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Unveiling the dynamic linkages between energy, forex and financial markets amidst natural and man-made outbreaks

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Abstract

Purpose – This paper aims to analyze the dynamic linkages of the energy market with the forex market. The energy market is measured by crude oil WTI, while the forex market is proxied by Brazilian real (RBRL), Mexican peso (RMXN), South African rand (RZAR), Turkish lira (RTRY) and British pound sterling (RGBP) exchange rate.

Design/methodology/approach – For the study, daily observations of these constituent asset classes extending from December 31, 2019, to August 16, 2022, are taken as the data. Furthermore, it is categorized into two different sub-samples in the form of the COVID-19 outbreak (December 31, 2019 to February 23, 2022) and the Russo–Ukraine invasion (February 24, 2022 to August 16, 2022). For empirical estimation, Diebold and Yilmaz model (2014) and Barunik and Krehlik test (2018) are used to examine the dynamic linkages.

Findings – The study concludes that the Mexican peso (RMXN) receives and transmits the highest spillover, while crude oil (RCOWTI) receives and transmits the least volatility to the network connection in full sample. In addition, the authors report that the dynamic linkage is not constant in the short, medium and long run. Furthermore, the spillover index in the Russo–Ukraine invasion is higher (29.92%) than full observation (22.03%) and COVID-19 outbreak (21.10%) in the short run.

Originality/value – This paper ventures to offer insight to investors, traders and policymakers based on normal trading days and crisis periods.

Keywords Dynamic linkages, Energy market, Forex market, COVID-19, RUSSO–Ukraine invasion

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1. Introduction

For the past two decades, the global economy witnessed an uncountable number of financial, economic, health, social and political crises at regional and global levels. Very often, a crisis that emerges in one country blows out to other countries, causing spillover effects (Adekoya *et al.*, 2022; Fasanya *et al.*, 2021). The liberalization of countries and the development of financial markets have significantly increased the level of uncertainty, reduced the divergence benefits and compelled investors to choose lucrative substitute asset such as crude oil (Mensi *et al.*, 2021). Especially notable was the 2008 global economic recession, which had a detrimental impact on global markets and economic dynamics. Financial markets reportedly started to integrate more tightly than ever before shortly after the crisis (Miller and Ratti, 2009; Turhan *et al.*, 2014; Maghyereh *et al.*, 2016; Toyoshima and Hamori, 2018). Due to the "too connected to fail" issue, there has been a lot of focus on the interconnectedness of financial firms since the global financial crisis (GFC) of 2008. Because of their decentralization and a relatively low entrance barrier, forex markets (FX) draw a lot of interest from investors. Forex markets are responsive to variations in the political and economic climate because of the enormous trade sizes and unceasing activities on swapping days. Government involvement and macro news are typically thought to have a considerable impact on FX market volatility. To be more precise, the timing and macroeconomic strategies affect how the currency markets respond (Wen and Wang, 2020).

Although having started more than ten years prior, the repercussions of the GFC of 2008 were still being considered. On the other hand, we saw the arrival of the COVID-19 crisis, which was a blowout in the various economies and has put the world at the helm. The spread of the global health crisis of COVID-19 adversely affected the global economy and caused severe economic storm clouds. COVID-19 crisis has led to incidences such as plunging share markets, debilitating world economies and havoc in market swings (Schmidhuber, 2020; Fasanya *et al.*, 2021). The blowout of COVID-19 was unusual and has had a considerable negative effect on the global economy (Nekhili *et al.*, 2021), which can be characterized by three primary categories; demand shock, brought on by traveling restrictions, quarantines and other global instabilities that have affected consumer goods and services, leisure industry; supply shock caused by interruptions in world distribution channels and financial shock (Fasanya *et al.*, 2021). European and Asian stock markets plunged following the collapse of the US market. Many studies have shown how the global crisis changed the pattern of the associations among financial markets (Bouri *et al.*, 2021; Fasanya *et al.*, 2021; Arya and Singh, 2022). Although uncertainties have increased considerably due to the spread of the COVID-19 crisis, the shocks to the financial market and the oil market are parallel. The spread of COVID-19 led to an unprecedented fall in oil prices, while the supply was also affected. In May 2020, global oil prices witnessed a sharp decline, with WTI futures falling to the minimum in four years. Further, equity markets around the world crashed as a consequence of the widespread COVID-19 outbreak in Europe and the USA. Oil prices are generally traded in foreign exchange, more generally in dollar value (Ozturk and Cavdar, 2021). Many studies have shown a degree of association of exchange rates with energy prices (Farzanegan and Markwardt, 2009; Basher *et al.*, 2012; Turhan *et al.*, 2014; Zhang, 2017; Singh *et al.*, 2018; Ding *et al.*, 2021; Zhang and Hamori, 2021). The currency is also an important component in assessing the financial position of a country. Deteriorating the exchange rate adversely affects the purchasing power of a country, leading to many economic issues such as inflation (Ozturk and Cavdar, 2021). The COVID-19 crisis and sharp drop in energy prices have caused sharp swings in forex markets. The exchange rate of many emergent nations was affected considerably during the pandemic, such as the Brazilian real, Mexican peso and the Turkish lira. Further, the Deutsche Bank Currency Volatility Index saw an increase of 10% during the blowout of the crisis.

While the repercussions of the COVID-19 emergency were still being felt worldwide and many countries were still recuperating, Russia's invasion of Ukraine began on February 24, 2022. The enduring Russia–Ukraine conflict is the utmost protruding in Europe and poses a severe threat to the world economy (Adekoya *et al.*, 2022; Liadze *et al.*, 2022). It is pertinent to investigate the impact of the war due to several reasons. First, despite being a bilateral war, it created a situation of outrage across many countries, necessitating harsh sanctions on Russia from certain developed nations, such as the USA and the EU (Astrov *et al.*, 2022; Ozili, 2022). Second, the war has had an impact on the availability of crude oil, which is the highly dealt commodity on the earth, as evidenced by the fact that numerous countries of Europe depend on Russian energy exports (OECD, 2020). These supply disruptions cause to increase in crude oil prices globally, reaching their highest level in eight years (Tank and Ospanova, 2022). Third, the foreign exchange market also has not been exempted from the severe losses and dramatic swings due to war. Immediately preceding Moscow deployed soldiers into Ukraine on February 24, the Russian rubble was swapping at around 80 to the dollar, but it falls by 40% in the succeeding days, tumbling to an unexpected level of 150 per dollar. Such increased forex volatility has been evidenced to be very affluent for many stakeholders and also places strain on economic activities, distressing the monetary value of companies. Furthermore, the interconnectedness among markets has amplified the prospects of spill effects among various markets, resulting in the alteration of investors' strategies considering Russia's invasion of Ukraine (Alam *et al.*, 2022). Thus, the Russia–Ukraine war appears to have worldwide considerable repercussions on financial markets and investors' confidence despite the immediate concern with just two countries. Against these backdrops, the present study is an attempt to determine the magnitude of dynamic connectedness between energy prices and the foreign currency market considering the repercussions of the COVID-19 blowout and the Russia–Ukraine invasion. The study provides a useful contribution to the academic literature in the following ways: first, crude oil prices are now termed as an asset, influencing the macroeconomic performance of trading countries (Singh *et al.*, 2018; Turhan *et al.*, 2014). A surge in energy prices places strain on the fiscal balance and also is a well-acknowledged source of forex shock causing foreign rate fluctuations (Qiang *et al.*, 2019); thus, examining the underlying causes and transmission mechanism of these shocks offers important information for market participants as well as for central banks and decision-makers while formulating fiscal policies. Second, the relationship between the two variables may have a different impact, depending on the tranquility of the crisis, such as the energy prices sharply declined during the COVID-19 period, while there is a rise in the prices of crude oil during the ongoing Russia–Ukraine war, signifying that the financial and macroeconomic repercussions of both could diverge. Consequently, this study intends to determine the magnitude of dynamic connectedness between crude oil and the foreign currency market considering the COVID-19 outbreak and the Russia–Ukraine evasion. We examine the dynamic linkages of energy market (crude oil WTI) with forex market based on daily observations spanning from December 31, 2019, to August 16, 2022, as a full sample. Further, the full sample is separated into two different sub-samples like COVID-19 outbreak (December 31, 2019, to February 23, 2022) and Russo–Ukraine invasion (February 24, 2022, to August 16, 2022) to determine the connectedness between these two markets. This paper uses Diebold and Yilmaz model (2014) and Barunik and Krehlik model (2018) for empirical estimation. We document that Mexican peso (RMXN) receives and transmits the highest spillover, while crude oil (RCOWTI) receives and transmits the least volatility to the network connection in the full sample. Additionally, it reveals that the dynamic linkage is not constant in different frequencies.

