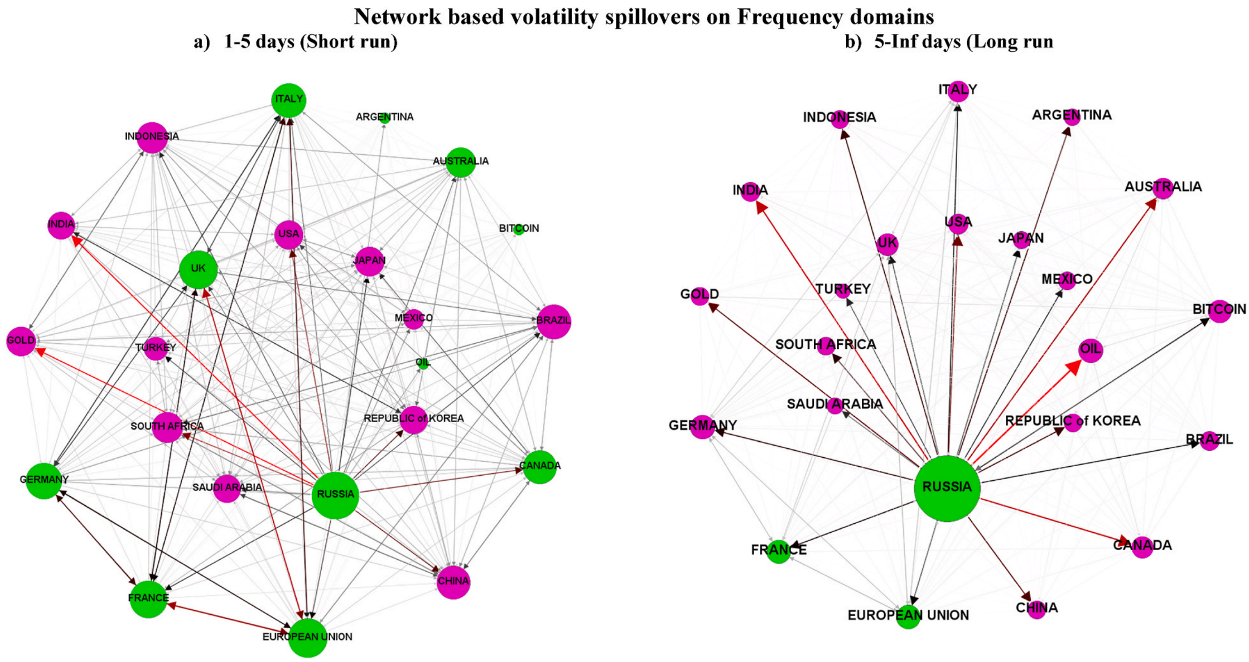


Fig. 18. Connectivity table network of volatilities at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

pp. 22–29: Chatziantoniou, Floros, & Gabauer, 2022). It is interesting to observe that, Argentina, Canada, India, and the US initially depict a receiving spike for a short while of spillovers, and later continued as net transmitters of the spillover towards other markets, commodities, and cryptos. This could be possible because initially these markets have received a sudden shock from the GPC crisis then their economic environment converts to be a transferor of the shock. It is important for the investors, hedgers, and diversifiers from around the world to capitalize on this finding as also suggested by (Bedowska-Sojka et al., 2022; Grima & Caruana, 2017; Wang & Liu, 2016) for international investment diversification.

4.3. Directional return spillover connectedness

Next, Fig. 4 portrays comprehensive return connectedness amidst G20 markets, crypto and commodities. In pursuance of this intricate web, it is propounded that high intensity of inter-connectedness among the variables under study persists. The markets of India, China. Japan, Republic of Korea, Australia, Argentina, Indonesia, Turkey, Saudi Arabia and Bitcoin has surfaced as net transmitters of return spillovers albeit inter se inter-connection among these is of very low intensity. At the same time, the markets of EU, Italy. Germany, France, South Africa, UK, Russia, U.S.A, Canada, Brazil, Mexico, Oil and Gold are the net recipients. Contrastingly, a notable integration amidst net receivers is observed. The regional economic integration i.e., EU and it's member countries i.e., Germany. France and Italy have manifested intensified inter-connection, thus embodying a strong cluster of networks. EU is the largest net receiver of return spillovers and commodity markets of Gold and Oil has surfaced as the smallest receivers of spillovers.

Next, pre and during COVID-19 analysis is shown in Fig. 5a and b, where 5a exhibits bilateral binary linkages among many G20 markets, contrarily the commodities i.e., Gold and Oil along with Bitcoin has showcased very low and indigent inter-connection across the panel. Markets of EU, UK, Germany, France, Italy, Canada, South-Africa, U.S.A, Mexico, Russia, Brazil and Argentina are net transmitters of return spillovers whereas the residual variables are net receivers. Bitcoin and Gold has emerged as the largest receivers of system shocks. Additionally, Fig. 5b illustrates a robust and more constricted inter-linkages induced by notable hike in bilateral connectedness across the variables. In contrast with Pre-crisis period decrease in the level of contribution towards system connectedness from net transmitters and receivers is also observed. Notably Australia transformed into a net transmitter during COVID-19. Gold, Oil and Bitcoin maintains the status quo of being the tiniest recipients of return spillovers. From Fig. 5a and b, it is quite evident that COVID-19 has major impacts on the spillovers among the sample variable as strong network and linkages are display during COVID-19, which is also justified by the previous findings (Apergis & Apergis, 2020; Bouri et al., 2021c; Corbet et al., 2020; Fry-McKibbin et al., 2022; Gharib et al., 2021; Okorie & Lin, 2021; Rizwan, Ahmad, & Ashraf, 2020).

Further, the dynamics of transmission and reception of return spillovers Pre and during Russia-Ukraine war displays in Fig. 6a and b, where mostly similar view as pre-COVID-19 diagram with less intensity. USA, UK, EU, Italy, Germany, France, Canada, Russia, Mexico, Brazil, South Africa, and Argentina are the net transmitters, conversely the remaining are net receivers. Moreover, Fig. 6b exhibits the network connectedness during the Russia-Ukraine war. High degree of return connectedness can be observed during the war time. Also, a substantial transformation is reported in the status of net transmitters and receivers in comparison with Pre-War period, where India, Australia, Korea and Turkey along with the oil market has emerged as net transmitters whereas the markets of

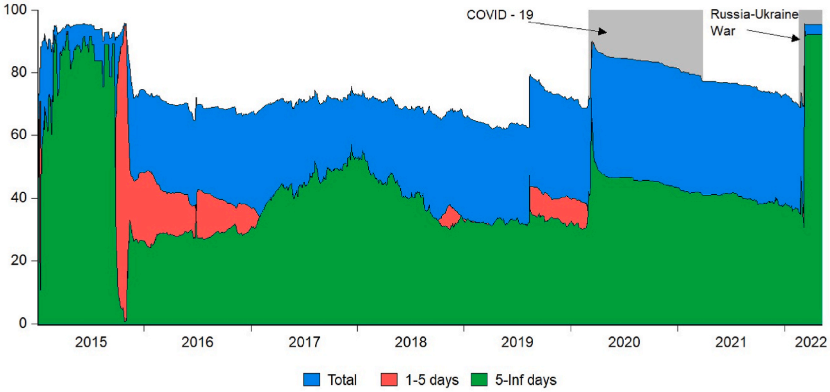


Fig. 19. Total time-varying volatility connectedness between commodities, crypto and G20 markets at the short and long runs. Notes: System-wide total dynamic connectedness index is based on a 1st-order TVP-VAR with a 1st-order delay length and a 28-level GFEVD.

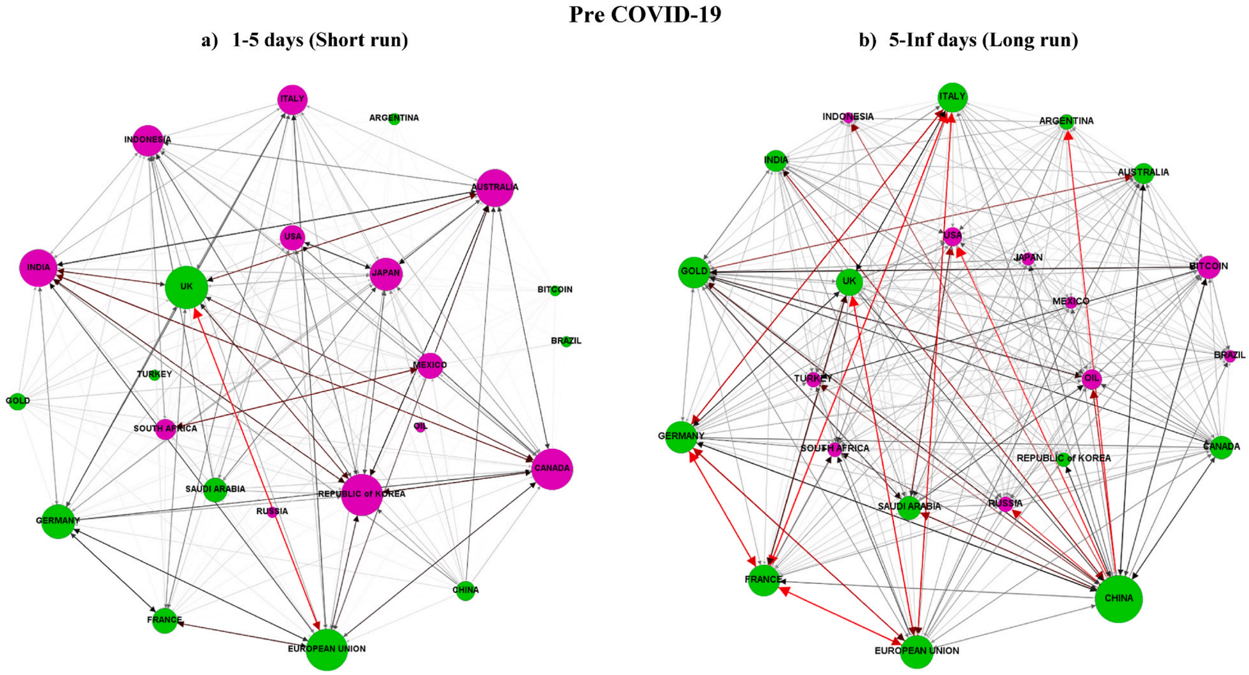


Fig. 20. Total Connectivity table network of volatilities pre COVID-19 at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

USA, Canada, Brazil and Mexico have converted into net receivers. In contrast with COVID-19 crisis, markets of India, Republic of Korea and Turkey along with oil market has been transformed into net transmitters from net recipients. Transforming behavior of Oil from net recipient to net receiver, strong connectedness of gold underscores the potent effect of invasion on the commodity index of oil and gold, confirming the findings of (Alam, Tabash, Billah, Kumar, & Anagreh, 2022; Bedowska-Sojka et al., 2022; Umar et al., 2022). Important to focus, those solid linkages of Bitcoin and more specifically emergence of a notable bidirectional linkage between Russia and Bitcoin. It is confirming the effect of Russian-Ukraine war on cryptocurrency market (Khalfaoui, Gozgor, & Goodell, 2022; Gnazzo, 2022; Theiri, Nekhili, & Sultan, 2023).

4.4. The dynamic volatility connectedness network spillovers

In the next stage, volatility linkages are being explored. The comprehensive static volatility spillover inter-connectedness across all the study subjects is encapsulated in Table 3. On an average 76.56% of the total deviation of the forecast errors is induced by the shocks generated from endogenous variables of our study in the 28 step ahead gross forecast error variance disruption (GFEVD) with a 1st order lag. Russia has developed as the largest contributor of volatility spillovers (481.92%) weakly followed by Germany (117.79%),

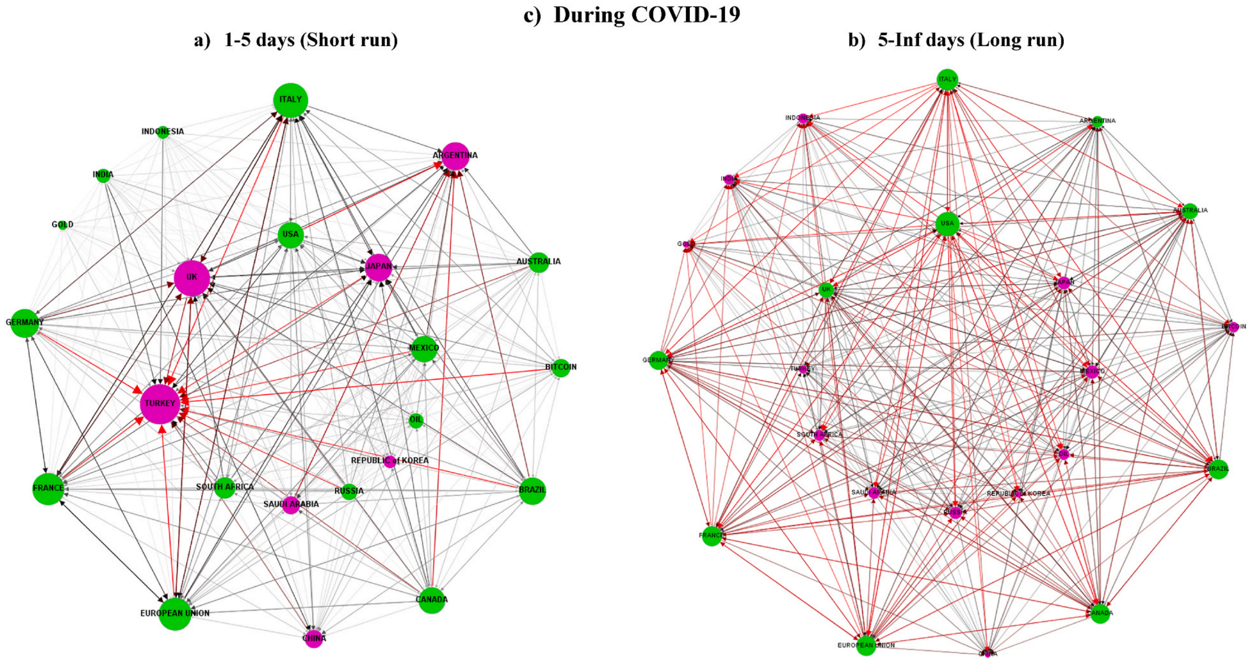


Fig. 21. Total Connectivity table network of volatilities during COVID-19 at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

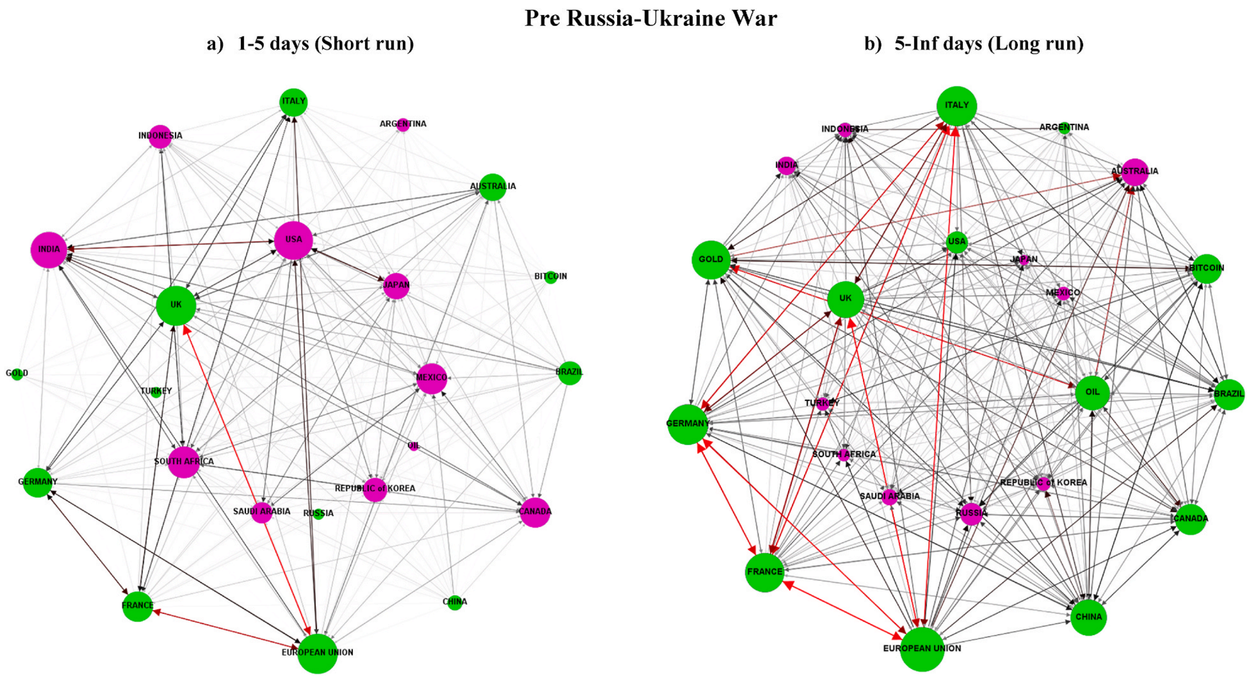


Fig. 22. Total Connectivity table network of volatilities pre-Russia-Ukraine war at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

EU (112.23%) and France (107.46%). China is the smallest contributor (14.69%) followed by Argentina (17.44%) and Turkey (20.66%). EU absorbs the largest quantity of spillovers (95.47%) from the system. Russia has emerged as the smallest recipient of spillovers (37.62) followed by Argentina (53.11) and Oil market (63.76%). Conclusively, markets of Russia (444.3), Germany (24.61%), EU (16.76%), U.S.A (16%), France (15.18%), Italy (6.55%) and Canada (6.27%) are the net transmitters while the remaining are the net receivers of volatility spillovers.