The remainder of this manuscript is as follows. Section 2 furnishes a detailed review of the literature. Section 3 outlines data and preliminary analysis that focuses on data description, including patterns of the data. Section 4 describes the econometric models, followed by Sections 5 and 6, which provide empirical results and conclusions, respectively.

2. Review of literature

The idea of investigating an association of crude oil with the forex market is fundamental to financial risk management and hedging but to find the research gap on the association of these two assets classes, extensive literature reviews are done. Using a paradigm that looked at both constant and variable characteristics, Panas and Ninni (2000) observed the occurrences of pandemonium and monotonic oscillations in everyday oil prices for the Rotterdam and Central Asian fuel markets and found evidence of pandemonium in various oil products. Using the VAR framework, Farzanegan and Markwardt (2009) studied the repercussions of crude prices on macroeconomic variables in Iran and found the asymmetric effects of oil prices with increasing as well as decreasing oil prices. They also reported strong positive repercussions from increasing oil price variations to economic output growth. Miller and Ratti (2009) analyzed the co-integrating association between crude oil prices and world stock indices for the period extending from 1971 to 2008 using a VECM considering the structural breaks and found that the stock index retorts adversely to increasing oil prices in the long run. Further, they found varying natures of repercussions between crude prices and stock prices, suggesting the occurrences of various stock markets and oil price bubbles during the study period. Mehrara and Mohaghegh (2011) studied the macroeconomic performance in oil exporter developing countries using panel vector auto-regression (VAR), impulse response and VDC procedure and found that oil shocks considerably influence the economic output and money supply, while the oil prices are largely affected by their lags, with considerable influence from output and money shocks. Basher *et al.* (2012) used the structural VAR model and impulse response model to explore the dynamic nexus between oil prices and foreign exchange rate and found that an intensification in oil prices leads to a decline in stock prices and foreign exchange rates. Further, they illustrated that increasing oil production causes a decline in oil prices, while economic activity causes an increase in oil prices.

Wu *et al.* (2012) examined volatility spillover from crude prices to corn spot and futures prices considering daily observation. The result revealed that as the ratio of gasoline to ethanol usage rises above a certain point, the price of crude oil conveys a favorable volatility spillover effect to corn prices, and maize price swings become more energy-driven. Charlot and Marimoutou (2014) examined the dynamic connectedness among the foreign exchange rates, S&P 500 stock prices, crude oil WTI and the expensive alloys (yellow metal, silver and platinum) for the period 2005–2012 by linking the one variable volatility with the implied Markov decision tree (HMDT) and switching regime model. They found that the variables shift from one regime to another while reaching the highest during the sub-crisis 2008 and the Tohoku upheaval in Japan. Mensi *et al.* (2014) observed the repercussions of OPEC news proclamations on the volatility spillover and persistence in the OPEC countries using the VAR-BEKK and VAR-DCC for the day-to-day cash prices of commodities. They found that the announcements of the OPEC news considerably influence the oil prices and the relationship between oil and commodities as well as the oil–cereal nexus. They also found the persistent decline in volatility for crude oil and gasoline returns. Singleton (2014) contemplated the repercussions of investors’ movements and financial market circumstances on returns in crude oil futures markets considering the interaction between inefficient information about fiscal activities and the oil market. They found that investor flows and medium-term growing rates of spot and managed money spread situations considerably affect future prices. Using the DCC model, Turhan *et al.* (2014) analyzed the nexus between oil prices and currency rates of G20 countries and reported an adverse relation between the two, with the worsened circumstances during the period of the US invasion of Iraq in 2003 and global financial crisis in 2008. Maghyereh *et al.* (2016) investigated the directional linkage between oil and stock prices in 11 foremost global stock markets for the period from 2008 to 2015 using the DY (2012) method and documented a two-way spillover between oil and stock indices with greater repercussions from energy market to stock markets. They also reported that the varying transmission pattern from 2009 to 2012 indicates the recovery tenure from the subprime crisis.

Further, Luo and Ji (2018) investigated spillover between US crude futures and China's agronomic commodity futures' volatility by applying the combination of multivariable heteroscedasticity. They found a weak volatility spillover effect from US crude oil to China's agrarian commodities and leverage effects, with increased market interdependence for adverse volatility. Zhang (2017) observed the nexus of oil shocks with stock index returns of six advanced countries using the Diebold and Yilmaz method (2012) and found a very weak spillover of oil price deviation to the global financial system, although they reported that oil prices increasingly contribute to the stock market during rolling window approach. Singh *et al.* (2018) considered the direction-wise network volatility spill effect between crude oil and nine currency pairs during 2008–2009 and 2014–2016. The study reported that the crude prices considerably influence the total volatility spill effect in the currency market with inverse dynamics during oil crisis periods. Furthermore, they reported that EUR/USD was more delicate to the crude price variations than other currencies and are passing the distinctive shocks to other currency pairs. Toyoshima and Hamori (2018) analyzed return and dynamic linkages between global energy markets from January 1, 1991 to April 27, 2018, using the DY and BK methodology. The result reveals that the WTI oil index was contributing less to both return and volatility spillover effect with long-term factor contributing to returns. Further, they found that total connectedness in returns and volatility spillover increased during the GFC 2008. By applying the TVP-VAR framework, Bouri *et al.* (2021) illustrated the presence of severe deviations in the time-varying patterns of return associations across several assets, i.e. yellow metal, crude oil, stock prices, currencies and bonds due to the blowout of COVID-19. They found that the dynamic linkage among five assets was modest and relatively constant proceeding to the blowout of the COVID-19 crisis while the pattern of linkage varied due to the COVID-19 outbreak. They also reported that the equities and US index was the larger spreader of shock before the crisis period, whereas the bond market was the larger transmitter during the COVID-19 outbreak. Ding *et al.* (2021) explored the time and frequency spillover among the oil, yellow metal and forex markets using hidden volatility indices and found that the repercussions of forex markets on oil and yellow metal markets were larger, and the forex markets of industrialized countries were the main transmitters. They also showed that the short-term risk spillover was robust during the European crisis and the COVID-19 crisis, with the euro, Australian and Canadian currency being the larger risk spreaders during the crisis, while yellow metal and oil were net risk recipients. Using the DY approach and rolling window analysis, Fasanya *et al.* (2021) inspected dynamic interactions between COVID-19 and the foreign currency market using the day-to-day observation extending from December 31, 2019, to April 10, 2020, of six larges traded currencies. They found greater connectedness between the COVID-19 crisis and the returns volatility of the currencies. Zhang and Hamori (2021) studied the return and volatility spillover between the COVID-19crisis, the crude prices and the stock prices by using the Diebold and Yilmaz (2014) and Baruník and Křehlík (2018) framework and found that the return spillover effect primarily arises in short run, while the volatility spillover appears in long run. They further illustrated that the arrival of COVID-19 created an unparalleled risk, leading to a decline in oil prices and prompting the US stock market circuit breaker. Adekoya *et al.* (2022) used TVP-VAR to analyze how oil relates to important financial assets based on daily data extending from January 3, 2022, to February 23, 2022, and from February 24, 2022, to March 11, 2022. During the conflict, oil switches from being a net receiver of spillover to a net transmitter of spillover. Using the TVP-VAR model, the interconnectivity is also discovered to be time-varying with evidence of a greater spillover throughout the early stages of the war, followed by a gradual decline. In the similar vein, Goodell *et al.* (2023) undertook a study on dynamic linkage among various assets like renewable energy, digital and traditional assets applying TVP-VAR. They found that non-fungible tokens are considered as resilient asset for the diversification among examined assets. Further, Nepal *et al.* (2024) undertook a study on nexus between carbon emission and forex markets using wavelet analysis. They found that the co-movement between these two assets is not identical in COVID-19 and Russia–Ukraine invasion. In addition, Tabassum *et al.*, 2024a, Tabassum *et al.*, 2024b, and Lohana *et al.*, 2024, undertook studies on connectedness on various asset classes and found heterogeneity in linkage.

In sum, there are extant reviews of the prose on dynamic linkages of energy prices, financial markets, foreign exchange and other financial assets. However, very few studies have been undertaken considering the energy prices and forex market covering the repercussions like COVID-19 Russia–Ukraine war. Additionally, the linkage of one market with another market differs in various time and frequency horizons. On this note, we attempt to unravel the dynamic nexus between crude oil and the foreign exchange market to bridge this gap considering the impact of the COVID-19 crisis and the Russia–Ukraine invasion in the short, medium and long run to furnish evidence of portfolio diversification opportunities.

3. Data and preliminary analysis

This paper analyzes the dynamic linkages of crude oil WTI (RCOWTI) with select exchange rates such as Brazilian real (RBRL), Mexican peso (RMXN), South African rand (RZAR), Turkish lira (RTRY) and British pound sterling (RGBP). For empirical estimation, we collect daily observations of constituent asset classes from December 31, 2019, to August 16, 2022, as a full sample. Further, it is categorized into two different sub-samples in the form of COVID-19 outbreak (December 31, 2019, to February 23, 2022), which is in accordance with the study of Corbet *et al.* (2021); Ashok *et al.* (2022) and Russo–Ukraine invasion (February 24, 2022, to August 16, 2022). The daily raw observations are converted into daily log returns dividing $\log(Y_t)$ by $\log(Y_{t-1})$. The non-trading days are removed from empirical estimation to ensure consistency and comparability across analyzed markets under examination. The major reason behind considering these asset classes is that the foreign exchange rate was hit hard by the global market sell-off during COVID-19 outbreak and remained weak during that tenure. Further, the enduring Russia–Ukraine conflict is the utmost protruding and poses a severe threat to the world economy, which has had an impact on the availability of crude oil (Adekoya *et al.*, 2022; Liadze *et al.*, 2022). The data description of the constituent markets is mentioned in Table 1:

Further, Figures 1 and 2 encapsulate the time-series plot of raw and return series of crude oil (COWTI) and foreign exchange rates, respectively. The examined series have a stochastic trend as the changes appear in an uncertain way. It is observed that no series is witnessed with negative value, except crude oil during 2020 (COVID-19 outbreak). In addition, these raw series are non-stationary because no series follows mean reverting process. To remove the stochastic trend and make it stationary, we convert each series into log return; the same has

Table 1. Data description of energy and forex market

Markets	Proxies	Abbreviations	Data source
Energy	Crude oil WTI	RCOWTI	Bloomberg
Forex	Brazilian real	RBRL	
	Mexican peso	RMXN	
	South African rand	RZAR	
	Turkish lira	RTRY	
	British pound sterling	RGBP	

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Figure 1. Plot of raw series of crude oil and constituent exchange rates

been confirmed from augmented Dickey–Fuller (ADF) test shown in Table 2. Further, these return series possess volatility clustering because higher changes are followed by higher changes and low changes are followed by low changes.

To know the statistical properties of crude oil and constituent foreign exchange rates, descriptive statistics is presented in Table 2, which is based on daily data extending from December 30, 2019, to August 16, 2022. We notice that each series yields positive return, and RTRY (0.0016) has highest average return, followed by RCOWTI (0.0015). The crude oil asset is more risky/unstable as its standard deviation is high (0.0412) than rest of exchange rates. The skewness (non-zero value) and kurtosis (superior to 3) values are different for all the series, which depict that these markets have different dynamic characteristics and ensures the presence of asymmetries in each series. It indicates that each asset (analyzed exchange rate and crude oil) may realize either very large or very small

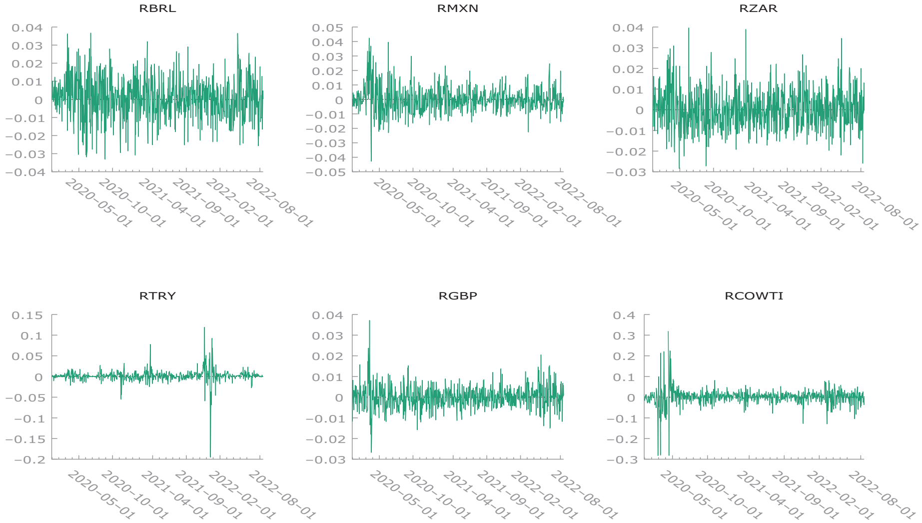

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Figure 2. Plot of log return of crude oil and constituent exchange rates

Table 2. Descriptive statistics of crude oil and constituent exchange rates

Series	Mean	Minimum	Maximum	SD	Skewness	kurtosis	JB test	ADF test
RBRL	0.0003	−0.0330	0.0367	0.0115	−0.0572	0.3692	5.27***	−8.31***
RMXN	0.0001	−0.0427	0.0424	0.0089	0.5036	4.0091	288.22***	−8.25***
RZAR	0.0002	−0.0284	0.0396	0.0099	0.4212	0.5780	29.87***	−8.04***
RTRY	0.0016	−0.1950	0.1192	0.0150	−2.3731	53.4120	82306.90***	−9.36***
RGBP	0.0001	−0.0267	0.0372	0.0057	0.4782	3.9927	482.51***	−9.89***
RCOWTI	0.0015	−0.2822	0.3196	0.0412	0.0290	18.6940	9974.90***	−7.16***

Source: Authors' own presentation

returns. Because each series is witnessed with fat tails in probability distribution, it departs from normality, which is confirmed from Jarque–Bera (JB) test at 0.01% significant level. Further, ADF test is used to check the stationarity in each series. The result exhibits that each series is stationary at 0.01%.

Further, the degree of associations along with overall distribution among these variables is displayed in Figure 3 in the form of static correlation. We notice that RZAR and RMXN have a high positive correlation, followed by RBPL and RMXN. Notably, crude oil is negatively correlated with each foreign exchange rate, except RBPL. To be precise, static correlation does not differentiate the connectedness among various asset classes due to which investors will not be in position to identify the diversification opportunities in different tenure (Yadav *et al.*, 2024). For the same, Diebold and Yilmaz (2014) and BK (2017) test are used to investigate the dynamic linkage of shocks within and network connection.

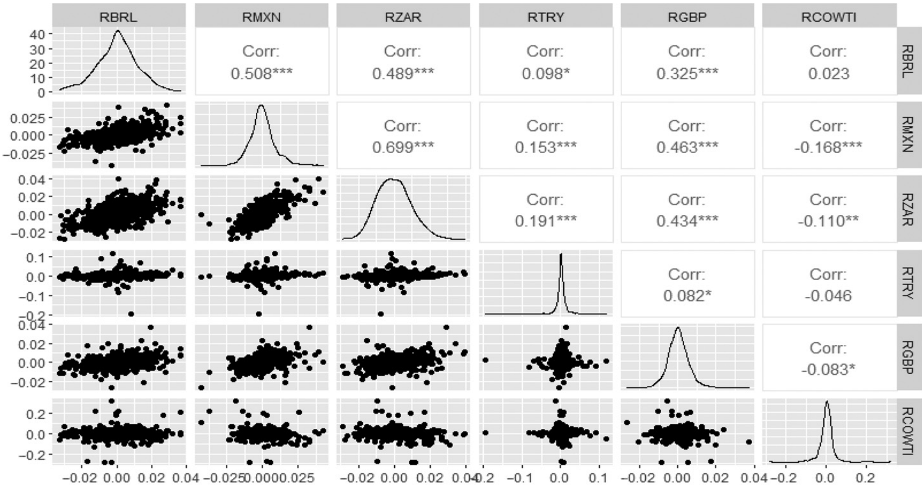

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Figure 3. Static correlation among analyzed markets

4. Econometric models

We use Diebold and Yilmaz model (2014) and Baruník and Křehlík test (2018) to examine the dynamic linkages of energy market with forex market. The detailed elaboration of these models is as follows.