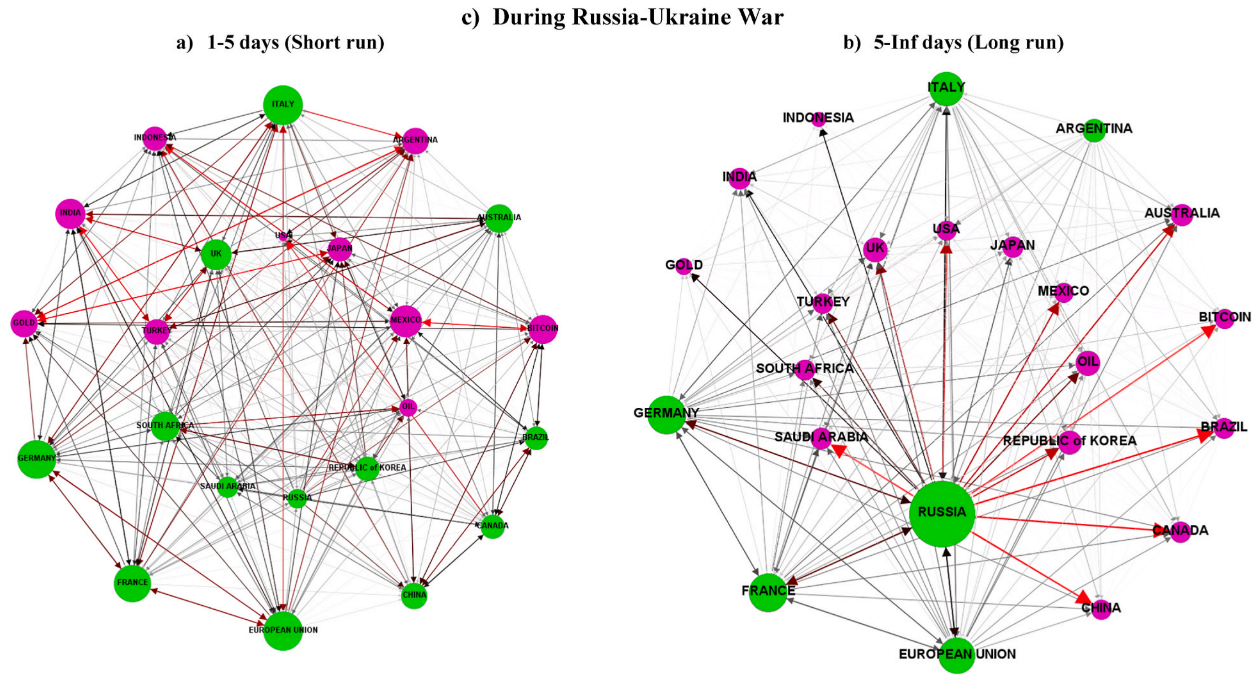


Fig. 23. Total Connectivity table network of volatilities during-Russia-Ukraine war at the short and long terms between commodities, crypto and G20 markets. Notes: See Fig. 2.

4.5. Averaged total time varying volatility spillovers & net volatility spillovers

Fig. 7 demonstrates the trends of movements of volatility linkages within different time frames enclosing connectedness among all the variables under study. The first spike was noted at the end of 2019 in congruence with the news of outbreak of COVID-19 in the Wuhan city of China in December 2019. The juncture of highest surge is plotted around the 1st quarter of 2020 that reached the level of 95% as WHO had declared it as a global pandemic on 11th March. But the spillover began to settle down and touched the lowest point of 78% until the second wave of the pandemic strikes the suffering economies. But this time the ripple effects of volatility spillovers was not massive as it goes only to the highest of 80% at the end of 2021 but this time enhanced fluctuation in spikes is observed. Owed to the inception of Russian-Ukraine conflict, the spillovers proliferated to the paramount of 98% which imply the strong and short-term effects of Russian invasion in Ukraine on Oil, Gold, Bitcoin, and all the G20 markets.

Net volatility spillover amongst the sample assets is portrayed in Fig. 8. A comprehensive impact of COVID-19 and Russian-Ukraine military conflict can be observed, where Bitcoin, Gold, Oil, China, Indonesia, India, Japan, and Korea are the net recipients. Remaining markets more specifically European markets are net transmitters. Special to mention that fragile economies like Argentina, South Africa, Mexico, and Turkey are changing their status from net transmitters to net receivers and vice-versa. Another interesting thing is that Russia during COVID-19 is consistent receiver but due to war it transformed into largest transmitter.

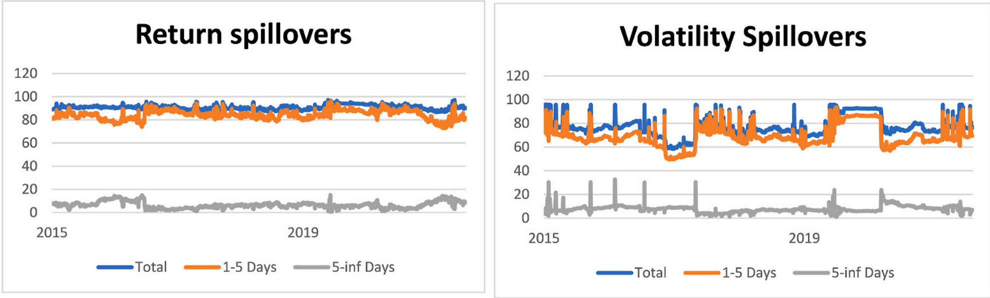
4.6. Directional volatility spillover connectedness

From Fig. 9, it can clearly be observed that market of Russia has emerged as the largest transmitter of volatility shocks with enhanced intensity across Gold, Oil, Bitcoin and G20 markets with the exception of members of EU. EU and its constituents in congruence with USA & Canada are the rest net transmitters of spillovers across the panel. A significant unilateral transmission of risk from Russia towards Oil, Gold and Bitcoin is noted. Empirical juxtaposition with total return connectedness propounds that EU and its members along with USA, Russia and Canada that displays significant reception of return spillovers are peculiarly generating transmission of volatility spillovers. Indisputably, it is revealed that unlike return inter-linkages the volatility inter-connection amidst the study variables exhibits low intensity of outflows and inflows.

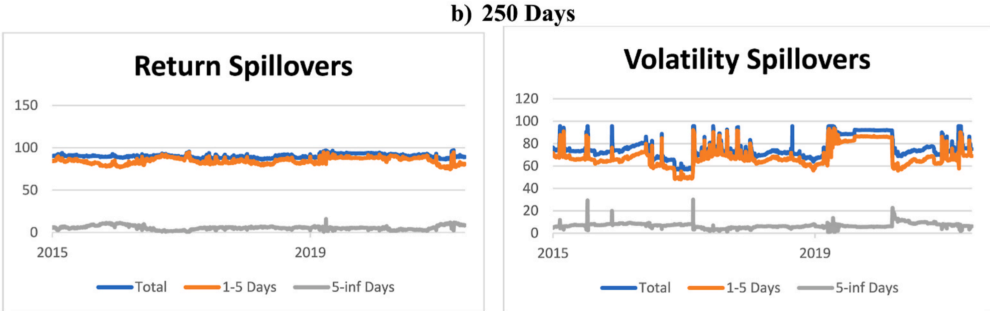
Fig. 10a and b displays the network of inter-connection of volatility spillovers pre and during COVID-19 period. Evidently, substantial volatility network spillover can be seen during the COVID-19 compared with pre-COVID time. The potency of transmission is more than of reception during this phase. Markets of Japan, Republic of Korea, India, South Africa, Saudi Arabia, Indonesia, Russia and Turkey accompanied by the markets of Gold, Oil and Bitcoin are the net recipients of volatility spillovers and the rest are net transmitters. Importantly, bilateral linkage among European countries and UK is reported owing to Brexit. Also, Oil markets and the markets of Turkey and Russia are the smallest receivers of risk shocks generated across the panel. On the other hand, during the pandemic, the markets of Russia and South Africa have transformed into net transmitters from receivers complimented with augmentation in the contribution towards system connectivity. Italy converted into a net transmitter with reduced intensity. The markets of Australia, Canada, Brazil, EU,

2. Robustness check using different rolling windows

a) 200 Days



b) 250 Days



c) 300 Days

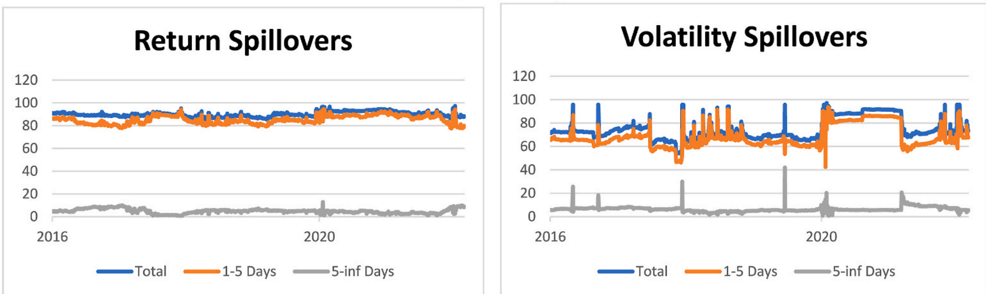


Fig. 24. Dynamic total, short and long connectedness for commodities, crypto and G20 markets returns using DY (2014) and BK (2018). These dynamic total spillover indices are calculated from the generalized forecast error variance decompositions using three alternative rolling window sizes (200, 250 and 300 days, respectively) and a forecast horizon of H = 100 days.

France, Germany, UK, USA, Mexico, South Africa and Russia are the net transmitters while the residuals are the net recipients. Commodity markets of Gold & Oil followed by crypto-currency Bitcoin endured as net recipients but with hiked degree of connectedness. China persisted as the smallest net receiver. These findings confirmed the solid effects of COVID-19 on the volatility of commodities, cryptocurrencies, and world markets (Corbet et al., 2020; Okorie & Lin, 2021; Li, W. 2021; Gharib et al., 2021; Naeem, Peng, Bouri, Shahzad, & Karim, 2022; Naeem, Qureshi, Rehman, & Balli, 2022; Fry-McKibbin et al., 2022; Shaikh, I. 2022; Balcilar et al., 2021).

Fig. 11a and b, which displays the total dynamic volatility connectedness before and during the Russia-Ukraine conflict. The results indicate that before the conflict, in comparison the markets of Russia, Australia, and South Africa were net transmitters of return spillovers but became receivers of volatility spillovers generated by other variables. On the other hand, the market of Australia emerged as the net dispatcher of spillovers, despite being the largest receiver of return spillovers. The EU, along with its members, the UK, USA, Canada, Australia, Mexico, and Brazil, were the net disseminators of spillovers, while the rest of the variables were net recipients. The study also shows the network of assets' interlinkages during the Russian-Ukrainian conflict. It is important to note that the contribution towards connectedness, especially reception, was much less during the crisis compared to the pandemic and pre-war time frame. After the onset of the war crisis, the markets of Russia, Japan, and Oil transformed into net transmitters of volatility spillovers, while the markets of USA, UK, Canada, Australia, Brazil, and Mexico became net receivers of spillovers. Furthermore, the article differentiates between the Russia-Ukraine conflict and the COVID-19 crisis. It is significant to note that the markets of Italy, Japan, and Oil emerged as net transmitters during the invasion crisis, while the markets of UK, USA, Canada, Australia, South Africa, Mexico, and Brazil acted as net receivers of volatility shocks. In conclusion, the markets of Russia, EU, France, Germany, Italy, Japan, Argentina, and Oil were net transmitters of volatility spillovers, while the remaining markets were net receivers of such spillovers.

Table 4
Dynamic Hedge ratios.

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (Bitcoin/Markets)	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*
BITCOIN/GOLD	0.05	0.06	0	0.18	0.63	0.34	0.22	1.13	0.15	0.12	0	0.37	0.36	0.15	0.21	0.65
BITCOIN/OIL	0.02	0.04	−0.03	0.08	0.32	0.23	0.07	0.65	0.08	0.06	0	0.2	0.02	0	0.02	0.03
BITCOIN/ARGENTINA	−0.02	0.04	−0.1	0.03	0.33	0.14	0.18	0.58	0.12	0.1	0	0.33	0.44	0.01	0.42	0.45
BITCOIN/AUSTRALIA	0.05	0.1	−0.05	0.22	0.82	0.61	0.24	1.63	0.28	0.2	0.01	0.65	0.12	0	0.12	0.12
BITCOIN/BRAZIL	−0.02	0.04	−0.09	0.03	0.39	0.23	0.15	0.69	0.1	0.08	−0.02	0.24	0.49	0.02	0.46	0.52
BITCOIN/CANADA	0.05	0.11	−0.08	0.26	1.73	1.47	0.35	3.97	0.46	0.31	0.03	1.05	0.49	0	0.49	0.5
BITCOIN/CHINA	−0.1	0.11	−0.3	0	0.53	0.26	0.26	1.07	0.03	0.13	−0.18	0.26	0.1	0	0.09	0.1
BITCOIN/FRANCE	0.03	0.09	−0.09	0.18	0.97	0.67	0.34	1.94	0.28	0.2	0.01	0.64	0.33	0.06	0.21	0.41
BITCOIN/GERMANY	0.03	0.09	−0.08	0.17	0.96	0.61	0.37	1.84	0.3	0.21	0.01	0.68	0.35	0.11	0.17	0.5
BITCOIN/INDIA	−0.12	0.11	−0.3	0	0.73	0.46	0.18	1.31	0.07	0.14	−0.12	0.31	0.11	0.02	0.09	0.14
BITCOIN/INDONESIA	−0.07	0.08	−0.23	0	0.2	0.12	0.05	0.42	0.04	0.11	−0.14	0.24	0.59	0.01	0.59	0.6
BITCOIN/ITALY	−0.05	0.08	−0.18	0.04	0.92	0.6	0.37	1.71	0.18	0.16	0	0.48	0.43	0.09	0.26	0.53
BITCOIN/JAPAN	−0.05	0.09	−0.2	0.04	0.58	0.36	0.21	1.04	0.09	0.15	−0.13	0.36	0.15	0.03	0.1	0.19
BITCOIN/KOREA	−0.09	0.1	−0.26	0.01	0.31	0.18	0.11	0.62	0.02	0.11	−0.16	0.2	−0.18	0	−0.18	−0.18
BITCOIN/MEXICO	−0.09	0.08	−0.24	0	0.5	0.3	0.21	0.91	0.14	0.14	−0.05	0.37	0.63	0.01	0.61	0.63
BITCOIN/RUSSIA	0.07	0.07	0	0.21	0.44	0.24	0.15	0.9	0.2	0.12	0.01	0.42	−6.92	13.1	−38.55	−0.01
BITCOIN/SAUDI.ARABIA	−0.1	0.12	−0.31	0.01	0.44	0.16	0.23	0.65	0.05	0.19	−0.28	0.31	−0.1	0	−0.1	−0.1
BITCOIN/SOUTH.AFRICA	−0.02	0.05	−0.09	0.05	0.52	0.27	0.22	0.88	0.14	0.11	0.01	0.35	0.24	0	0.24	0.25
BITCOIN/TURKEY	−0.02	0.05	−0.09	0.04	0.36	0.16	0.15	0.61	0.08	0.09	−0.05	0.26	−0.09	0	−0.09	−0.08
BITCOIN/UK	−0.03	0.09	−0.18	0.09	0.87	0.53	0.36	1.64	0.25	0.18	0.01	0.58	0.52	0.1	0.35	0.64
BITCOIN/USA	−0.08	0.13	−0.31	0.09	1.18	0.94	0.28	2.43	0.34	0.29	−0.11	0.84	0.99	0.14	0.76	1.2
BITCOIN/EU	0	0.09	−0.14	0.13	1.01	0.67	0.41	1.95	0.31	0.23	0.01	0.72	0.45	0.08	0.29	0.57
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (Gold/Markets)	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*
GOLD/OIL	0.09	0.03	0.04	0.14	0.08	0.03	0.04	0.13	0.1	0.05	0.03	0.2	0.16	0.05	0.08	0.24
GOLD/ARGENTINA	0.1	0.05	0.03	0.18	0.05	0.02	0.02	0.09	0.09	0.05	0.02	0.2	0.23	0.08	0.12	0.34
GOLD/AUSTRALIA	0.19	0.05	0.11	0.27	0.09	0.04	0.03	0.16	0.2	0.06	0.11	0.31	0.3	0.1	0.15	0.44
GOLD/BRAZIL	0.23	0.06	0.14	0.34	−0.03	0.02	−0.05	0	0.19	0.07	0.1	0.32	0.34	0.11	0.18	0.5
GOLD/CANADA	0.58	0.15	0.37	0.86	0.19	0.1	0.07	0.39	0.61	0.19	0.34	0.96	0.34	0.11	0.16	0.5
GOLD/CHINA	0.06	0.04	0	0.14	0.09	0.06	0.02	0.19	0.08	0.06	−0.01	0.18	0.24	0.08	0.12	0.35
GOLD/FRANCE	0.17	0.07	0.07	0.3	−0.02	0.04	−0.07	0.05	0.18	0.09	0.05	0.33	0.05	0.02	0.03	0.09
GOLD/GERMANY	0.09	0.04	0.02	0.17	0.01	0.04	−0.05	0.08	0.14	0.08	0.01	0.26	0.05	0.02	0.03	0.08
GOLD/INDIA	0.09	0.05	0.02	0.17	−0.04	0.03	−0.08	0.01	0.1	0.07	0.01	0.21	0.14	0.06	0.07	0.22
GOLD/INDONESIA	0.07	0.04	0.02	0.14	−0.15	0.06	−0.24	−0.07	0.06	0.05	−0.01	0.13	0.26	0.09	0.13	0.39
GOLD/ITALY	0.1	0.04	0.03	0.18	−0.03	0.03	−0.07	0.03	0.12	0.07	0.02	0.23	0.11	0.04	0.05	0.17
GOLD/JAPAN	0.22	0.07	0.11	0.34	0.08	0.06	0.01	0.18	0.19	0.08	0.08	0.34	0.31	0.11	0.14	0.46
GOLD/KOREA	0.07	0.04	0.02	0.15	−0.1	0.05	−0.19	−0.04	0.04	0.05	−0.03	0.12	0.11	0.04	0.05	0.16
GOLD/MEXICO	0.22	0.07	0.12	0.36	−0.02	0.03	−0.06	0.03	0.22	0.08	0.1	0.36	0.24	0.08	0.12	0.35
GOLD/RUSSIA	0.16	0.05	0.09	0.26	−0.01	0.03	−0.05	0.04	0.16	0.06	0.07	0.26	0.57	0.97	0	2.71
GOLD/SAUDI.ARABIA	−0.02	0.04	−0.08	0.04	0.11	0.04	0.06	0.19	0.04	0.08	−0.08	0.18	0.23	0.08	0.11	0.35
GOLD/SOUTH.AFRICA	0.2	0.06	0.12	0.3	0.02	0.03	−0.03	0.07	0.21	0.07	0.12	0.34	0.26	0.09	0.13	0.38
GOLD/TURKEY	0.14	0.05	0.07	0.24	0.1	0.06	0.03	0.2	0.15	0.07	0.06	0.3	0.07	0.02	0.03	0.1
GOLD/UK	0.33	0.11	0.17	0.52	0.03	0.04	−0.03	0.1	0.3	0.12	0.11	0.5	0.21	0.08	0.11	0.32
GOLD/USA	0.3	0.13	0.11	0.53	−0.03	0.05	−0.11	0.04	0.32	0.17	0.09	0.63	0.09	0.03	0.05	0.13
GOLD/EU	0.24	0.08	0.12	0.39	−0.03	0.04	−0.08	0.05	0.24	0.11	0.08	0.42	0.09	0.03	0.05	0.13
GOLD/BITCOIN	0.05	0.1	0	0.37	0.16	0.09	0.07	0.35	0.1	0.22	0.01	0.49	0.05	0.02	0.02	0.07

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (OIL/Markets)	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*
OIL/GOLD	0.11	0.03	0.06	0.17	0.23	0.15	0.11	0.53	0.14	0.08	0.05	0.25	0.89	0.32	0.52	1.59
OIL/ARGENTINA	0.27	0.12	0.09	0.49	0.36	0.29	0.17	0.87	0.23	0.15	0.08	0.5	0.21	0.04	0.16	0.29
OIL/AUSTRALIA	0.36	0.08	0.25	0.5	0.74	0.46	0.38	1.36	0.42	0.15	0.25	0.64	0.46	0.08	0.34	0.62
OIL/BRAZIL	0.34	0.09	0.21	0.52	0.44	0.23	0.24	0.82	0.35	0.13	0.2	0.59	0.59	0.1	0.45	0.78
OIL/CANADA	1.26	0.28	0.89	1.76	1.89	0.86	0.77	3.78	1.2	0.38	0.76	1.87	0.42	0.08	0.31	0.58
OIL/CHINA	0.15	0.06	0.06	0.26	0.84	0.75	0.22	2.69	0.19	0.18	0.07	0.38	0.52	0.09	0.39	0.69
OIL/FRANCE	0.49	0.14	0.28	0.75	1.05	0.53	0.58	2.01	0.57	0.21	0.31	0.93	−0.01	0	−0.02	−0.01
OIL/GERMANY	0.41	0.11	0.27	0.63	0.88	0.46	0.48	1.89	0.48	0.18	0.27	0.77	−0.17	0.04	−0.25	−0.1
OIL/INDIA	0.19	0.07	0.09	0.32	0.62	0.33	0.37	1.48	0.28	0.14	0.13	0.5	0.38	0.1	0.24	0.55
OIL/INDONESIA	0.1	0.05	0.04	0.19	0.53	0.27	0.28	1.09	0.14	0.1	0.05	0.27	0.51	0.1	0.37	0.7
OIL/ITALY	0.42	0.12	0.25	0.63	0.96	0.55	0.48	1.91	0.5	0.21	0.28	0.81	0.04	0.01	0.03	0.06
OIL/JAPAN	0.13	0.05	0.06	0.22	0.39	0.28	0.18	0.97	0.17	0.12	0.07	0.33	0.48	0.08	0.34	0.6
OIL/KOREA	0.22	0.07	0.13	0.36	0.33	0.28	0.13	0.92	0.24	0.13	0.11	0.45	0.4	0.07	0.3	0.54
OIL/MEXICO	0.48	0.15	0.28	0.75	0.67	0.4	0.35	1.57	0.48	0.2	0.28	0.85	0.23	0.04	0.17	0.31
OIL/RUSSIA	0.56	0.13	0.39	0.76	0.97	0.48	0.5	2.1	0.58	0.2	0.34	0.88	7.49	14.24	0.02	42.55
OIL/SAUDI.ARABIA	0.19	0.07	0.09	0.32	0.73	0.52	0.3	1.69	0.33	0.21	0.14	0.61	0.36	0.08	0.26	0.51
OIL/SOUTH.AFRICA	0.32	0.09	0.2	0.52	0.55	0.41	0.26	1.65	0.34	0.16	0.2	0.59	0.31	0.06	0.23	0.42
OIL/TURKEY	0.15	0.06	0.08	0.28	0.54	0.41	0.19	1.34	0.17	0.13	0.06	0.38	−0.04	0.01	−0.06	−0.03
OIL/UK	0.72	0.2	0.45	1.1	0.93	0.52	0.43	2.15	0.74	0.25	0.45	1.19	0.32	0.09	0.18	0.48
OIL/USA	0.89	0.3	0.41	1.43	1.24	0.69	0.54	2.66	0.83	0.35	0.37	1.47	0.05	0.01	0.03	0.07
OIL/EU	0.62	0.16	0.38	0.91	1.05	0.56	0.55	2.08	0.65	0.24	0.36	1.04	−0.02	0	−0.02	−0.01
OIL/BITCOIN	0.02	0.04	−0.01	0.14	0.24	0.21	0.06	0.71	0.08	0.17	0	0.37	0.02	0	0.01	0.02
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (EU/Markets)	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*	*MN*	*STD.D*	*5%*	*95%*
EU/GOLD	0.04	0.02	0.02	0.08	−0.01	0.02	−0.04	0.02	0.06	0.03	0.02	0.11	0.13	0.05	0.07	0.21
EU/OIL	0.1	0.04	0.06	0.15	0.16	0.06	0.06	0.26	0.11	0.05	0.06	0.19	0	0	−0.01	0
EU/ARGENTINA	0.18	0.09	0.07	0.32	0.23	0.08	0.13	0.37	0.18	0.09	0.07	0.33	0.37	0.08	0.29	0.54
EU/AUSTRALIA	0.38	0.11	0.26	0.57	0.54	0.14	0.36	0.79	0.44	0.11	0.29	0.64	0.78	0.17	0.6	1.13
EU/BRAZIL	0.2	0.07	0.13	0.32	0.28	0.07	0.19	0.41	0.22	0.08	0.14	0.36	0.77	0.16	0.6	1.09
EU/CANADA	0.67	0.16	0.47	0.91	1.21	0.45	0.54	1.98	0.73	0.17	0.49	1.04	0.6	0.14	0.46	0.89
EU/CHINA	0.16	0.07	0.08	0.26	0.31	0.17	0.1	0.58	0.17	0.08	0.08	0.32	0.57	0.12	0.44	0.82
EU/FRANCE	0.89	0.07	0.78	1.02	0.97	0.09	0.85	1.12	0.91	0.07	0.79	1.03	0.94	0.04	0.87	0.99
EU/GERMANY	0.81	0.11	0.67	1.02	0.9	0.08	0.79	1.02	0.85	0.1	0.71	1.03	0.95	0.2	0.69	1.33
EU/INDIA	0.35	0.14	0.23	0.54	0.53	0.16	0.32	0.86	0.42	0.16	0.25	0.64	0.68	0.12	0.52	0.93
EU/INDONESIA	0.2	0.09	0.11	0.31	0.34	0.12	0.19	0.59	0.21	0.09	0.12	0.35	0.45	0.11	0.35	0.68
EU/ITALY	0.6	0.09	0.46	0.75	0.81	0.1	0.64	0.99	0.66	0.11	0.5	0.84	0.84	0.08	0.73	0.97
EU/JAPAN	0.2	0.07	0.13	0.31	0.41	0.14	0.24	0.65	0.25	0.09	0.15	0.42	0.53	0.09	0.39	0.71
EU/KOREA	0.29	0.12	0.19	0.47	0.38	0.16	0.19	0.63	0.29	0.11	0.18	0.47	0.51	0.11	0.39	0.75
EU/MEXICO	0.38	0.12	0.24	0.59	0.51	0.11	0.35	0.71	0.41	0.13	0.26	0.64	0.79	0.17	0.61	1.14
EU/RUSSIA	0.3	0.11	0.18	0.45	0.54	0.13	0.36	0.77	0.35	0.12	0.2	0.53	−3.79	7	−19.9	−0.01
EU/SAUDI.ARABIA	0.17	0.08	0.1	0.28	0.35	0.14	0.17	0.58	0.23	0.11	0.11	0.44	0.26	0.06	0.2	0.4
EU/SOUTH.AFRICA	0.32	0.09	0.22	0.49	0.48	0.13	0.3	0.71	0.36	0.11	0.24	0.56	0.67	0.15	0.52	0.99
EU/TURKEY	0.2	0.09	0.11	0.35	0.46	0.22	0.18	0.84	0.23	0.11	0.11	0.46	0.51	0.11	0.4	0.74
EU/UK	0.91	0.11	0.75	1.1	0.81	0.11	0.62	1.01	0.88	0.11	0.73	1.07	1.13	0.17	0.93	1.48
EU/USA	0.68	0.21	0.39	1.02	0.86	0.24	0.49	1.25	0.67	0.2	0.4	1	0.61	0.14	0.45	0.88
EU/BITCOIN	0	0.01	−0.01	0.01	0.1	0.06	0.03	0.21	0.05	0.12	0	0.28	0.13	0.05	0.07	0.21

Notes: This table illustrate the hedge ratios, among bitcoin, gold, oil and G20 markets in pre and during COVID-19 and War.

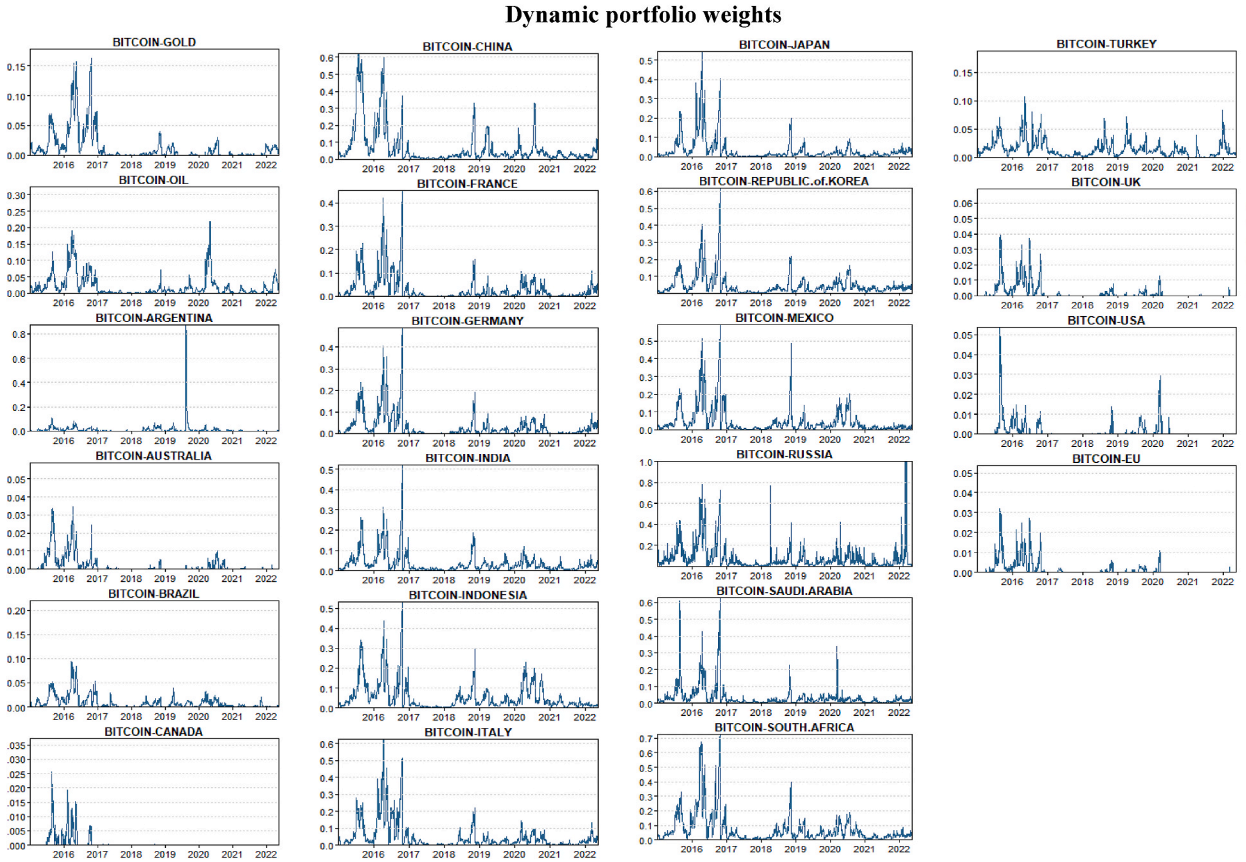


Fig. 25. Dynamic optimal portfolio weights pairs (Bitcoin/all other markets).