4.1 Diebold and Yilmaz (2014) model

The multivariate time-series analysis method pioneered by Diebold and Yilmaz (2014) is extensively used in assessments of dynamic linkages among various assets class. This method is based on the disintegration of variance into the VAR and analyzes the connectedness by the calculation of the predicted error variance (FEVD) from a generalized VAR. Further, it can be applied on a large number of variables and also allows for the evaluation of the total directional spillover effect as well as the net and pair-wise spillover. This model is elaborated considering the below equation, following *N* variable VAR model:

$$Z_t = \sum_{j=1}^{J} \theta_j Z_{t-j} + \omega_t \tag{1}$$

where $Z_t = (Z_{1t}, Z_{2t}, \ldots\ldots, Z_{Nt})$ is a vector of variables at time t, θ_j, $j = 1, 2, 3.,j$ are N $\times$ N parameter matrix and $\omega_t \sim N(0, \Sigma)$ is a vector of iid random errors. It is assumed that the roots of these series are outside the unit circle; thus, the VAR model can be expressed as the following moving-average MA (∞) representation:

$$Z_t = \sum_{k=0}^{\infty} A_k \omega_{t-k} \text{ where } A_k = \sum \theta_k A_{j-k}.$$

The VAR framework assumes that all the variables are endogenous, and the generalized predicted error variance decomposition is described as follows:

$$\lambda_{il}(H) = \frac{\sigma_{ll}^{-1} \sum_{h=0}^{H-1} \left(e'_i A_h \sum e_l\right)^2}{\sum_{h=0}^{H-1} \left(e'_i A_h \sum A'_h e_l\right)} \tag{2}$$

where, σ_{ll} and e_i are the mean root dispersion diagonal vector, respectively, with a unit value for the ith element, which includes zero value for others. The $\lambda_{il}(H)$ denotes the contribution of kth series to the deviation of predicted error of the component j (Mensi *et al.*, 2021). Consequently, each component of the decomposition of the matrix can be normalized by its division. The spillover index is an $\mathrm{n} \times n$ matrix $\Theta(\mathrm{H}) = \theta_{il}(H)$, with every component providing the contribution made by variable j to the predicted error variance of variable i. Each component of the variance decomposition matrix is expressed as follows:

$$(\Theta_H)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{n} (\Theta_H)_{j,k}}, \quad with \sum_{k=1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k} = 1 \ and \sum_{k=1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k} = \mathrm{N} \tag{3}$$

Mathematically, the total spillover (Tsp) index is computed as follows:

$$Tsp(H) = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{\sum_{i,l=1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}} \times 100 = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{n} \times 100, \tag{4}$$

Likewise, the direction-wise spillover obtained by market i from all the other markets l is expressed as:

$$Dsp_{i\to l}(H) = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{\sum_{i,l=1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}} \times 100 = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{n} \times 100, \tag{5}$$

Similarly, the directional spillover obtained by market j from all the other markets i is expressed as:

$$Dsp_{l\to i}(H) = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{\sum_{i,l=1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}} \times 100 = \frac{\sum_{i,l=1,i\neq 1}^{n} \left(\widetilde{\Theta}_H\right)_{j,k}}{n} \times 100, \tag{6}$$

Accordingly, the net volatility spillover (Nsp) is computed as follows:

$$Nsp_i(H) = Dsp_{i\to l}(H) - Dsp_{l\to i}(H) \tag{7}$$

The net spillover indicates how much each market's volatility is, on average, transferred to other markets. The net pair-wise volatility spillover is computed by differentiating the gross volatility spillover effect from market *j* to market *i* (Tiwari *et al.*, 2018).

4.2 Baruník and Křehlík (2018) test

Baruník and Křehlík (2018) introduced a procedure that examines the spillover or dynamic connectedness in frequency domain approach and works out the spectral analysis of variance decomposition. While the Diebold and Yilmaz (2014) model analyzed the connectedness as shock transmitting from one market to another, the BK method observes the spillover in long-, medium- and short-term frequencies. Thus, besides estimating the direction of time volatility, it also estimates the spillover in the frequency domain (Umar *et al.*, 2019; Nasreen *et al.*, 2020). The impulse response function Θ_H in the chronic domain is used to estimate the frequency domain. A frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega}\Psi_h$ is extractable from the Fourier transform of the coefficient Ψ with $i = \sqrt{-1}$. The generalized causality spectrum over the frequency band $\omega =$ (-π, π) can be illustrated as:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1}\sum_{h=0}^{\infty}\left(\left|\Psi(e^{-iw})\Sigma_{j,k}\right|^2\right)}{\sum_{h=0}^{\infty}\left(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw})\right)_{jj}} \tag{8}$$

where $\Psi(e^{-iw})$ is the impulse response Fourier transforms. The term $(f(\omega))_{j,k}$ represents the percentage of the *j*th variable spectrum at frequency ω to the *k*th variable due to the deviation. Thus, it is also called the measure of within-frequency causality. The real generalized forecast error variance decompositions can be calculated as below:

$$\Gamma_j(\omega) = \frac{\left(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw})\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw})\right)_{jj}d\lambda'} \tag{9}$$

where the power of the *j*th variable at a certain frequency provides the total of the frequencies to a persistent figure of 2π. The generalized causality spectrum is the squared modulus of the weighted complex numbers producing a real number. Thus, the frequency band $d = (a, b)$:a, $b \in (-\pi, \pi)$, $a < b$ is obtained. Correspondingly, the generalized forecast error variance decomposition, on the frequency band *d*, is determined as follows:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_b^{\alpha}\Gamma_j(\omega)(f(\omega))_{j,k}d\omega, \tag{10}$$

The scaled generalized FEVD on the frequency band *d* can be demarcated as:

$$\left(\widetilde{\Theta}_d\right)_{j,k} = \frac{(\Theta_d)_{j,k}}{\sum_k (\Theta_\infty)_{j,k}} \tag{11}$$

Thus, the frequency spillover on the frequency band *d* is demarcated as:

$$C_d^F = \left(\frac{\sum_{j \neq k} (\Theta_\infty)_{j,k}}{\sum (\Theta_\infty)_{j,k}} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum (\Theta_\infty)_{j,k}} \right) \times 100 \tag{12}$$

Next, the overall spillover containing the frequency band *d* can be expressed as below:

$$C_d^w = \left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \left(\widetilde{\Theta}_d\right)_{j,k}} \right) \times 100 \tag{13}$$

5. Empirical result and discussion

For an empirical estimation, the result obtained from Diebold and Yilmaz model (2014) and Baruník and Křehlík test (2018) is documented in this section.

5.1 Dynamic linkages using the Diebold and Yilmaz model (2014)

We report the Diebold and Yilmaz model in three time periods exhibiting full observations, COVID-19 tenure and Russian–Ukraine invasion period in Table 3 under Panels A, B and C, respectively. The reason behind categorizing full period into COVID-19 outbreak and Russian invasion is that the distinct feature of this COVID-19 outbreak triggers the severe impacts that have changed the exchange rate structures. In addition, there is evidence of another episode of turmoil in both energy market and forex market during Russian–Ukraine invasion, which spikes the energy prices and devastated the exchange rate (Mohamad, 2022). In all panels of Table 3, diagonal element of matrix shows the within spillover, while off-diagonal element of matrix furnishes cross-market spillover. Apart from this, "From" and "To" indicate the spillover obtained from and contributed to other assets class, respectively (Yadav *et al.*, 2024). As regards the estimates of main diagonal element (own variable shocks) in Panel A of Table 3, we document that 92.36% of volatility evolution of crude oil is attributable to within market shock, whereas only 7.64% is attributed to other market (network) connection. In addition, 59.99% shock evolution of Brazilian real (RBRL), 48.96% shock evolution of Mexican peso (RMXN), 50.01% volatility evolution of South African rand (RZAR), 91.97% shock evolution of Turkish lira (RTRY) and 62.20% shock evolution of British pound sterling (RGBP) are induced within the market, which is also known as idiosyncratic shock or own variable shock.