Overall, these findings have implications for investors and policymakers as they provide insights into the dynamics of volatility spillovers during times of crisis and the interconnectivity of markets. The study highlights the importance of monitoring the transmission of shocks across markets and the need for effective risk management strategies to mitigate the impact of such shocks.

4.7. Network based return spillovers on frequency domains

Next, the study employed TVP-VAR based frequency connectedness framework which is combination of Baruník and Křehlík (2018), and Antonakakis, Chatziantoniou, et al. (2020) framework to uncover the return and volatility spillover dynamics in terms of short and long-term behaviour. Short and long run return spillover relationship network is plotted in Fig. 12a (short run) and 12b (long run), here return spillover is more pronounced in short-run. In the short-run, Bitcoin, EU, Italy, Germany, France, Canada, USA, UK, South Africa, Russia, and Mexico are transmitting risk spillover towards Oil, Gold, and remaining capital markets. While, in the long-run Bitcoin, Oil, Gold, Indonesia, India, China, Australia, Japan, Turkey, Saudi Arabia, and Korea receiving return spillover from rest of the markets. Importantly, Bitcoin (Brazil and Argentina) transformed from transmitter (receiver) in short-run to receiver (transmitter) in long-run. In short-run, EU (Brazil) is prominent transmitter (receiver). On the other side, Canada (Argentina) is playing the same role in longer time frame. Additionally, Fig. 13 display the total (blue), short (red), and long runs (green) return spillover presentation overtime. Clear spikes during COVID-19, and Russia-Ukraine conflict confirm strong hit of return spillover on all the markets in the system. During COVID-19 total, short, and long runs TCI reaches to 90%, 60%, and 38% respectively. Whereas, total (88%), short (70%), and long (15%) are observed during military tussle between Russia and Ukraine (Gabauer & Gupta, 2018). The nature of return spillovers undergoes a significant transformation in the remaining period of observation. Important to note that during Russia-Ukraine conflict long-term connectedness continuously declining only short-term shows high prickle leads total connectedness to rise. There are complex variations in the connectedness of the system due to short-term and long-term factors. Following turbulent periods marked by high levels of uncertainty, markets gradually stabilize, and investors display reduced levels of apprehension. In stable and expanding markets, the declining uncertainty means that future shocks can propagate more quickly, and their effects on the system decrease in a matter of days. This leads to the emergence of short-term connectedness.

Fig. 14a and b exhibits the connectivity among various variables in the short run and long run in the pre-COVID 19 times. There is strong connectivity among variables in the long run. The network clearly shows that there are minor changes in the 1–5 days (short run) and 5-Inf days (long run). In the short run, eleven markets transferring returns spillover which includes Bitcoin, EU, Germany,

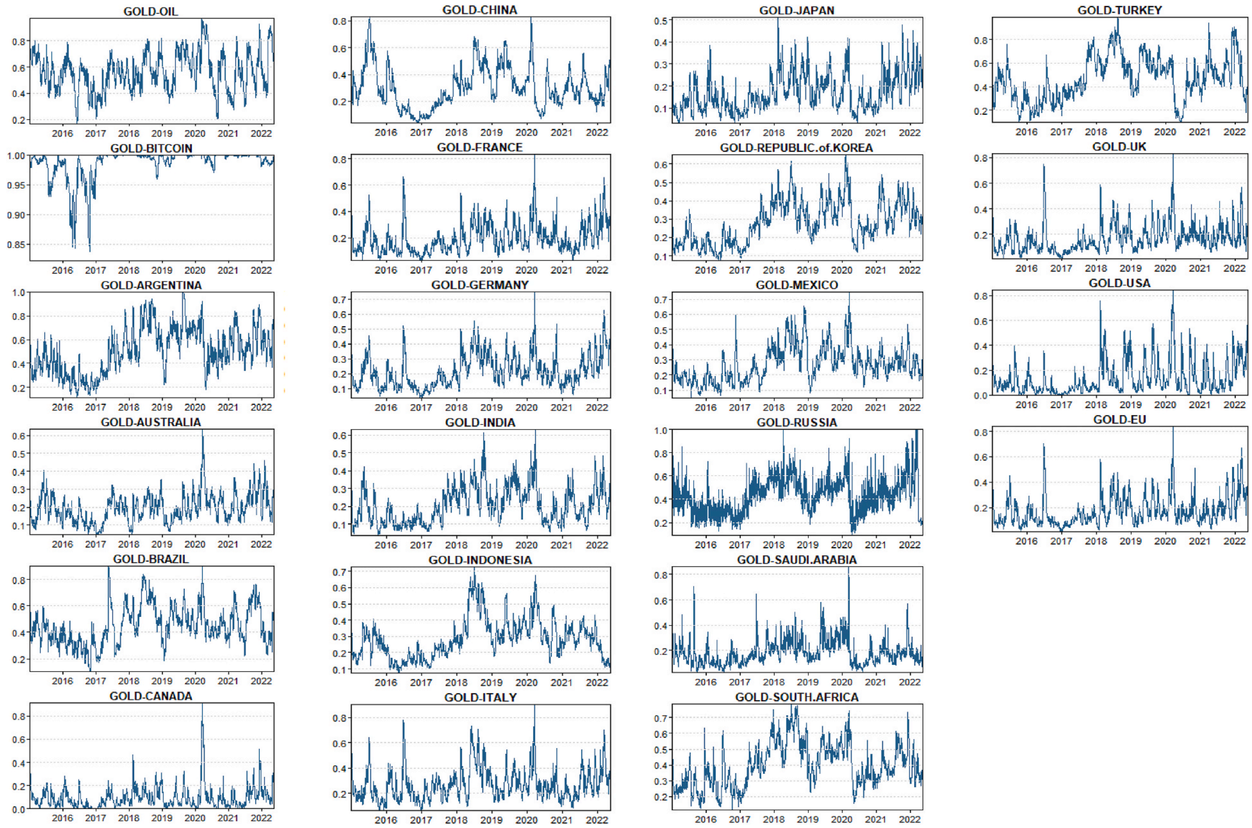


Fig. 26. Dynamic optimal portfolio weights pairs (Gold/all other markets).

France, Italy, Canada, USA, UK, South Africa, Russia, and Mexico. Whereas in the long run, Brazil, and Argentina joins the transmitters and Russia started absorbing the spillover generated due to risk variations. Among G20 markets Japan, India, Indonesia, Turkey and Saudi Arabia have become smaller receiver in the long run. Similarly, Gold, Oil, and Bitcoin also followed the same path. On the other hand, Canada, USA, UK, Germany, France, EU have become bigger transmitter in the long run. Further, countries like Argentina and Brazil have become net transmitters and Russia has become a net receiver in long run. Supplementary, during COVID-19 the network is shown by Fig. 15a and b also highlights major changes in short run and long run. It is observed that there is very strong connectivity among variables both in short run and long run. There are ten receiver and thirteen transmitters in long run as compare to eleven receiver and twelve transmitters in the short run. Argentina has become transmitter from receiver whereas Australia, South Africa and Oil has become receiver in long run. Countries like Italy, Canada, UK, USA, and Bitcoin have become smaller transmitter whereas China has become smaller receiver. Republic of Korea is the biggest receiver. This strong nest of connectedness during COVID-19 has shown strong effects on commodities, cryptocurrencies, and G20 markets in short and long runs (Balcilar, Gabauer, & Umar, 2021; Shaikh, I. 2022; Balcilar et al., 2022; Phiri, Anyikwa, & Moyo, 2023). The changes in the spillover effects of returns during the COVID-19 pandemic have significant economic implications. The shift in transmission and absorption of returns spillover among countries and commodities can impact their economic performance and stability. Understanding these changes and their implications can help policymakers and investors make informed decisions and manage their risks in the global market.

Further, Fig. 16a and b exhibits the connectivity among variables before Russia-Ukraine war. The density of connectivity has increased in the long run-in comparison to short run. EU along with its member nations are the key transmitters. Strong return connectivity in long-run with EU, Canada, and France are the largest transmitters while Australia and Korea are biggest recipients. From short to long runs Argentina and Brazil have transformed into net transmitter whereas Russian and Bitcoin have become net receiver. Contrast to during Russian invasion, Fig. 17a and b exhibits, compared to pre-war time the less connectedness exist during the time of Russia invasion in Ukraine. Fig. 17a and b, describe the linkages amongst the samples during the conflict time. Comparative strong linkages exist for long-run where USA, and Bitcoin are the largest transmitters. Interesting to see that Indonesia is the central transmitter and Gold is acting as safe haven in short-term. It is also observed that Italy, EU and commodity Gold have become bigger receiver, Brazil has become smaller receiver whereas cryptocurrency Bitcoin and Canada are the largest spreader of risk generated on account of return variability. Further countries like China, Germany and India have transmuted to receiver in the long run. During conflict time, linkages among sample variables are complex and dynamic. Implications for investors and policymakers include risk transmission, safe-haven assets, sensitivity to external shocks, and shifts in risk levels over time.

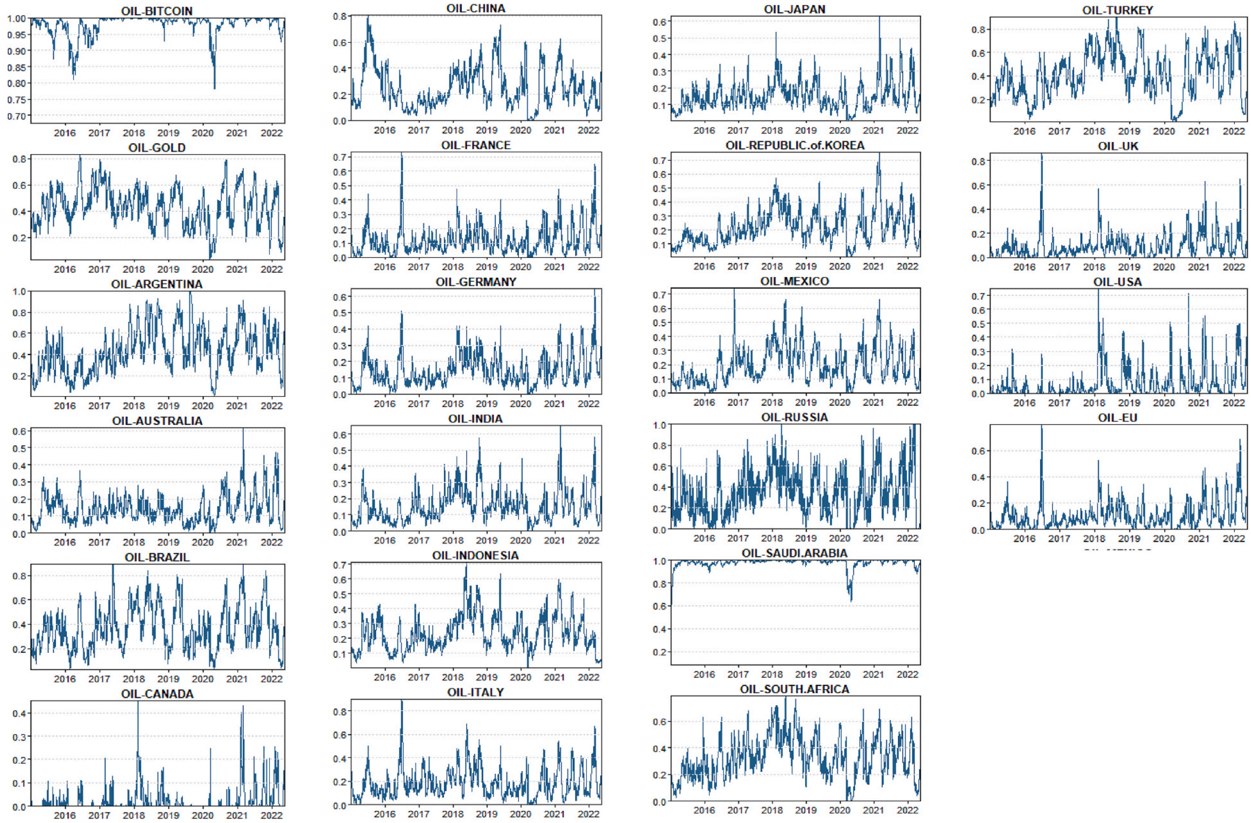


Fig. 27. Dynamic optimal portfolio weights pairs (Oil/all other markets).

4.8. Network based volatility spillovers on frequency domains

Moving ahead Fig. 18a and b exhibits the network-based volatility spillovers on frequency domains. Figure show that Bitcoin, Italy, Argentina, Australia, Canada, EU, France, Germany, UK, Oil, and Russia are transferring volatility in the short run whereas in the long run a major change is seen where only Russia, EU, and France are the spreaders and rest all the assets absorbing the volatility shock. In the long run Russia is emerged as the biggest transmitter closely followed by France and European Union. On comparing note, it is observed that Italy, Argentina, Australia, Canada, Germany, UK, Oil, and Bitcoin have converted to net receiver in the long run. It is interesting to observe that Russia majorly transferring volatility spillover to Oil, India, Canada, and Australia. This is possibly because Russia's dependence on oil exports, political instability, trade relationships, and financial market linkages. Next, Fig. 19 experience high volatility events during 2015, 2020 (due to COVID-19), and 2022 (on account of Russia Ukraine war). During COVID-19 total volatility level crossed 95% and long-term volatility also touches to 80% initially but during Russia invasion total and long-term volatility further experience high level nearly to 95% (see Fig. 20).

Next, the study investigates the dynamics of volatility connectedness among variables in the short and long run, pre and during the COVID-19 pandemic. The findings suggest that there is less connectivity among variables in the pre-COVID era, which strengthens during the pandemic. The major transferor of volatility in the short run is the EU, while China is the major transferor in the long run. Italy, Australia, Canada, and India are observed to be transmitters in the long run, while Bitcoin, Brazil, and Turkey are receivers. Moreover, the study reveals that Turkey is the strongest generator of volatility in the short run during the pandemic, while the UK, Japan, and Argentina are other shock creators. The long-run pattern shows that G7 markets (excluding Japan), EU, Argentina, Australia, Brazil, and Canada receive the shock from the system, indicating that shocks generated in the short run by a few markets are absorbed by a large number of markets in the longer term. Additionally, the study finds that China and gold have become bigger transmitters, while the UK/Mexico are the smallest transmitters/receivers. Overall, the study provides important insights into the dynamics of volatility connectedness among variables during the COVID-19 pandemic. The findings suggest that the pandemic has increased the connectivity among variables, with some markets being major generators of volatility in the short run, and others absorbing the shock in the long run.

Further, volatility spillovers of pre and during Russia-Ukraine war in the short and long run are analyzed and findings are displayed in Fig. 22a–b and 23a-b, respectively (see Fig. 21). It reveals less connectivity among variables in short-run. Eleven markets are net receivers and twelve net transmitters in the short run, while thirteen net receivers and ten net transmitters in the long run. The comparison between short and long run shows that Argentina has become a transmitter in the long run, while Australia has become a

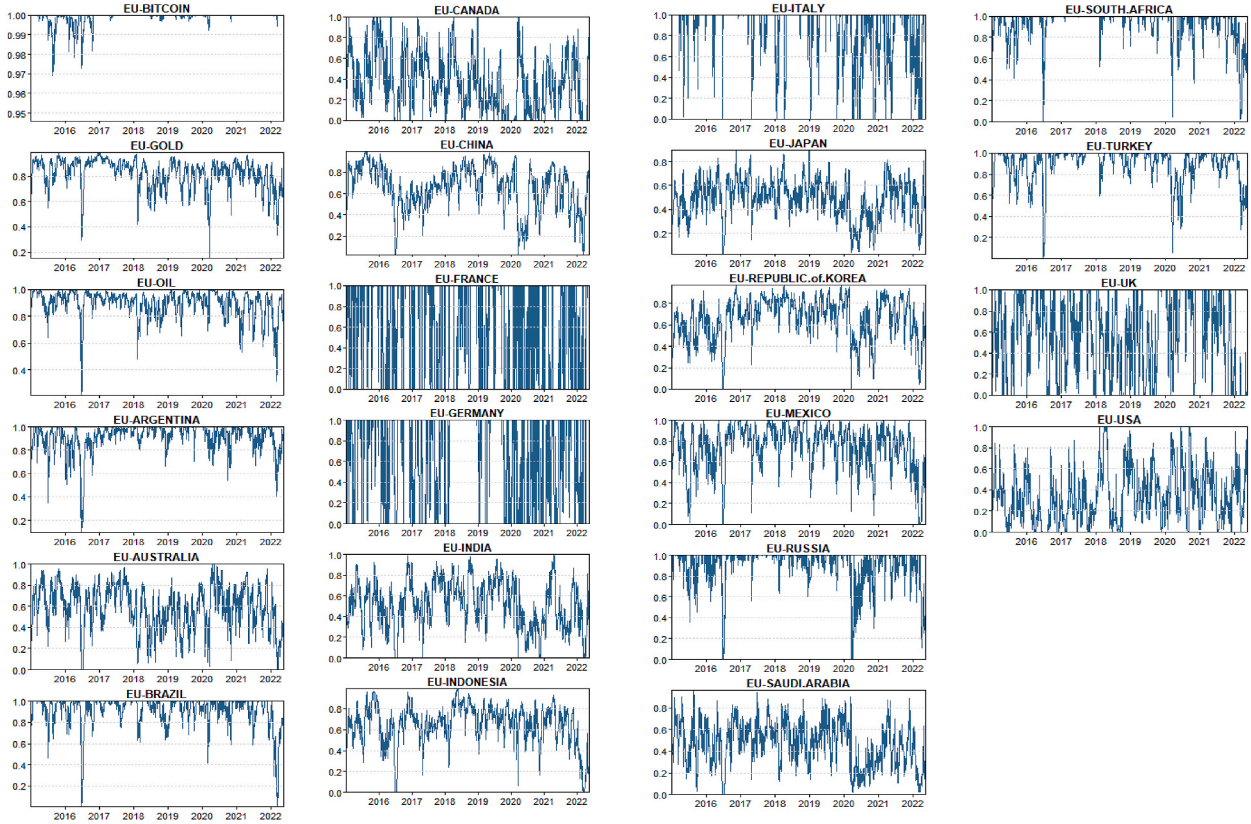


Fig. 28. Dynamic optimal portfolio weights pairs (EU/all other markets).

receiver. In contrast, Bitcoin, Canada, and Gold have become larger transmitters, whereas India and Indonesia are smaller receivers in the long run. Furthermore, during war story turn into a different picture, where ten net receivers and thirteen net transmitters in the short run. At the same time, Russia (largest), EU, Germany, France, Italy, and Argentina (smallest) are found as transmitters in the long run. On comparison note, Argentina has become a transmitter in the long run, while Australia, China, Saudi Arabia, South Africa, Brazil, Canada, UK, and Korea transmuted into net receivers in the long run. Russia, which is heavily involved in the Ukraine war, has become a bigger transmitter (Umar et al., 2022; Alam et al., 2022), and USA has become a slightly bigger receiver in the long run. Importantly, Gold and to some extent Bitcoin are played role of safe heaven during this geopolitical tension in the investment portfolio (Baur & Smales, 2020; Selmi, Bouoiyour, & Wohar, 2022). Overall, the findings of the study provide important insights into the dynamics of volatility connectedness during times of geopolitical tensions. The results suggest that some markets become net transmitters or receivers of volatility in the short run, while others absorb the shock in the long run. These findings have important implications for policymakers and investors in managing risks and optimizing portfolio allocation in times of high volatility (see Fig. 24).

4.9. Robustness testing

In the realm of finance research, conducting robustness tests is essential for enhancing the credibility and validity of findings, particularly for studies reliant on statistical analysis. Robustness testing is a critical aspect of finance research as it subjects results to sensitivity tests and alternative specifications, ensuring their reliability. Financial data can be noisy and biased, and robustness tests address these concerns. Therefore, robustness testing is conducted on frequency connectedness through sensitivity test by applying 200, 250, and 300 days rolling windows and forecast horizon of 100 days on return as well as volatility. Robustness findings are consistent with our main outcomes where TCI show high spikes during CIVID-19 and Russian-Ukraine geopolitical conflict. Previous studies have been adopted these robustness tests, such as: (Alam et al., 2022; Balli, Billah, & Chowdhury, 2022; Billah, Balli, et al., 2023; Diebold & Yilmaz, 2009, 2012; Diebold & Yılmaz, 2014).

4.10. Portfolio implications

To comprehend net pairwise spillovers relationship among sample assets, 22 bivariate portfolios are created, and results are presented in Table 4, it shows the dynamic hedge ratios results before and during COVID-19 pandemic and Russia-Ukraine war. The mean column refers to the average proportion of the asset in the portfolio. Like, BITCOIN/GOLD mean value was 0.05 meaning that average weight of BITCOIN in the portfolio was 5% before COVID-19 pandemic and during pandemic it is 0.63 that is 63% increase in

Table 5
Dynamic portfolio weights.

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (Bitcoin/ Markets)	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*
BITCOIN/GOLD	0.36	0.33	0.04	0.99	0.19	0.2	0	0.65	0.3	0.29	0.04	0.99	0.11	0.07	0.01	0.22
BITCOIN/OIL	0.38	0.32	0.05	1	0.41	0.31	0.04	0.97	0.35	0.29	0.06	0.99	0.43	0.09	0.29	0.59
BITCOIN/ ARGENTINA	0.35	0.3	0.05	0.99	0.32	0.17	0.06	0.63	0.32	0.27	0.04	0.99	0.2	0.01	0.19	0.22
BITCOIN/ AUSTRALIA	0.2	0.3	0.01	0.98	0.12	0.16	0	0.43	0.16	0.26	0.01	0.96	0.1	0	0.09	0.1
BITCOIN/BRAZIL	0.33	0.3	0.05	0.99	0.26	0.22	0.03	0.66	0.29	0.27	0.05	0.99	0.08	0.01	0.07	0.09
BITCOIN/CANADA	0.18	0.29	0.01	0.96	0.08	0.16	0	0.38	0.13	0.25	0	0.94	0.05	0	0.05	0.05
BITCOIN/CHINA	0.26	0.31	0.02	1	0.08	0.08	0	0.23	0.2	0.27	0.02	0.99	0.14	0.01	0.13	0.15
BITCOIN/FRANCE	0.19	0.29	0.01	0.98	0.1	0.13	0	0.3	0.15	0.25	0.01	0.97	0.14	0.08	0.07	0.3
BITCOIN/GERMANY	0.2	0.29	0.01	0.98	0.1	0.13	0	0.31	0.15	0.25	0.01	0.97	0.12	0.11	0.03	0.35
BITCOIN/INDIA	0.2	0.29	0.02	0.96	0.1	0.17	0	0.55	0.16	0.24	0.02	0.96	0.14	0.04	0.09	0.21
BITCOIN/ INDONESIA	0.23	0.29	0.02	0.97	0.18	0.18	0.02	0.54	0.19	0.25	0.02	0.96	0.04	0	0.03	0.04
BITCOIN/ITALY	0.24	0.3	0.02	0.98	0.1	0.13	0	0.33	0.19	0.26	0.01	0.98	0.15	0.1	0.07	0.36
BITCOIN/JAPAN	0.2	0.29	0.02	0.96	0.06	0.09	0	0.23	0.15	0.24	0.01	0.91	0.08	0.03	0.04	0.15
BITCOIN/KOREA	0.22	0.28	0.03	0.97	0.16	0.14	0.02	0.51	0.19	0.24	0.03	0.95	0.15	0	0.14	0.15
BITCOIN/MEXICO	0.24	0.29	0.03	0.97	0.16	0.16	0	0.44	0.2	0.25	0.02	0.94	0.04	0	0.04	0.05
BITCOIN/RUSSIA	0.27	0.32	0.02	0.99	0.17	0.17	0	0.5	0.23	0.28	0.02	0.99	0.38	0.41	0	0.99
BITCOIN/SAUDI. ARABIA	0.22	0.3	0.02	0.98	0.12	0.09	0.03	0.32	0.17	0.26	0.01	0.93	0.09	0	0.09	0.1
BITCOIN/SOUTH. AFRICA	0.31	0.29	0.05	0.99	0.18	0.18	0.01	0.55	0.25	0.26	0.04	0.98	0.14	0	0.14	0.14
BITCOIN/TURKEY	0.33	0.29	0.06	0.99	0.13	0.11	0.02	0.38	0.3	0.27	0.06	0.99	0.16	0.02	0.15	0.19
BITCOIN/UK	0.19	0.29	0.01	0.96	0.1	0.14	0	0.31	0.15	0.25	0.01	0.95	0.07	0.05	0.03	0.15
BITCOIN/USA	0.16	0.27	0.01	0.94	0.09	0.15	0	0.39	0.12	0.24	0	0.88	0.02	0.02	0	0.07
BITCOIN/EU	0.18	0.29	0.01	0.97	0.08	0.11	0	0.24	0.14	0.25	0	0.96	0.11	0.07	0.05	0.26
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (Gold/ Markets)	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*
GOLD/OIL	0.54	0.12	0.35	0.74	0.72	0.16	0.48	0.98	0.57	0.14	0.33	0.81	0.93	0.07	0.77	1
GOLD/ARGENTINA	0.48	0.22	0.17	0.89	0.66	0.14	0.37	0.84	0.52	0.21	0.19	0.88	0.8	0.16	0.56	1
GOLD/AUSTRALIA	0.17	0.06	0.08	0.27	0.33	0.13	0.15	0.53	0.21	0.09	0.09	0.35	0.46	0.23	0.19	0.84
GOLD/BRAZIL	0.45	0.15	0.23	0.72	0.57	0.12	0.35	0.78	0.47	0.14	0.25	0.72	0.54	0.23	0.25	0.91
GOLD/CANADA	0.09	0.06	0.01	0.19	0.19	0.17	0.02	0.55	0.1	0.1	0	0.26	0.41	0.24	0.15	0.81
GOLD/CHINA	0.32	0.17	0.07	0.61	0.31	0.19	0.09	0.78	0.3	0.16	0.08	0.6	0.58	0.21	0.31	0.9
GOLD/FRANCE	0.18	0.1	0.06	0.38	0.31	0.12	0.13	0.52	0.2	0.11	0.06	0.43	0.6	0.18	0.34	0.87
GOLD/GERMANY	0.2	0.09	0.08	0.36	0.33	0.11	0.19	0.53	0.22	0.1	0.09	0.4	0.53	0.14	0.31	0.75
GOLD/INDIA	0.19	0.09	0.08	0.34	0.33	0.1	0.17	0.52	0.21	0.1	0.08	0.38	0.56	0.23	0.29	0.88
GOLD/INDONESIA	0.27	0.13	0.12	0.55	0.42	0.12	0.23	0.63	0.29	0.12	0.12	0.53	0.39	0.22	0.15	0.77
GOLD/ITALY	0.28	0.12	0.12	0.53	0.35	0.13	0.19	0.61	0.28	0.12	0.13	0.53	0.64	0.19	0.37	0.92
GOLD/JAPAN	0.17	0.08	0.07	0.32	0.2	0.09	0.1	0.37	0.18	0.08	0.07	0.32	0.39	0.23	0.15	0.81
GOLD/KOREA	0.25	0.1	0.11	0.42	0.44	0.15	0.22	0.68	0.28	0.11	0.12	0.46	0.52	0.19	0.29	0.83
GOLD/MEXICO	0.26	0.13	0.1	0.5	0.44	0.11	0.25	0.61	0.29	0.12	0.11	0.49	0.44	0.21	0.2	0.8
GOLD/RUSSIA	0.34	0.12	0.16	0.56	0.41	0.12	0.25	0.63	0.36	0.13	0.17	0.61	0.46	0.44	0	1
GOLD/SAUDI. ARABIA	0.24	0.11	0.1	0.42	0.41	0.16	0.16	0.68	0.23	0.12	0.09	0.46	0.41	0.22	0.17	0.79
GOLD/SOUTH. AFRICA	0.41	0.15	0.21	0.69	0.49	0.11	0.33	0.68	0.41	0.14	0.2	0.66	0.61	0.22	0.33	0.94
GOLD/TURKEY	0.46	0.18	0.22	0.79	0.41	0.18	0.14	0.7	0.49	0.18	0.19	0.81	0.56	0.18	0.34	0.85
GOLD/UK	0.14	0.1	0.03	0.33	0.35	0.12	0.16	0.54	0.18	0.11	0.04	0.39	0.46	0.22	0.19	0.79
GOLD/USA	0.11	0.11	0.02	0.36	0.26	0.15	0.07	0.54	0.13	0.12	0.02	0.38	0.54	0.19	0.29	0.81
GOLD/EU	0.15	0.09	0.04	0.32	0.3	0.11	0.14	0.5	0.17	0.11	0.05	0.38	0.58	0.18	0.33	0.85
GOLD/BITCOIN	0.64	0.33	0.01	0.96	0.81	0.2	0.35	1	0.7	0.29	0.01	0.96	0.89	0.07	0.78	0.99
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (OIL/Markets)	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*
OIL/GOLD	0.46	0.12	0.26	0.65	0.28	0.16	0.02	0.52	0.43	0.14	0.19	0.67	0.07	0.07	0	0.23
OIL/ARGENTINA	0.43	0.24	0.11	0.89	0.44	0.24	0.01	0.76	0.45	0.22	0.11	0.85	0.32	0.08	0.17	0.46
OIL/AUSTRALIA	0.13	0.05	0.05	0.23	0.11	0.1	0	0.33	0.14	0.08	0.04	0.29	0.09	0.04	0.03	0.17
OIL/BRAZIL	0.4	0.16	0.15	0.67	0.32	0.18	0.02	0.62	0.38	0.16	0.11	0.64	0.1	0.05	0.03	0.18
OIL/CANADA	0.01	0.03	0	0.04	0.02	0.07	0	0.1	0.02	0.04	0	0.09	0.08	0.04	0.03	0.15
OIL/CHINA	0.27	0.16	0.09	0.59	0.16	0.19	0	0.61	0.25	0.15	0.05	0.55	0.13	0.05	0.04	0.23

(*continued on next page*)

Table 5 (*continued*)

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (OIL/Markets)	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*
OIL/FRANCE	0.11	0.1	0.02	0.3	0.06	0.07	0	0.2	0.11	0.1	0.01	0.28	0.23	0.07	0.12	0.37
OIL/GERMANY	0.13	0.08	0.03	0.27	0.08	0.08	0	0.25	0.13	0.08	0.02	0.28	0.2	0.08	0.1	0.37
OIL/INDIA	0.15	0.07	0.06	0.28	0.11	0.08	0	0.23	0.15	0.08	0.05	0.29	0.16	0.09	0.05	0.32
OIL/INDONESIA	0.23	0.11	0.07	0.45	0.17	0.14	0	0.44	0.23	0.11	0.07	0.45	0.07	0.03	0.02	0.13
OIL/ITALY	0.2	0.13	0.06	0.46	0.09	0.11	0	0.32	0.18	0.12	0.03	0.41	0.25	0.1	0.12	0.45
OIL/JAPAN	0.16	0.07	0.07	0.3	0.09	0.07	0	0.22	0.15	0.07	0.05	0.29	0.07	0.04	0.03	0.15
OIL/KOREA	0.2	0.09	0.06	0.35	0.25	0.18	0	0.55	0.21	0.1	0.05	0.4	0.13	0.05	0.05	0.22
OIL/MEXICO	0.19	0.13	0.03	0.42	0.18	0.15	0	0.45	0.19	0.12	0.02	0.4	0.11	0.04	0.05	0.18
OIL/RUSSIA	0.22	0.13	0.06	0.4	0.11	0.14	0	0.4	0.23	0.16	0.03	0.49	0.39	0.45	0	1
OIL/SAUDI. ARABIA	0.18	0.09	0.06	0.33	0.18	0.17	0	0.51	0.15	0.1	0.03	0.32	0.09	0.04	0.03	0.16
OIL/SOUTH. AFRICA	0.35	0.15	0.11	0.62	0.26	0.18	0	0.55	0.33	0.14	0.08	0.57	0.18	0.06	0.08	0.29
OIL/TURKEY	0.42	0.16	0.16	0.7	0.22	0.21	0	0.6	0.43	0.18	0.11	0.71	0.21	0.06	0.11	0.32
OIL/UK	0.07	0.1	0	0.2	0.1	0.12	0	0.37	0.08	0.09	0	0.25	0.12	0.07	0.04	0.29
OIL/USA	0.05	0.09	0	0.25	0.05	0.11	0	0.29	0.06	0.09	0	0.26	0.19	0.08	0.09	0.32
OIL/EU	0.08	0.09	0.01	0.22	0.06	0.07	0	0.22	0.09	0.09	0	0.25	0.21	0.07	0.12	0.36
OIL/BITCOIN	0.62	0.32	0	0.95	0.28	0.16	0.02	0.52	0.65	0.29	0.01	0.94	0.57	0.09	0.41	0.71