Turning to the network connection of markets, it reveals that Mexican peso (RMXN) receives highest spillover (8.51%), followed by South African rand (RZAR), which is 8.33% from constituent exchanges rates and crude oil markets, while crude oil (RCOWTI) receives least volatility from other markets. On the other hand, Mexican peso contributes/transmits highest (10.36%) shock compared to constituent assets class followed by RZAR (9.89%); the least contributor to the volatility is crude oil (0.62%). This suggests that crude oil marginally connected to rest of assets class as it is least recipient and transmitter of the volatility. Additionally, Mexican peso is more dominant to other exchange rates and crude oil because of its high connectedness (both in the form of transmission and receipt of shock). The major

Table 3. Results derived from Diebold and Yilmaz model (2014) for spillover

	RCOWTI	RBRL	RMXN	RZAR	RTRY	RGBP	FROM
Panel (A) – Spillover using Diebold and Yilmaz model (2014) based on full observation							
RCOWTI	92.36	0.75	3.66	1.61	0.33	1.28	1.27
RBRL	0.42	59.99	15.79	15.90	0.85	7.05	6.67
RMXN	1.57	12.55	48.96	24.84	1.25	10.82	8.51
RZAR	0.57	12.35	24.82	50.01	1.84	10.40	8.33
RTRY	0.37	0.97	2.51	3.63	91.97	0.54	1.34
RGBP	0.77	7.2	15.40	13.33	1.10	62.20	6.3
TO	0.62	5.64	10.36	9.89	0.89	5.02	32.42
NET	−0.65	−1.03	1.85	1.56	−0.45	−1.28	
Panel (B) – Spillover using Diebold and Yilmaz model (2014) during COVID-19							
RCOWTI	89.70	1.24	4.94	2.68	0.31	1.14	1.72
RBRL	0.82	61.26	15.84	16.06	1.02	4.99	6.46
RMXN	1.92	12.48	49.31	25.09	1.24	9.97	8.45
RZAR	0.92	12.26	25.19	51.11	2.12	8.40	8.15
RTRY	0.40	1.12	2.40	4.14	91.34	0.61	1.44
RGBP	0.79	5.33	15.50	11.53	1.35	65.50	5.75
TO	0.81	5.40	10.64	9.92	1.00	4.18	31.96
NET	−0.91	−1.06	2.19	1.77	−0.44	−1.57	
Panel (C) – Spillover using Diebold and Yilmaz model (2014) during Russo–Ukraine invasion							
RCOWTI	88.50	1.46	0.53	2.42	0.63	6.47	1.92
RBRL	1.14	50.99	15.14	16.51	1.04	15.18	8.17
RMXN	2.97	12.71	42.89	23.30	3.00	15.12	9.52
RZAR	0.08	13.67	23.57	42.69	2.42	17.58	9.55
RTRY	0.39	3.40	4.55	1.56	89.34	0.77	1.78
RGBP	2.30	13.93	17.09	19.34	1.30	46.05	8.99
TO	1.15	7.53	10.15	10.52	1.40	9.18	39.92
NET	−0.77	−0.64	−0.63	0.97	−0.38	0.19	

Source: Authors' own presentation

reasons behind highest transmission and recipient of Mexico peso with network connection is that Mexico is a small open economy due to which it experiences free capital mobility with floating exchange rate regime and least intervention. This result is in the consonance with Wang *et al.* (2014) and Bush and Noria (2021) and differs from Tiwari *et al.* (2018). Next, we emphasize on the net directional connectedness to identify whether variables under examination receive greater shocks than it transmits. A net spillover of any market with positive value signifies that the respective assets class/market is a net transmitter, while a negative value indicates that the asset is net receiver. In case of crude oil (RCOWTI), Brazilian real (RBRL), Turkish Lira (RTRY) and British pound sterling (RGBP), there is evidence of negative net spillover of –0.65%, –1.03%, –0.45% and –1.28%, respectively. It indicates that these assets are considered as net receivers of shocks/volatility from other constituent markets. This study reports that in the entire system of the full sample, the British pound sterling (RGBP) emerged as the largest receiver of the volatility. As regards the net transmission of the volatility in the system, Mexican peso (RMXN) and South African rand (RZAR) have positive net spillover estimates with 1.85% and 1.56%, respectively.

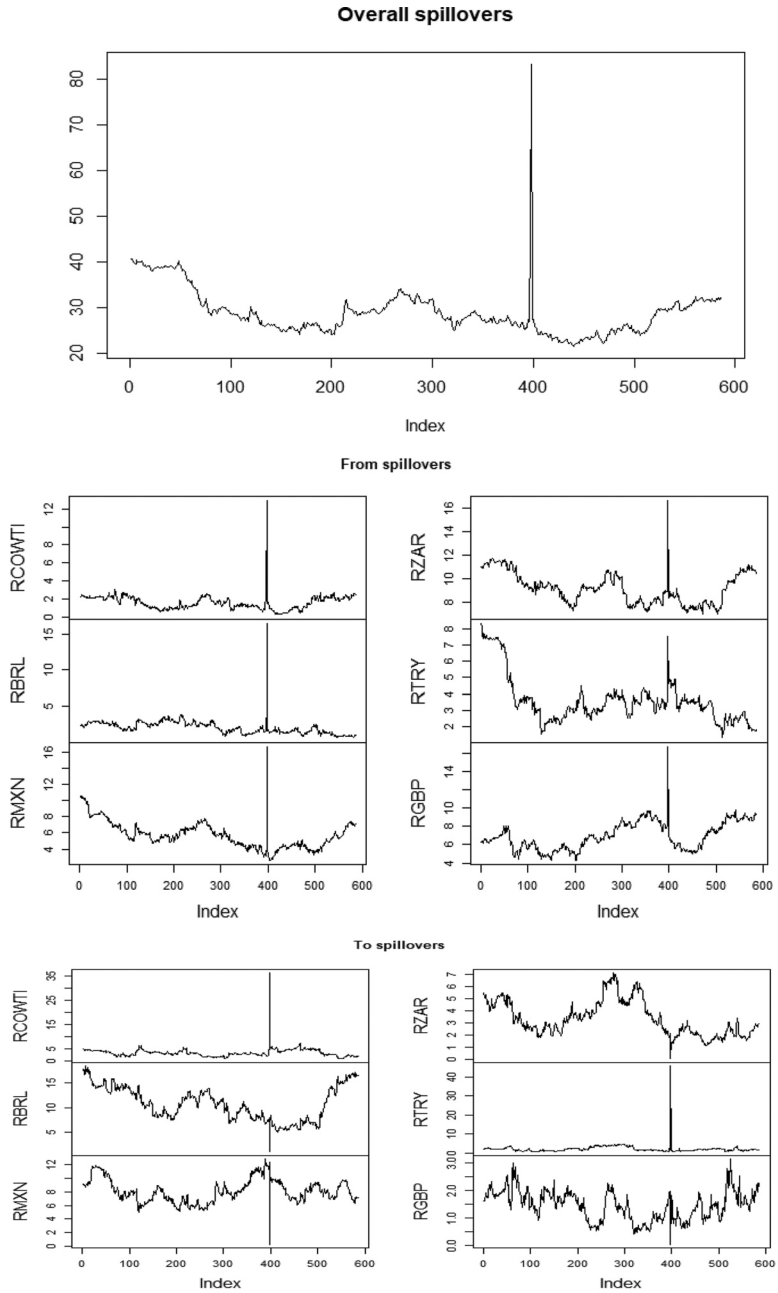
In Panel B of Table 3, the directional spillover (TO and FROM) obtained from Diebold and Yilmaz (2014) during the COVID-19 outbreak is encapsulated. Referring to the table, it is observed that highest shock evolution (91.34%) of Turkish Lira (RTRY) is attributed by its own behavior/shock. The volatility of Mexican peso is least affected by its own shock. Considering the volatility spillover from other markets, we notice that Mexican peso is the highest receiver (8.45%), followed by South African rand (8.15%), while Turkish Lira is the least receiver (1.44%) of volatility spillover from other markets. As regards contribution/transmission of volatility to network connection, the Mexican peso is the highest transmitter followed by South African rand with 10.64% and 9.92%, respectively. Further, crude oil, Brazilian real, Turkish lira and British pound sterling are net receivers with –0.91%, –1.06%, –0.44% and 1.57%, respectively, during the COVID-19 outbreak. As Mexican peso (MXN) and South African rand (RZAR) have witnessed with positive net spillover, this signifies that these exchange rates are net transmitters as they contribute more than they receive the volatility.