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (EU/Markets)	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*	*MN*	*STD. D*	*5%*	*95%*
EU/GOLD	0.85	0.09	0.68	0.96	0.7	0.11	0.5	0.86	0.83	0.11	0.62	0.95	0.42	0.18	0.15	0.67
EU/OIL	0.92	0.09	0.78	0.99	0.94	0.07	0.78	1	0.91	0.09	0.75	1	0.79	0.07	0.64	0.88
EU/ARGENTINA	0.9	0.14	0.62	1	0.94	0.09	0.76	1	0.9	0.13	0.64	1	0.8	0.16	0.45	0.97
EU/AUSTRALIA	0.6	0.18	0.27	0.85	0.6	0.25	0.17	0.94	0.6	0.19	0.25	0.87	0.26	0.16	0	0.51
EU/BRAZIL	0.94	0.11	0.74	1	0.93	0.12	0.68	1	0.92	0.12	0.7	1	0.37	0.22	0	0.71
EU/CANADA	0.45	0.23	0.07	0.83	0.2	0.34	0	1	0.4	0.26	0	0.86	0.26	0.12	0.03	0.43
EU/CHINA	0.71	0.18	0.38	0.94	0.5	0.3	0.1	0.95	0.66	0.2	0.27	0.93	0.48	0.19	0.11	0.72
EU/FRANCE	0.83	0.32	0	1	0.57	0.48	0	1	0.76	0.37	0	1	0.91	0.23	0.37	1
EU/GERMANY	0.88	0.28	0	1	0.81	0.36	0	1	0.85	0.31	0	1	0.33	0.34	0	0.96
EU/INDIA	0.58	0.17	0.27	0.81	0.57	0.27	0.09	0.98	0.56	0.2	0.21	0.84	0.45	0.21	0.06	0.77
EU/INDONESIA	0.69	0.16	0.39	0.91	0.68	0.22	0.23	0.96	0.67	0.17	0.35	0.9	0.27	0.1	0.07	0.4
EU/ITALY	0.99	0.06	0.91	1	0.81	0.3	0.07	1	0.96	0.12	0.71	1	0.89	0.25	0.23	1
EU/JAPAN	0.57	0.14	0.31	0.77	0.34	0.18	0.09	0.66	0.52	0.16	0.22	0.75	0.25	0.1	0.09	0.44
EU/KOREA	0.69	0.18	0.33	0.89	0.71	0.28	0.24	1	0.68	0.18	0.34	0.9	0.41	0.15	0.11	0.61
EU/MEXICO	0.79	0.2	0.38	1	0.86	0.19	0.45	1	0.78	0.2	0.38	1	0.23	0.14	0	0.45
EU/RUSSIA	0.88	0.15	0.6	1	0.79	0.24	0.33	1	0.86	0.17	0.53	1	0.48	0.42	0	0.99
EU/SAUDI. ARABIA	0.62	0.16	0.32	0.85	0.66	0.27	0.24	0.99	0.56	0.2	0.2	0.85	0.32	0.1	0.12	0.44
EU/SOUTH. AFRICA	0.97	0.1	0.77	1	0.9	0.18	0.5	1	0.95	0.12	0.7	1	0.55	0.26	0.01	0.88
EU/TURKEY	0.93	0.13	0.67	1	0.65	0.34	0.09	1	0.9	0.16	0.54	1	0.48	0.16	0.14	0.68
EU/UK	0.52	0.38	0	1	0.81	0.31	0	1	0.61	0.35	0	1	0.04	0.13	0	0.26
EU/USA	0.33	0.25	0	0.8	0.31	0.33	0	1	0.34	0.24	0	0.8	0.42	0.2	0.07	0.7
EU/BITCOIN	0.82	0.29	0.03	0.99	0.92	0.11	0.76	1	0.86	0.25	0.04	1	0.89	0.07	0.74	0.95

Notes: This table illustrate the optimal portfolio weights, among bitcoin, gold, oil and G20 markets in pre and during COVID-19 and War.

the BITCOIN proportion in the portfolio. The result in the table further highlights the fact that the proportion of BITCOIN was less in the portfolio before COVID-19 and during pandemic time it has increased substantially in comparisons to commodities like gold, oil and equities market of main developed countries such as USA, UK, Australia, Canada etc. So, we can notice that BITCOIN becomes an important financial asset during pandemic times. But similar uniform results are not seen in case of Russia-Ukraine war. Like in case of BITCOIN/GOLD, before war its proportion was 0.15 that is 15% and during war it has increased to 0.36 that is 36% which means that during war BITCOIN proportion has increased. But in case of BITCOIN/OIL the proportion decreased from 0.08 to 0.02 that is 8%–2%. The other important observation that BITCOIN/RUSSIA had shown substantial portion of decrease in portfolio from 2% (0.02) to −69.2% (−6.92). Similarly, countries which are geographically closer to Russia and Ukraine have shown negative impact in its BITCOIN proportion of change like Turkey, Korea and Japan.

On the other side if we look GOLD in comparisons to commodities and Markets, the proportion of GOLD has decreased from pre-COVID19 to during COVID-19 in all the countries except in Saudi Arabia where it has increased from −0.02 to 0.11 that is from −2% to 11%. Similarly, during the event of War, the GOLD has shown reverse pattern. The proportion of GOLD has increased from pre-war time to during the war except in countries like Canada, France, German, Italy, Turkey, USA and EU. Moreover, in case of OIL its proportion has been increased from pre-COVID19 to during pandemic in all the markets. Even the proportion of OIL has increased in the event of Pre-War and during the War except in some countries like Argentina, Canada, France, Germany, Italy, Mexico, South Africa, Turkey, UK and the USA. Further it is seen a substantial portion of increase in OIL portfolio of Russia, from 0.58 to 7.49 (5.8%–

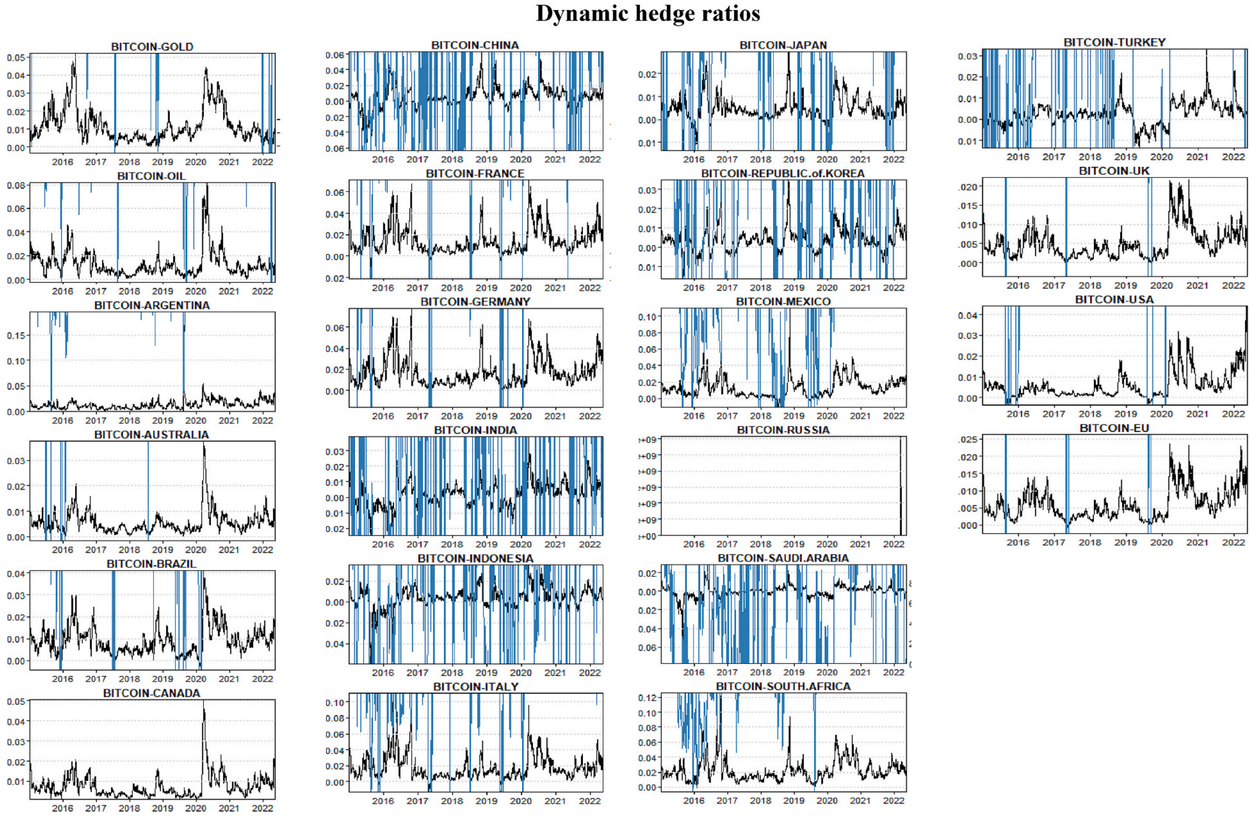


Fig. 29. Dynamic optimal hedge ratios pairs (Bitcoin/all other markets).

74.9%). Besides this the proportion of EU markets have increased during the pandemic except in UK. The proportion of EU have decreased from before and during the war except in France, and USA.

This study utilizes a dynamic hedging strategy for optimal portfolio management, and highlights the importance of dynamic over stable hedging in achieving optimal results. The authors present Figs. 25–28, which illustrate the dynamic behavior of optimal portfolio weights for different hedging pairs and provide insights into the impact of economic events on the portfolio weights. Fig. 25 displays the dynamic optimal portfolio weights pairs for Bitcoin and all other markets. The highest volatility of portfolio weights is observed during 2016–17, when a long position in all sample assets was hedged against Bitcoin. This volatility can be attributed to economic events such as the contraction of the Japanese economy, negative developments in the Greek debt crisis, and the Brexit vote. During the COVID-19 pandemic, the portfolio weights for hedging against Bitcoin varied for Argentina, Mexico, while during Russia-Ukraine war it is pertinent for Russia, and Turkey. Fig. 26 presents the portfolio weights for hedging Gold and all other markets. The portfolio weights changed more rapidly during the COVID-19 pandemic, and hedging against oil and the Russian market with gold showed significant variation during the war. From Fig. 27, the portfolio weights changed significantly for hedging any sample market against oil, during the Russia-Ukraine conflict as Russia and Ukraine together are the largest exporters of oil to the world. Interestingly, the portfolio weights for hedging against Bitcoin with the EU market showed low variability. However, European markets were highly sensitive in terms of portfolio weights when a long position in the USA and European market was hedged with the EU market. In contrast, the study highlights the importance of dynamic hedging strategies in achieving optimal portfolio management, it could be valuable for investors in managing their portfolios in dynamic market environments.

Alternatively, in Table 5 another diversification strategy is displayed related to optimal hedge ratios i.e., optimal portfolio weights. The results of the dynamic optimal portfolio weights for four-assets paired portfolios consisting of Bitcoin, Gold, Oil, and EU market paired with other sample assets in the system. Mean column describes the average proportion of the asset in the portfolio, while 5% quantile are shown by Q (5%) and Q (95%) express 95% quantile. Here, Q (5%) signify the market turmoil (crisis) while Q (95%) describes a bullish phase in the market. The Bitcoin panel shows that except Bitcoin/oil portfolio, all other portfolio proportion of Bitcoin (mean values) has declined during COVID-19 as well as war time. For example, Bitcoin/Oil were 0.04 and 099 during the Q (5%) and Q (95%) time respectively in pre COVID-19 but during COVID-19 it has reached to 0.00 and 0.64. Implying that Bitcoin weight has been gone down remarkably during market turmoil, such as the COVID-19 pandemic and Russian-Ukraine war time.

Additionally, in panel 2 of Table 5 (Gold to other assets) exceptionally mean portfolio proportion increased in the markets even during crises. Also, portfolio weights are also increased during COVID-19 and Russian-Ukraine war. Suggesting gold behave like a safe haven not only during COVID-19 but also during geopolitical tension between Russia and Ukraine. According to the findings of (Salisu, Raheem, & Vo, 2021; Wen, Tong, & Ren, 2022), gold constantly acts as haven asset compared with the US stocks and other precious metals like Silver,

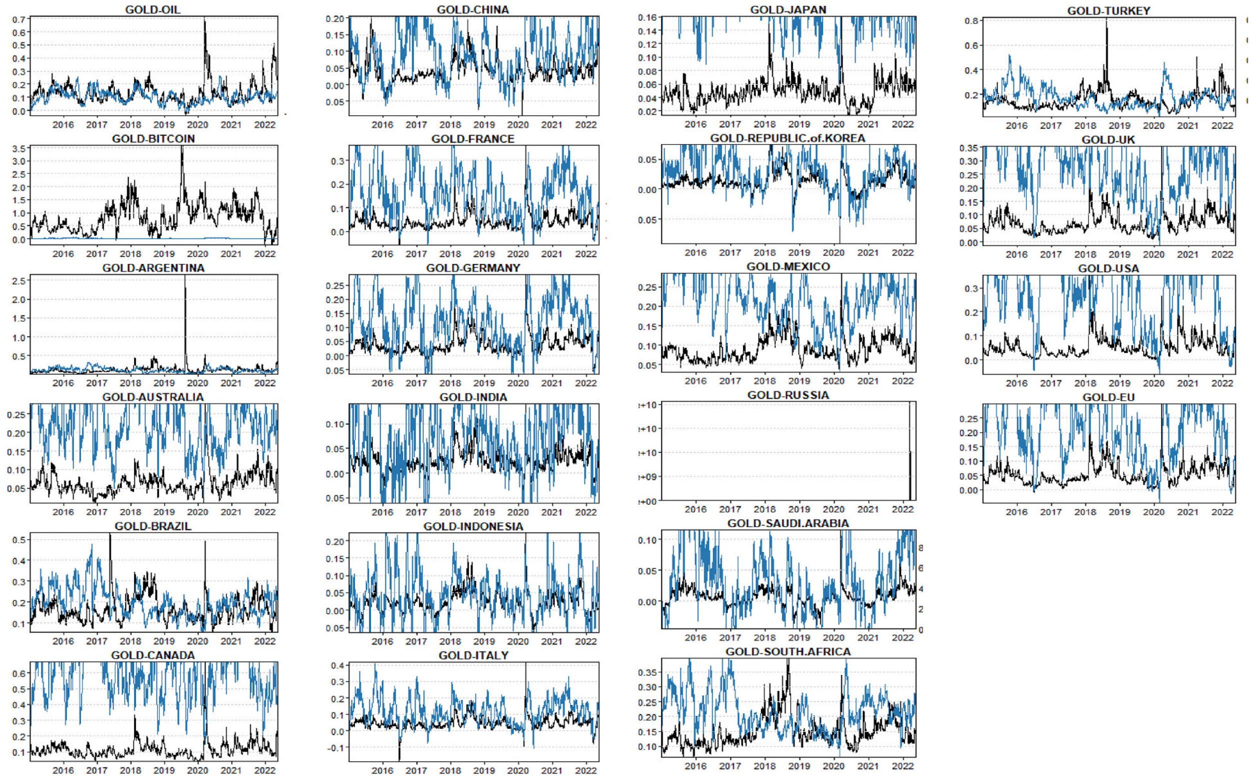


Fig. 30. Dynamic optimal hedge ratios pairs (Gold/all other markets).

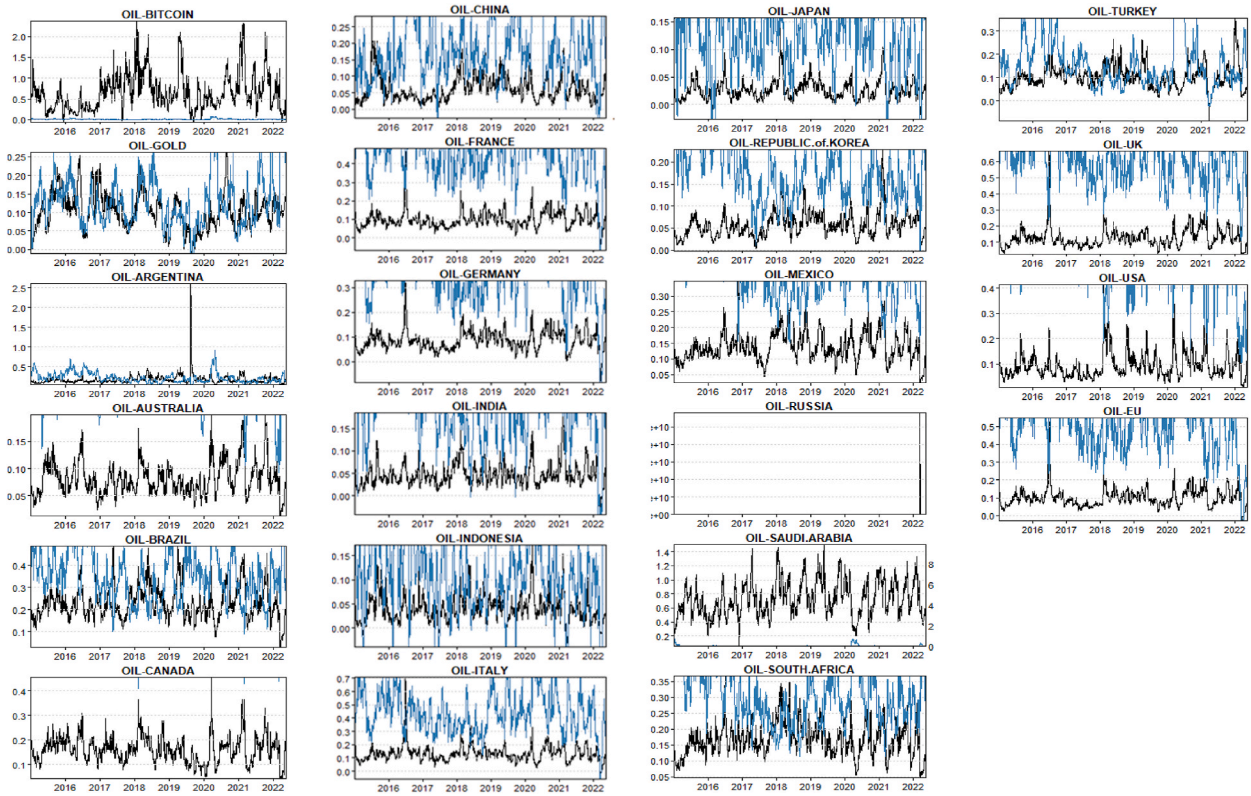


Fig. 31. Dynamic optimal hedge ratios pairs (Oil/all other markets).

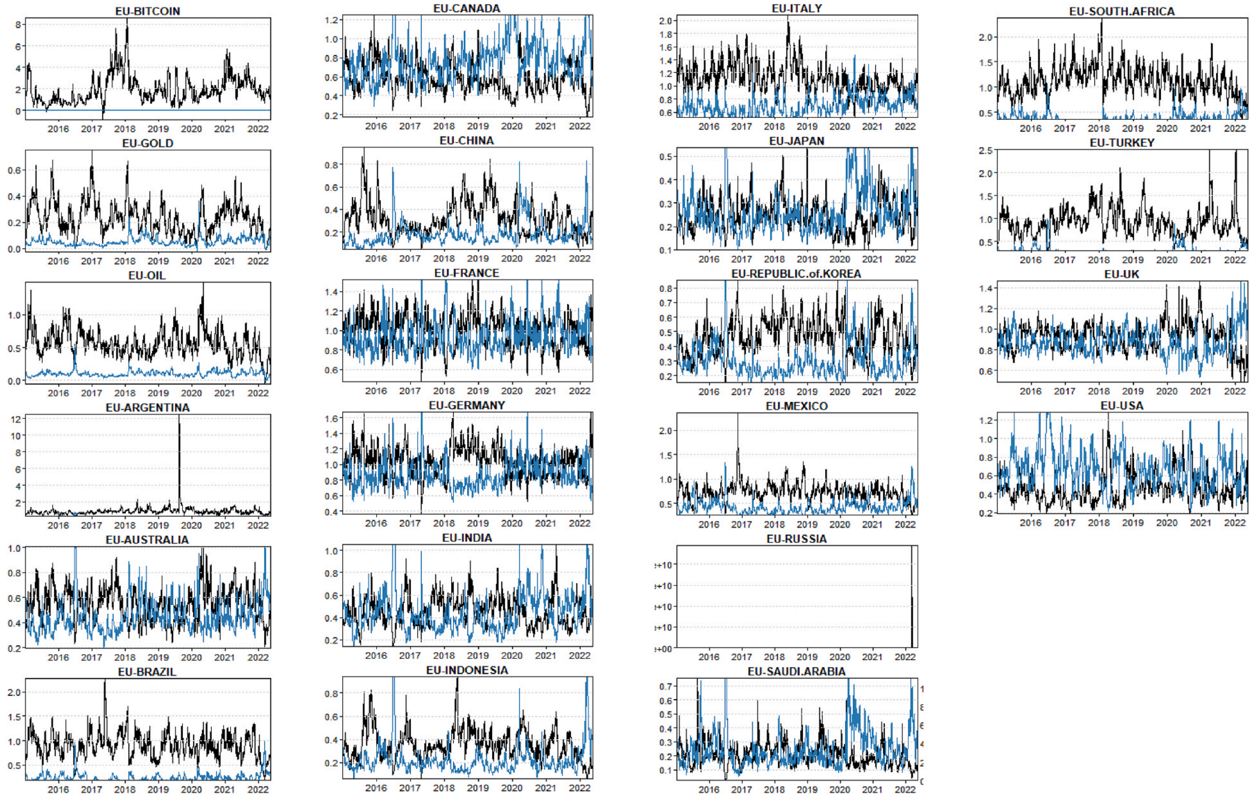


Fig. 32. Dynamic optimal hedge ratios pairs (EU/all other markets).

Palladium and Platinum during COVID-19. This finding could be utilized on the line above mentioned studies for hedging and portfolio diversification. Subsequently, in case of oil and EU markets panel except few cases overall portfolio share has been diminished drastically in both the uproar phases. In the light of above findings, inferences can be drawn that COVID-19 and Russian-Ukraine war has multi-faceted consequences on the portfolio mean returns and portfolio proportion for the pairs of Bitcoin, Oil, and EU markets which support the findings of (Salisu, Ebuh, & Usman, 2020; Raheem, 2021; Zhang, Chen, & Shao, 2021; Pham & Do, 2022).

The time-varying behavior of optimal hedge ratios are shown in Figs. 29–32. In Fig. 29, the hedge ratios for a long position in most of the assets display high volatility during COVID-19 when hedged with cryptocurrencies (Bitcoin) market. Taking long position during COVID-19 also generate high volatility for almost all the assets more particularly some fragile economies like Argentina, Turkey, and South Africa for Gold, which shows high spike in hedge ratios in Fig. 30. Similarly hedge ratios are too much varying for hedging Bitcoin, Argentina, Canada, Saudi Arabia, and South Africa against Oil. At the same time, high movement of hedge ratios are exhibited in Fig. 32 throughout the sample period for taking long position in all sample assets when hedged for EU market. Importantly, Russia's long position against Bitcoin, Gold, Oil, and EU revealed very high volatility in hedge ratios. Importantly, these findings are also confirmed the effects of these crises on sample markets, it could be useful for investors, hedgers, policy makers to take proactive decisions to manage their pandemic and geopolitical risks.

Furthermore, to suggest better portfolio out of the given portfolios in order to make suggestion to investors, we need to assess the different strategies on the basis of hedging effectiveness of the different portfolios. With the use of hedging effectiveness investors can reduce the risk of the portfolios through hedge position by either applying dynamic portfolio weights or dynamic hedge ratio strategies.

According to the findings shown in Table 6, panel 1 suggest that in all cases hedging effectiveness of Bitcoin generate better returns to investors by hedging their position using dynamic portfolio weights strategy. Hedging effectiveness goes down during COVID-19 and Russian-Ukraine tussle, but intensity was greater during COVID-19. Highest effectiveness was achieved with USA in pre-COVID-19 and with Japan before war time, while during COVID-19 in Japan most effectiveness was present and Indonesia in the time of Russia Ukraine conflict. It is also verifying that there are not only cheapest hedges (shown in Tables 4 and 5) but also displaying most effective hedging.

Even more, almost similar results are observed from panel 2 (i.e., Gold), hedging effectiveness has gone down during COVID-19 and Russian-Ukraine war. But Oil, Argentina, and Bitcoin effectiveness became insignificant during COVID-19 and during GPC. Interestingly, in case of oil hedging effectiveness has increased during COVID-19 and Russian-Ukraine tussle. During COVID-19 China and Japan has shown highest HE values, while during war Canada and Japan highest HE is observed. Further, EU market pairs was displayed very low HE with many insignificant pairs, during COVID-19 except few cases all shown negative HE values which implies that it is not contributing positive returns to the portfolio rather generating negative returns that could also be verified from Table 5.

Table 6
Hedging effectiveness.

	PRE COVID-19				During COVID-19				PRE-WAR				During WAR			
Pairs (Bitcoin/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
BITCOIN/GOLD	0.83	0	0	0.99	0.65	0	0.11	0.43	0.8	0	0.02	0.72	0.85	0	0	0.99
BITCOIN/OIL	0.81	0	0	0.98	0.28	0.02	0.09	0.51	0.74	0	0.02	0.6	0.59	0	0	0.99
BITCOIN/ARGENTINA	0.79	0	0	0.96	0.46	0	0.11	0.42	0.72	0	0.02	0.64	0.65	0	0.07	0.7
BITCOIN/AUSTRALIA	0.95	0	0	0.99	0.76	0	0.11	0.44	0.92	0	0.03	0.51	0.89	0	0	0.99
BITCOIN/BRAZIL	0.85	0	0	0.98	0.44	0	0.19	0.15	0.8	0	0.04	0.44	0.83	0	0.04	0.84
BITCOIN/CANADA	0.96	0	0	0.99	0.69	0	0.27	0.03	0.92	0	0.1	0.03	0.9	0	0.02	0.9
BITCOIN/CHINA	0.92	0	0	0.98	0.91	0	0.05	0.74	0.91	0	0	0.95	0.83	0	0	0.99
BITCOIN/FRANCE	0.95	0	0	0.99	0.77	0	0.22	0.09	0.92	0	0.04	0.41	0.78	0	0.04	0.85
BITCOIN/GERMANY	0.95	0	0	1	0.78	0	0.21	0.1	0.92	0	0.04	0.39	0.8	0	0.05	0.78
BITCOIN/INDIA	0.95	0	0	1	0.8	0	0.04	0.78	0.93	0	0	0.94	0.82	0	0	0.98
BITCOIN/INDONESIA	0.93	0	0	0.96	0.75	0	0.02	0.89	0.9	0	0	0.95	0.92	0	0.03	0.87
BITCOIN/ITALY	0.92	0	0	0.99	0.7	0	0.3	0.01	0.89	0	0.04	0.39	0.74	0	0.06	0.74
BITCOIN/JAPAN	0.95	0	0	0.99	0.92	0	0.05	0.7	0.94	0	0	0.92	0.91	0	0	1
BITCOIN/KOREA	0.93	0	0	0.96	0.8	0	0.02	0.89	0.91	0	0	1	0.87	0	0	0.98
BITCOIN/MEXICO	0.92	0	0	0.97	0.71	0	0.12	0.39	0.88	0	0.02	0.62	0.88	0	0.04	0.82
BITCOIN/RUSSIA	0.9	0	0	0.99	0.67	0	0.15	0.26	0.85	0	0.03	0.56	0.58	0	0.04	0.85
BITCOIN/SAUDI.ARABIA	0.95	0	0.01	0.92	0.76	0	0.02	0.89	0.93	0	0.01	0.91	0.92	0	0	1
BITCOIN/SOUTH.AFRICA	0.86	0	0	0.99	0.7	0	0.11	0.43	0.84	0	0.02	0.74	0.81	0	0.01	0.95
BITCOIN/TURKEY	0.84	0	0	0.98	0.81	0	0.07	0.59	0.81	0	0.01	0.87	0.82	0	0	1
BITCOIN/UK	0.95	0	0	0.99	0.78	0	0.2	0.12	0.92	0	0.03	0.45	0.86	0	0.03	0.87
BITCOIN/USA	0.97	0	0	0.95	0.71	0	0.22	0.08	0.93	0	0.07	0.13	0.83	0	0.15	0.39
BITCOIN/EU	0.96	0	0	1	0.8	0	0.24	0.06	0.93	0	0.04	0.34	0.79	0	0.05	0.79

	PRE COVID-19				During COVID-19				PRE-WAR				During WAR			
Pairs (Gold/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GOLD/OIL	0.4	0	0.02	0.76	−0.08	0.6	0.01	0.94	0.32	0	0.01	0.78	−0.03	0.87	0.15	0.4
GOLD/ARGENTINA	0.57	0	0	0.94	0.2	0.13	0.02	0.87	0.46	0	0.01	0.78	0.13	0.47	0.13	0.46
GOLD/AUSTRALIA	0.8	0	0.01	0.9	0.39	0	0.03	0.84	0.71	0	0.03	0.55	0.55	0	0.07	0.71
GOLD/BRAZIL	0.47	0	0.05	0.41	0.21	0.1	−0.02	0.87	0.42	0	0.03	0.57	0.31	0.05	0.12	0.52
GOLD/CANADA	0.83	0	0.06	0.28	0.39	0	0	1	0.74	0	0.04	0.37	0.59	0	0.07	0.69
GOLD/CHINA	0.67	0	0.01	0.86	0.8	0	0.02	0.88	0.69	0	0.01	0.91	0.33	0.04	0.07	0.72
GOLD/FRANCE	0.82	0	0	0.94	0.46	0	−0.01	0.97	0.74	0	0.01	0.79	0.49	0	−0.01	0.94
GOLD/GERMANY	0.81	0	0	0.96	0.45	0	0.01	0.96	0.73	0	0.02	0.68	0.52	0	−0.03	0.89
GOLD/INDIA	0.83	0	0	1	0.53	0	−0.01	0.93	0.77	0	0	0.94	0.55	0	0.02	0.9
GOLD/INDONESIA	0.75	0	0	0.98	0.48	0	0.01	0.97	0.69	0	−0.01	0.87	0.65	0	0.04	0.83
GOLD/ITALY	0.72	0	0	1	0.43	0	−0.03	0.85	0.66	0	−0.01	0.9	0.45	0	−0.03	0.87
GOLD/JAPAN	0.8	0	0.01	0.92	0.76	0	0.04	0.8	0.79	0	0.01	0.85	0.63	0	0.04	0.84
GOLD/KOREA	0.79	0	0	0.99	0.54	0	−0.02	0.89	0.72	0	0	0.98	0.56	0	0.01	0.95
GOLD/MEXICO	0.72	0	0.02	0.71	0.44	0	−0.01	0.95	0.65	0	0.01	0.75	0.6	0	0.04	0.84
GOLD/RUSSIA	0.63	0	0.01	0.81	0.36	0	0	0.98	0.56	0	0.02	0.71	0.28	0.08	0.01	0.97
GOLD/SAUDI.ARABIA	0.79	0	0	0.95	0.56	0	0.03	0.83	0.75	0	0	0.99	0.69	0	0.03	0.87
GOLD/SOUTH.AFRICA	0.56	0	0.03	0.61	0.31	0.01	0.02	0.88	0.51	0	0.04	0.35	0.41	0.01	0.09	0.63

(*continued on next page*)

Table 6 (*continued*)