Looking at the Russian–Ukraine invasion tenure, we notice that the highest shock evolution is attributable by RTRY of 89.34% due to within-market shock, whereas only 10.66% is attributed to other market (network) connections. In addition, 88.50% of RCOWTI, 50.99% of RBRL, 42.89% of RMXN, 42.69% of RZAR and 46.05% of RGBP's shock evolution is determined because of its own behavior. In examined markets, RZAR is least affected by exchange rates by its own shock. At the same time, it receives the highest shock (9.55%) from its network connection. It is RTRY that absorbs the least volatility (1.78%) from other markets considered under investigation. Turning to the contribution of shock, RZAR transmits the highest shock by 10.52%, followed by RMXN with 10.15%, while RCOWTI contributes the least shock (1.15%). The RZAR and RGBP are net transmitters, and the rest of the markets are net receivers.

Further, the graphical plot of "Overall," "From" and "To" dynamic linkage of crude oil with constituent markets is displayed in Figure 4. In this figure, the observations such as 1, 100, 200, 300, 400, 500, 600 fall under December 30, 2019, May 15, 2020, October 2, 2020, February 21, 2021, July 9, 2021, November 26, 2021, and April 15, 2022, respectively. The overall spillover is highest in July 2021, while the lowest in the beginning of 2022. Considering "From spillover," it signifies that RCOWTI, RBRL and RMXN follow a similar pattern, while the pattern of RGBP, RTRY and RZAR is not uniform. Looking at the contribution to network connection in the form of "To spillover," the behavior of RCOWTI and RTRY is the same, and these markets contribute the highest at the beginning of 2021. Surprisingly, RBRL, RZAR and RGBP are spotted with the lowest contribution of volatility at the beginning of 2021.

5.2 Dynamic linkages using Baruník and Křehlík test (2018)

Diebold and Yilmaz (2014) models show that dynamic linkage or connectedness is constant in the short, medium and long run, which does not furnish the magnitude of volatility in different time period (Yadav *et al.*, 2024). On this note, further, Baruník and Křehlík (2018) test is used to separate the dynamic linkages over the period of time. Table 4, 5 and 6 encapsulate the connectedness of full observations, COVID-19 outbreak period and Russo–Ukraine, respectively. To ease the interpretation, Frequency cycles 1, 2 and 3 indicate the connectedness in short, medium and long run. These frequency cycles cover 1–10 days, 10–15 days and 15 to infinity, respectively. Further, WTH and ABS indicate the within and absolute connectedness among examined markets (Gupta *et al.*, 2020). Based on "To" and "From," net connectedness is determined making the difference between these connectedness. Turning to the short run of Table 4, we observe that RZAR is the highest receiver (6.32%), followed by RMXN (5.87), whereas RZAR is the highest contributor (7.07), followed by RZAR (6.43), respectively. The least receiver exchange rate is RTRY (0.85), and the least transmitter is RCOWTI (0.36). As regards the net spillover of the volatility, we report that RCOWTI and RBRL are net receivers, while RMXN, RZAR, RTRY and RGBP are net transmitters. As regards Frequency 2 (medium run), RMXN and RGBP are the highest receivers of volatility (1.61), followed by RBRL (1.36), while RZAR is the



Source: Created by the authors

Figure 4. Graphical plot of dynamic linkages using Diebold and Yilmaz (2014)

Table 4. Dynamic connectedness using BK test (2018) on full observations

	RCOWTI	RBRL	RMXN	RZAR	RTRY	RGBP	FROM_ABS
Frequency 1: short run (1 day to 10 days)							
RCOWTI	68.99	0.66	2.49	0.79	0.12	1.23	0.88
RBRL	0.28	44.95	11.01	10.62	0.46	4.66	4.51
RMXN	0.79	9.19	34.35	16.91	0.83	7.51	5.87
RZAR	0.42	9.21	18.96	37.64	1.27	8.08	6.32
RTRY	0.33	0.58	1.68	2.07	62.51	0.45	0.85
RGBP	0.32	4.40	8.30	8.16	0.38	43.31	3.60
TO_ABS	0.36	4.01	7.07	6.43	0.51	3.65	22.03
NET	−0.52	−0.5	1.2	0.11	0.34	0.05	
Frequency 2: medium run (10 days to 15 days)							
RCOWTI	15.24	0.06	0.77	0.50	0.11	0.03	0.25
RBRL	0.09	9.58	3.05	3.23	0.23	1.55	1.36
RMXN	0.48	2.12	9.18	4.83	0.25	2.01	1.61
RZAR	0.10	1.99	3.71	7.77	0.34	1.46	1.27
RTRY	0.02	0.24	0.48	0.91	18.44	0.06	0.28
RGBP	0.27	1.66	4.24	3.06	0.41	11.69	1.61
TO_ABS	0.16	1.01	2.04	2.09	0.22	0.85	6.38
NET	−0.47	−0.35	0.43	0.82	−0.06	−0.76	
Frequency 3: long run (15 days to infinity)							
RCOWTI	8.13	0.03	0.40	0.32	0.09	0.03	0.15
RBRL	0.06	5.45	1.72	2.05	0.16	0.84	0.80
RMXN	0.30	1.25	5.44	3.11	0.17	1.30	1.02
RZAR	0.05	1.15	2.15	4.61	0.22	0.87	0.74
RTRY	0.02	0.16	0.35	0.65	11.02	0.03	0.20
RGBP	0.18	1.13	2.85	2.11	0.30	7.20	1.10
TO_ABS	0.10	0.62	1.25	1.37	0.16	0.51	4.01
NET	−0.05	−0.18	0.23	0.63	−0.04	−0.59	

Source: Authors' own presentation

highest contributor (2.09), followed by RMXN (2.04). With respect to long run, RMXN and RZAR are net transmitters, and the rest of the constituent markets are net receivers. In the long run, surprisingly, RGBP receives the highest connectedness (1.10), while RZAR is the highest transmitter (1.37) among constituent markets. The net connection in this frequency is similar to medium run as RMXN and RZAR are net contributors, and the rest of the markets are net receiver of the shocks. Summing up the total spillover, we notice that it is highest (22.03%), followed by medium run (6.38%). It indicates that as the time passes from short run to medium and long run, the total dynamic linkages decrease.

Referring to dynamic connectedness among various assets class during the COVID-19 outbreak (short run) presented in Table 5, we observe that RZAR, followed by RMXN, are highest receivers of shocks with 6.01% and 5.74%, respectively. On the other hand, RMXN transmits the highest (7.07%), followed by RZAR (6.31%) to the network connection. Like the full sample, RMXN and RZAR are net transmitters as these exchange rates contribute more than they receive the shocks. In the medium run, RMXN is the highest receiver and contributor to the shocks, with 1.63 and 2.19, respectively. It signifies that RMXN is a more risky investment alternative for the investors as it is much affected during the COVID-19 outbreak by/to network connection. Further, RMXN and RZAR are net transmitters, while the rest of the markets are net receivers. Surprisingly,

Table 5. Dynamic connectedness using BK test (2018) during the COVID-19 outbreak

	RCOWTI	RBRL	RMXN	RZAR	RTRY	RGBP	FROM_ABS
Frequency 1: short run (1 day to 10 days)							
RCOWTI	66.51	0.87	3.37	1.32	0.12	0.96	1.11
RBRL	0.60	46.37	11.04	10.91	0.52	3.12	4.37
RMXN	1.15	8.95	34.23	16.93	0.80	6.64	5.74
RZAR	0.72	8.90	18.80	37.78	1.42	6.23	6.01
RTRY	0.37	0.59	1.60	2.23	62.18	0.46	0.87
RGBP	0.49	3.01	7.62	6.46	0.42	44.03	3.00
TO_ABS	0.56	3.72	7.07	6.31	0.55	2.90	21.10
NET	−0.55	−0.65	1.67	0.30	−0.32	−0.10	
Frequency 2: medium run (10 days to 15 days)							
RCOWTI	15.19	0.23	1.02	0.82	0.10	0.09	0.38
RBRL	0.14	9.47	3.02	3.12	0.29	1.21	1.30
RMXN	0.48	2.18	9.38	4.90	0.25	1.99	1.63
RZAR	0.13	2.11	4.00	8.26	0.42	1.35	1.33
RTRY	0.01	0.31	0.46	1.11	18.22	0.10	0.33
RGBP	0.18	1.34	4.61	2.90	0.53	13.12	1.59
TO_ABS	0.16	1.03	2.19	2.14	0.26	0.79	6.57
NET	−0.22	−0.27	0.56	0.81	−0.07	−0.80	
Frequency 3: long run (15 days to infinity)							
RCOWTI	8.00	0.14	0.55	0.55	0.09	0.08	0.23
RBRL	0.08	5.42	1.78	2.04	0.21	0.67	0.79
RMXN	0.29	1.35	5.70	3.27	0.19	1.33	1.07
RZAR	0.07	1.25	2.39	5.07	0.29	0.83	0.80
RTRY	0.01	0.22	0.34	0.80	10.94	0.05	0.24
RGBP	0.11	0.98	3.27	2.16	0.40	8.36	1.15
TO_ABS	0.09	0.66	1.39	1.47	0.19	0.49	4.29
NET	−0.23	−0.13	0.32	0.67	−0.05	0.66	

Source: Authors' own presentation

RGBP receives the highest shocks (1.15) from network connection, followed by RMXN (1.07%) in Frequency 3 (long run). Apart from RMXN and RZAR, RGBP is another net transmitter of the shocks, which is an additional contributor in this juncture. The total shocks during the COVID-19 outbreak in different cycles decrease from short run to medium and long run, respectively.