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (Gold/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
GOLD/TURKEY	0.57	0	0.01	0.87	0.56	0	0.04	0.79	0.52	0	0.01	0.8	0.47	0	0.01	0.97
GOLD/UK	0.83	0	0.01	0.85	0.45	0	0.01	0.93	0.74	0	0.03	0.56	0.56	0	0	1
GOLD/USA	0.87	0	0.02	0.72	0.44	0	−0.02	0.9	0.78	0	0.03	0.56	0.54	0	0.01	0.95
GOLD/EU	0.84	0	0.01	0.92	0.5	0	−0.01	0.97	0.76	0	0.02	0.73	0.49	0	−0.02	0.91
GOLD/BITCOIN	0.41	0	0	0.99	0.03	0.86	0.01	0.94	0.29	0	0.01	0.81	0.16	0.37	0.02	0.94
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (OIL/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
OIL/GOLD	0.49	0	0.02	0.7	0.81	0	0.04	0.79	0.66	0	0.02	0.61	0.77	0	0.2	0.25
OIL/ARGENTINA	0.54	0	0.01	0.82	0.73	0	0.17	0.2	0.6	0	0.04	0.39	0.64	0	0.02	0.91
OIL/AUSTRALIA	0.82	0	0.03	0.58	0.86	0	0.12	0.4	0.83	0	0.05	0.3	0.86	0	0.03	0.87
OIL/BRAZIL	0.5	0	0.09	0.09	0.69	0	0.15	0.27	0.59	0	0.1	0.02	0.8	0	0.06	0.73
OIL/CANADA	0.85	0	0.26	0	0.84	0	0.22	0.08	0.84	0	0.19	0	0.89	0	0.02	0.9
OIL/CHINA	0.7	0	0.02	0.78	0.96	0	0.08	0.57	0.83	0	0.02	0.71	0.78	0	0.06	0.74
OIL/FRANCE	0.82	0	0.08	0.16	0.88	0	0.09	0.53	0.84	0	0.08	0.06	0.79	0	0	0.99
OIL/GERMANY	0.81	0	0.06	0.31	0.88	0	0.09	0.49	0.84	0	0.07	0.12	0.84	0	0.04	0.82
OIL/INDIA	0.84	0	0.01	0.88	0.88	0	−0.02	0.89	0.86	0	0	0.95	0.79	0	0.03	0.89
OIL/INDONESIA	0.77	0	0.01	0.84	0.82	0	−0.02	0.9	0.8	0	0	0.92	0.9	0	0.03	0.87
OIL/ITALY	0.71	0	0.09	0.1	0.85	0	0.02	0.86	0.78	0	0.08	0.09	0.77	0	−0.01	0.97
OIL/JAPAN	0.83	0	0	0.97	0.96	0	−0.01	0.95	0.89	0	−0.01	0.88	0.88	0	0.02	0.93
OIL/KOREA	0.81	0	0.02	0.79	0.88	0	0.01	0.93	0.83	0	0.01	0.9	0.83	0	0.03	0.87
OIL/MEXICO	0.74	0	0.08	0.16	0.85	0	0.11	0.44	0.79	0	0.08	0.08	0.87	0	0.01	0.97
OIL/RUSSIA	0.6	0	0.15	0	0.84	0	0.29	0.02	0.71	0	0.15	0	0.4	0.01	0.07	0.72
OIL/SAUDI.ARABIA	0.8	0	0.02	0.73	0.91	0	0.1	0.48	0.86	0	0.03	0.46	0.9	0	0.01	0.94
OIL/SOUTH.AFRICA	0.57	0	0.07	0.18	0.83	0	0.08	0.56	0.7	0	0.06	0.16	0.78	0	0.02	0.9
OIL/TURKEY	0.61	0	0.01	0.84	0.91	0	0.06	0.69	0.72	0	0.02	0.67	0.8	0	0	1
OIL/UK	0.83	0	0.13	0.01	0.88	0	0.09	0.49	0.85	0	0.11	0.01	0.85	0	−0.01	0.97
OIL/USA	0.88	0	0.09	0.1	0.86	0	0.15	0.28	0.86	0	0.11	0.01	0.84	0	0	1
OIL/EU	0.84	0	0.1	0.06	0.9	0	0.11	0.44	0.86	0	0.1	0.03	0.81	0	0	0.99
OIL/BITCOIN	0.45	0	0	0.97	0.65	0	0.02	0.9	0.52	0	0	0.95	0.51	0	0	1
PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (EU/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
EU/GOLD	0.17	0	0.01	0.89	0.04	0.77	0	0.99	0.11	0.01	0.01	0.76	0.59	0	−0.01	0.97
EU/OIL	0.03	0.6	0.07	0.2	−0.13	0.39	−0.08	0.59	−0.02	0.62	0.02	0.63	0.31	0.05	0	1
EU/ARGENTINA	0.1	0.08	0.04	0.43	−0.1	0.5	0.29	0.02	0	0.97	0.1	0.02	0.08	0.66	0.26	0.12
EU/AUSTRALIA	0.24	0	0.2	0	−0.05	0.74	0.43	0	0.12	0.01	0.28	0	0.47	0	0.36	0.02
EU/BRAZIL	0.04	0.47	0.18	0	−0.07	0.65	0.5	0	−0.02	0.72	0.26	0	0.31	0.05	0.45	0
EU/CANADA	0.27	0	0.42	0	0.05	0.74	0.66	0	0.18	0	0.54	0	0.62	0	0.18	0.31
EU/CHINA	0.26	0	0.05	0.36	0.62	0	0.11	0.4	0.38	0	0.05	0.23	0.28	0.09	0.28	0.09

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Table 6 (*continued*)

PRE COVID-19					During COVID-19				PRE-WAR				During WAR			
Pairs (EU/Markets)	*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*		*Dynamic Portfolio Weights*		*Dynamic hedge ratios*	
	HE	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*	*HE*	*p-value*
EU/FRANCE	0	0.97	0.94	0	0	0.98	0.98	0	0	0.96	0.95	0	0	0.99	0.97	0
EU/GERMANY	0.04	0.44	0.89	0	0	0.97	0.97	0	0.01	0.77	0.92	0	0.13	0.46	0.79	0
EU/INDIA	0.33	0	0.15	0.01	0.1	0.47	0.33	0.01	0.23	0	0.23	0	0.26	0.13	0.42	0.01
EU/INDONESIA	0.29	0	0.09	0.1	−0.03	0.86	0.14	0.28	0.19	0	0.1	0.02	0.68	0	0.09	0.62
EU/ITALY	−0.01	0.86	0.75	0	−0.05	0.74	0.87	0	−0.02	0.71	0.79	0	0.01	0.96	0.89	0
EU/JAPAN	0.36	0	0.03	0.6	0.54	0	0.14	0.28	0.42	0	0.06	0.21	0.6	0	0.07	0.69
EU/KOREA	0.25	0	0.14	0.01	0.12	0.37	0.28	0.02	0.17	0	0.16	0	0.41	0.01	0.2	0.25
EU/MEXICO	0.13	0.02	0.28	0	−0.09	0.55	0.52	0	0.04	0.35	0.36	0	0.5	0	0.35	0.03
EU/RUSSIA	0.08	0.13	0.27	0	−0.09	0.57	0.59	0	0.01	0.76	0.36	0	0.23	0.19	0.06	0.76
EU/SAUDI.ARABIA	0.34	0	0.07	0.19	0.14	0.31	0	0.99	0.33	0	0.07	0.11	0.68	0	0.03	0.85
EU/SOUTH.AFRICA	−0.03	0.65	0.39	0	−0.12	0.44	0.62	0	−0.07	0.12	0.43	0	0.23	0.17	0.46	0
EU/TURKEY	0.08	0.12	0.15	0.01	0.19	0.14	0.39	0	0.1	0.03	0.16	0	0.3	0.06	0.25	0.14
EU/UK	0.02	0.66	0.89	0	−0.04	0.81	0.87	0	0.01	0.79	0.85	0	0.34	0.03	0.81	0
EU/USA	0.42	0	0.24	0	−0.05	0.74	0.46	0	0.26	0	0.33	0	0.41	0.01	0.29	0.07
EU/BITCOIN	0.2	0	0	0.99	−0.09	0.54	0.11	0.44	0.03	0.51	0.02	0.74	0.08	0.68	0.04	0.84

Notes: This table illustrate the hedging effectiveness, among bitcoin, gold, oil and G20 markets in pre and during COVID-19 and War.

4.11. Discussions

First, COVID-19 in 2020 and now the Russian-Ukraine war in 2022 have shattered the economic activities, trade pattern, market returns, and commodities supply chains all around the world. During COVID-19 lockdowns were put in place leading to almost zero movements within and across borders, while during this geopolitical crisis (GPC) shortage of supply of many essential commodities including food grains has been experienced. Further, during these events, strong connectedness and spillovers are observed (Tables 2–5), their findings are similar to past research findings (Kumar et al., 2021, Fry-McKibbin et al., 2022; Liadze et al., 2022; Federle et al., 2022; Boungou & Yatié, 2022; Boubaker et al., 2022; Mensi et al., 2022; Chatziantoniou et al., 2022). Additionally, during GPC, TCI reached to 87.66% which is marginally higher than TCI (83.65%) level during COVID-19, it is due to (i) degree and intensity of effect of these crises events, and (ii) as this TCI further aggravated to the level generated by COVID-19 as COVID-19 crisis is continued. Furthermore, the variations in the dynamics appear to smooth out in the later stage of COVID-19 period.

As per the findings of the hedging and dynamic portfolio techniques during COVID-19 and Russian-Ukraine conflict portfolio weights has change and proportion of Bitcoin, EU markets, and Oil has increased. Contribution of Gold has fallen during COVID-19 but after the declaration of war gold share has increased. Hedging effectiveness is worthy and significant for Bitcoin, gold, and oil but not quite effective for EU markets during turmoil time.

5. Conclusions, policy implications, and limitations of the study

Previous studies have investigated the effects of the COVID-19, and Russian-Ukraine war crises on the commodities, crypto, and stock markets. We have utilized the method projected technique by Antonakakis, Chatziantoniou, et al. (2020), and the TVP-VAR method of Koop and Korobilis (2014), adjustment of the framework extended by Diebold and Yilmaz (2012) to understand the dynamics of return spillovers between the commodity, and Crypto markets. Researchers found that during COVID-19 and War in Ukraine depicts very strong connectedness among all sample commodities, bitcoin, and markets (G20) exist. Our findings display that during the COVID-19 crisis almost all sample assets have been impacted mostly in a similar fashion, particularly the EU, Canada, France Germany, and the UK were the principal supplier of volatility spillovers to other commodities, Bitcoin, and the remaining markets. On the contrary, Bitcoin, gold, and oil were the receivers from the rest of the commodities, and all the sample markets (Ghorbel et al., 2022).

More particularly, during such crises, the global uncertainty has shot up and influenced the time-varying connectedness patterns between the commodities and capital markets. On the other hand, during GPC conclusively it is observed that the markets of USA, Brazil, Saudi Arabia, Canada, Mexico, China, Indonesia, and Japan are the net receivers of the volatility spillovers effect, and the markets of Russia, Germany, France, European Union, Italy, U.K., Argentina, India, Australia, Turkey, Korea, and South Africa are the net transmitters of volatility spillovers (Boubaker et al., 2022; Boungou & Yatié, 2022; Umar, Bossman, et al., 2022). Here, attention is to be given towards Argentina, Turkey, and SAF because these are fragile economies due to economic issues like high-rate inflation, mounting of current account deficit, issues with exchange rate management, unemployment, high interest rate and low returns on securities. Above mentioned reasons make these countries more reactive to these crises which put a question; does these markets are more reactive to these crises? Firstly, these economies are net transmitters during GPC which approves that these are affected by crises. Secondly, before GPC, Argentina (−8.15%) and Turkey (−21.13%) were net receiver but during Russian invasion they turned net transmitters with net connectedness index of 22.08% and 15.41% respectively. It is the highest difference (refer Tables 2 and 3) in net connectedness index of these economies which confirms that these economies are not only shock absorber on account of GPC but also highly reactive to their fragile economic crisis (Bianchi, 2022; Sheefeni, 2022).

Furthermore, the time-varying net connectedness findings express sharp rise in TCI during COVID-19 as well during Russian-Ukraine war. Additionally, all commodities, crypto, and capital markets, more specifically among European and emerging markets show strong net transmitting behavior towards all remaining variables in the system. The study has policy implications that could be beneficial to crypto-market, commodity, and equity investors while taking investment decisions in such turmoil situations. Policy-makers should focus more on the links between cryptos, commodities, and their effects on financial markets, and vice-versa in the process of preparing strategies to diminish the spillovers between commodities and stock markets in such crises. The investors, policy makers, and financial planners of fragile markets (Argentina, Turkey, and SAF) must take special measures of hedging and investments in such tough times. As per the hedging portfolio results are very crucial to take portfolio decision in the turmoil time as Bitcoin, oil, and gold has shown increment pattern in the portfolio share and more effectiveness.

This research is being conducted in the specific period for GPC which carries some limitations on account of time and dynamicity of the environment and set path for future research. Firstly, further studies can also be conducted on Ukraine, and OPEC markets which are complementary sources of commodities more specifically oil and natural gas. Future research can target these research gaps to give a more robust understanding on sample assets during these crises. Moreover, further studies also can be conducted on sectoral indexes for a wide-ranging investigation of the dynamics of sectoral changes, and their risk and returns behavior during these turmoil events.

Data availability

Data will be made available on request.

Appendix

Table A.1
Correlation Coefficients of Variables

	ARG	AUS	BTC	BRA	CAN	CH	EU	FR	GER	GOLD	IND	INDO	ITL	JAP	MEX	OIL	KOREA	RUS	SA	SOU	TUR	UK	USA
ARG	1.00																						
AUS	0.24	1.00																					
BTC	0.11	0.11	1.00																				
BRA	0.42	0.43	0.11	1.00																			
CAN	0.46	0.28	0.17	0.22	1.00																		
CH	0.13	0.29	0.02	0.18	0.22	1.00																	
EU	0.37	0.32	0.14	0.23	0.40	0.22	1.00																
FR	0.35	0.38	0.13	0.33	0.38	0.20	0.38	1.00															
GER	0.35	0.44	0.14	0.48	0.35	0.20	0.36	0.29	1.00														
GOLD	0.12	0.15	0.08	0.19	0.27	0.07	0.11	0.09	0.09	1.00													
IND	0.23	0.45	0.05	0.34	0.42	0.28	0.49	0.48	0.46	0.04	1.00												
INDO	0.16	0.36	0.03	0.44	0.29	0.25	0.30	0.30	0.27	0.03	0.28	1.00											
ITL	0.31	0.43	0.12	0.46	0.36	0.15	0.40	0.38	0.26	0.07	0.41	0.23	1.00										
JAP	0.11	0.47	0.03	0.19	0.22	0.25	0.26	0.25	0.24	0.10	0.28	0.26	0.17	1.00									
MEX	0.38	0.45	0.08	0.26	0.32	0.19	0.39	0.29	0.26	0.14	0.42	0.35	0.33	0.22	1.00								
OIL	0.17	0.20	0.07	0.27	0.41	0.10	0.22	0.20	0.18	0.14	0.09	0.07	0.21	0.01	0.24	1.00							
KOREA	0.19	0.43	0.01	0.28	0.34	0.37	0.40	0.40	0.39	0.04	0.51	0.46	0.31	0.48	0.36	0.07	1.00						
RUS	−0.02	0.00	−0.04	0.00	0.01	0.03	−0.10	−0.11	−0.12	0.03	−0.01	0.00	−0.08	0.02	−0.02	0.11	0.02	1.00					
SA	0.16	0.28	0.03	0.24	0.30	0.18	0.28	0.27	0.26	0.05	0.28	0.23	0.26	0.17	0.24	0.20	0.21	0.04	1.00				
SOU	0.35	0.33	0.09	0.23	0.28	0.29	0.35	0.33	0.32	0.19	0.47	0.37	0.34	0.23	0.26	0.22	0.45	0.02	0.24	1.00			
TUR	0.22	0.27	0.06	0.31	0.34	0.10	0.42	0.40	0.39	0.13	0.30	0.23	0.36	0.15	0.35	0.11	0.24	0.02	0.16	0.42	1.00		
UK	0.34	0.39	0.12	0.21	0.31	0.24	0.31	0.38	0.34	0.15	0.30	0.32	0.28	0.27	0.26	0.27	0.41	−0.02	0.27	0.25	0.39	1.00	
USA	0.41	0.39	0.17	0.23	0.26	0.19	0.37	0.35	0.35	0.16	0.31	0.23	0.31	0.13	0.31	0.27	0.22	−0.03	0.22	0.41	0.27	0.33	1.00

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