Finally, we report the dynamic connectedness of constituent markets during Russo−Ukraine invasion in Table 6. In Frequency 1 (short run), it is observed that RGBP is the highest receiver (6.41%) of shocks, while RTRY is the least receiver (1.24). On the other hand, RMXN and RCOWT are the highest and least transmitter of the shocks, with 7.56% and 0.77%, respectively. The logic behind crude oil as least transmitter is that it is slow to respond the price signals demanding bigger price that brings the balanced market. As regards the net transmission, we report that RMXN and RGBP are the net contributors, and the rest of the assets class are net receiver from the network connection. Further, in the medium run, RGBP is highest receiver (1.69%) of shocks, while RCOWTI is the least receiver, with 0.21%. When it comes talking about transmission of shocks to the network connection, RZAR is considered as highest contributor (1.96%), and RTRY is least contributor (0.16%) of the shocks. Comparatively, in this tenure, half of the asset classes are net transmitters (RCOWTI, RMXN and RZAR), while other half of the asset classes

Table 6. Dynamic connectedness using BK test (2018) during Russo–Ukraine war

	RCOWT	RBRL	RMXN	RZAR	RTRY	RGBP	FROM_ABS
Frequency 1: short run (1 day to 10 days)							
RCOWTI	71.14	0.37	0.51	2.18	0.35	6.07	1.58
RBRL	1.12	37.01	10.98	10.97	0.91	10.95	5.82
RMXN	1.95	10.20	31.58	16.31	2.50	11.09	7.01
RZAR	0.07	11.17	19.38	33.73	2.19	14.35	7.86
RTRY	0.25	2.73	2.34	1.41	57.15	0.72	1.24
RGBP	1.21	9.74	12.14	14.14	1.21	35.49	6.41
TO_ABS	0.77	5.70	7.56	7.50	1.19	7.20	29.92
NET	−0.81	−0.12	0.55	−0.36	−0.05	0.79	
Frequency 2: medium run (10 days to 15 days)							
RCOWTI	11.42	0.63	0.01	0.15	0.18	0.31	0.21
RBRL	0.02	9.10	2.86	3.58	0.11	2.81	1.56
RMXN	0.67	1.81	7.42	4.52	0.40	2.57	1.66
RZAR	0.01	1.56	2.81	5.80	0.22	2.04	1.10
RTRY	0.09	0.59	1.26	0.11	20.26	0.04	0.35
RGBP	0.69	2.77	3.24	3.38	0.07	6.91	1.69
TO_ABS	0.25	1.23	1.70	1.96	0.16	1.29	6.58
NET	0.04	−0.33	0.04	0.86	−0.19	−0.4	
Frequency 3: long run (15 days to infinity)							
RCOWTI	5.94	0.46	0.01	0.08	0.09	0.09	0.12
RBRL	0.00	4.89	1.30	1.96	0.02	1.42	0.78
RMXN	0.35	0.70	3.89	2.47	0.09	1.46	0.85
RZAR	0.00	0.93	1.38	3.16	0.01	1.19	0.59
RTRY	0.04	0.08	0.95	0.04	11.93	0.01	0.19
RGBP	0.40	1.41	1.71	1.82	0.01	3.64	0.89
TO_ABS	0.13	0.60	0.89	1.06	0.04	0.69	3.41
NET	0.01	−0.18	0.04	0.47	−0.59	−0.20	

Source: Authors' own presentation

are net receivers (RBRL, RTRY and RGBP). At the end, in long run of Russo–Ukraine invasion, we observe that RGBP receives highest shocks (0.89%), while RCOWTI receives least shocks (0.12%). With respect to contribution to the network connection, it is observed that RZAR and RTRY are the highest and least transmitter to the constituent markets. The net spillover in this tenure is similar like medium run as RCOWTI, RMXN and RZAR are net transmitters, while the rest are net receivers.

Comparing the total magnitude of dynamic linkages in three different periods, we observe that the total spillover index in Russo–Ukraine invasion is the highest (29.92%) than full observation (22.03%) and COVID-19 outbreak (21.10%) in the short run. The reason behind high connectedness during invasion is that this man-made incident triggers large-scale humanitarian and adds downside risks around the globe than COVID-19 outbreak. Additionally, decline of remittance flows, rising the food price, fuel and other commodities compel crude oil and forex market to be connected.

6. Conclusion and policy implication

The energy market is visibly at the center stage, having its significance in various stages of general economic cycle, which is a linking pin, directly or indirectly, to all the economic activities (Khalfaoui *et al.*, 2021). The increase in energy price may impact transportation costs, electricity cost and fertilizer. On the other hand, forex market is emerged as one of the largest financial markets, which is affected by geopolitics, trade deals, economic stability and policies. These driving forces behave differently in normal trading days and crisis periods. On this note, this study lays stress on the dynamic linkages of crude oil WTI with select exchange rates considering full sample and crisis periods (COVID-19 outbreak and Russo−Ukraine invasion). These two incidents change the pattern of association between forex and energy markets (Fasanya *et al.*, 2021; Arya and Singh, 2022). In addition, there is evidence of another episode of turmoil in both energy market and forex market during Russian−Ukraine invasion, which spikes the energy prices and devastates the exchange rate (Mohamad, 2022).

In this paper, we use the Diebold and Yilmaz model (2014) and Baruník and Křehlík test (2018) to investigate the dynamic linkages of energy market (crude oil) with forex market, which is proxied by Brazilian real (RBRL), Mexican peso (RMXN), South African rand (RZAR), Turkish lira (RTRY) and British pound sterling (RGBP). The result obtained from the Diebold and Yilmaz (2014) model documents that Mexican peso (RMXN) receives and transmits the highest spillover, while crude oil (RCOWTI) receives and transmits the least volatility to network connection in the full sample. It is found that crude oil is marginally connected to the rest of asset classes as it is least recipient and transmitter of the volatility. Further, in the COVID-19 period, Mexican peso is considered highest receiver, while Turkish Lira is the least receiver of volatility shock from other markets. During the Russo−Ukraine invasion, South African rand (RZAR) is the highest receiver of shock, and South African (RTRY) absorbs least volatility. While transmitting, RZAR contributes the highest, and crude is the least transmitter of shock. It signifies that reaction and dynamic linkages of these markets differ in various time periods. The finding is in accordance with Bush and Noria (2021) and Arya and Singh (2022) and differs from Tiwari *et al.* (2018). As regards the Baruník and Křehlík test (2018), it is found that the dynamic linkage is not constant in the short, medium and long run. In addition, the total spillover index in Russo−Ukraine invasion is the highest (29.92%) than full observation (22.03%) and COVID-19 outbreak (21.10%) in the short run. The reason behind high connectedness during invasion is that this man-made outbreak triggers large-scale humanitarian and adds downside risks around the globe than the COVID-19 outbreak.

The findings obtained from these results venture to offer the policy implications in threefold: first, investors should prefer crude oil (RCOWTI) in their investment alternatives as it receives and transmits the least volatility to network connection. It ensures them that a small or huge fluctuation in forex market does not lead crude oil in storm clouds that can be an appropriate diversifier. Second, in the wake of the COVID-19 outbreak, traders and investors can emphasize on optimal weight of foreign exchange rates to hedge portfolio as Mexican peso (RMXN) and Turkish lira (RTRY) respond in the opposite direction, like RMXN receives the highest shock, and RTRY receives the least shock. Third, because there is evidence of high dynamic linkage during Russo−Ukraine invasion comparatively, the investors should avoid trading in man-made crisis like this invasion in short run; however, it can be enviable in the long run and does not erupt other analyzed markets.

This study is not left with limitations as it attempts to explore dynamic linkages of only two markets such as crude oil and foreign exchange market. It can be extended considering agricultural commodities, other energy market (natural gas), bullion market and metal market. In addition, wavelet analysis and dynamic conditional correlation (DCC) can be used for the empirical estimation.

References

Adekoya, O.B., Oliyide, J.A., Yaya, O.S. and Al-Faryan, M.A.S. (2022), "Does oil connect differently with prominent assets during war? Analysis of intra-day data during the Russia-Ukraine Saga", *Resources Policy*, Vol. 77, p. 102728.

Alam, M., Tabash, M.I., Billah, M., Kumar, S. and Anagreh, S. (2022), "The impacts of the Russia–Ukraine invasion on global markets and commodities: a dynamic connectedness among G7 and BRIC markets", *Journal of Risk and Financial Management*, Vol. 15 No. 8, p. 352.

Arya, V. and Singh, S. (2022), "Dynamics of relationship between stock markets of SAARC countries during COVID-19 pandemic", *Journal of Economic and Administrative Sciences*.

Ashok, S., Corbet, S., Dhingra, D., Goodell, J.W., Kumar, S. and Yadav, M.P. (2022), "Are energy markets informationally smarter than equity markets? Evidence from the COVID-19 experience", *Finance Research Letters*, Vol. 47, p. 102728, doi: 10.1016/j.frl.2022.102728.

Astrov, V., Grieveson, R., Kochnev, A., Landesmann, M. and Pindyuk, O. (2022), "Possible Russian invasion of Ukraine, scenarios for sanctions, and likely economic impact on Russia, Ukraine and the EU", February, pp. 1-28.

Baruník, J. and Křehlík, T. (2018), "Measuring the frequency dynamics of financial connectedness and systemic risk", *Journal of Financial Econometrics*, Vol. 16 No. 2, pp. 271-296, doi: 10.1093/jjfinec/nby001.

Basher, S.A., Haug, A.A. and Sadorsky, P. (2012), "Oil prices, exchange rates and emerging stock markets", *Energy Economics*, Vol. 34 No. 1, pp. 227-240, doi: 10.1016/j.eneco.2011.10.005.

Bouri, E., Cepni, O., Gabauer, D. and Gupta, R. (2021), "Return connectedness across asset classes around the COVID-19 outbreak", *International Review of Financial Analysis*, Vol. 73, p. 101646, doi: 10.1016/j.irfa.2020.101646.

Bush, G. and Noria, G.L. (2021), "Uncertainty and exchange rate volatility: evidence from Mexico", *International Review of Economics and Finance*, Vol. 75 No. C, pp. 704-722.

Charlot, P. and Marimoutou, V. (2014), "On the relationship between the prices of oil and the precious metals: revisiting with a multivariate regime-switching decision tree", *Energy Economics*, Vol. 44, pp. 456-467, doi: 10.1016/j.eneco.2014.04.021.

Corbet, S., Hou, Y., Hu, Y., Lucey, B. and Oxley, L. (2021), "Aye corona! the contagion effects of being named corona during the COVID-19 pandemic", *Finance Research Letters*, Vol. 38, p. 101591.

Diebold, F.X. and Yilmaz, K. (2014), "On the network topology of variance decompositions: measuring the connectedness of financial firms", *Journal of Econometrics*, Vol. 182 No. 1, pp. 119-134, doi: 10.1016/j.jeconom.2014.04.012.

Ding, Q., Huang, J. and Chen, J. (2021), "Dynamic and frequency-domain risk spillovers among oil, gold, and foreign exchange markets: Evidence from implied volatility", *Energy Economics*, Vol. 102, p. 105514, doi: 10.1016/j.eneco.2021.105514.

Farzanegan, M.R. and Markwardt, G. (2009), "The effects of oil price shocks on the Iranian economy", *Energy Economics*, Vol. 31 No. 1, pp. 134-151, doi: 10.1016/j.eneco.2008.09.003.

Fasanya, I.O., Oyewole, O., Adekoya, O.B. and Odei-Mensah, J. (2021), "Dynamic spillovers and connectedness between COVID-19 pandemic and global foreign exchange markets", *Economic Research-Ekonomska Istraživanja*, Vol. 34 No. 1, pp. 2059-2084, doi: 10.1080/1331677X.2020.1860796.

Goodell, J., Yadav, M.P., Ruan, J., Abedin, M. and Malhotra, N. (2023), "Traditional assets, digital assets and renewable energy: investigating connectedness during COVID-19 and the Russia-Ukraine war", *Finance Research Letters*, Vol. 58, doi: 10.1016/j.frl.2023.104323.

Khalfaoui, R., Baumöhl, E., Sarwar, S. and Výrost, T. (2021), "Connectedness between energy and nonenergy commodity markets: evidence from quantile coherency networks", *Resources Policy*, Vol. 74, p. 102318.

Liadze, I., Macchiarelli, C., Mortimer-Lee, P. and Juanino, P.S. (2022), "The economic costs of the Russia-Ukraine conflict", National Institute of Economic and Social Research, March, pp. 1-10, available at: www.niesr.ac.uk/wp-content/uploads/2022/03/PP32-Economic-Costs-Russia-Ukraine

Lohana, S., Yadav, M.P. and Rekha, A.G. (2024), "Volatility spillover from the Chinese stock market to the G20 stock markets in the wake of pandemic COVID-19", *Review of Pacific Basin Financial Markets and Policies*, Vol. 27 No. 2, doi: 10.1142/S0219091524500115.

Luo, J. and Ji, Q. (2018), "High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets", *Energy Economics*, Vol. 76, pp. 424-438, doi: 10.1016/j.eneco.2018.10.031.

Maghyereh, A.I., Awartani, B. and Bouri, E. (2016), "The directional volatility connectedness between crude oil and equity markets: new evidence from implied volatility indexes", *Energy Economics*, Vol. 57, pp. 78-93, doi: 10.1016/j.eneco.2016.04.010.

Mehrara, M. and Mohaghegh, M. (2011), "Macroeconomic dynamics in the oil exporting countries: a panel VAR study", *International Journal of Business and Social Science*, Vol. 2 No. 21, pp. 288-296, available at: http://e-resources.pnri.go.id:2056/docview/904532429?accountid=25704

Mensi, W., Hammoudeh, S. and Yoon, S.M. (2014), "How do OPEC news and structural breaks impact returns and volatility in crude oil markets? Further evidence from a long memory process", *Energy Economics*, Vol. 42, pp. 343-354.

Mensi, W., Hamed Al-Yahyaee, K., Vinh Vo, X. and Hoon Kang, S. (2021), "Dynamic spillover and connectedness between oil futures and European bonds", *The North American Journal of Economics and Finance*, Vol. 56, p. 101342, doi: 10.1016/j.najef.2020.101342.

Miller, J.I. and Ratti, R.A. (2009), "Crude oil and stock markets: stability, instability, and bubbles", *Energy Economics*, Vol. 31 No. 4, pp. 559-568, doi: 10.1016/j.eneco.2009.01.009.

Nasreen, S., Tiwari, A.K., Eizaguirre, J.C. and Wohar, M.E. (2020), "Dynamic connectedness between oil prices and stock returns of clean energy and technology companies", *Journal of Cleaner Production*, Vol. 260, doi: 10.1016/j.jclepro.2020.121015.

Nekhili, R., Mensi, W. and Vo, X.V. (2021), "Multiscale spillovers and connectedness between gold, copper, oil, wheat and currency markets", *Resources Policy*, Vol. 74, p. 102263, doi: 10.1016/j.resourpol.2021.102263.

Nepal, R., Yadav, M.P., Katoch, R., Gupta, H. and Kumar, A. (2024), "Co-movement between carbon emissions and forex market: a tale of COVID-19 outbreak and Russia-Ukraine invasion", *Resources Policy*, Vol. 90, doi: 10.1016/j.resourpol.2024.104853.

OECD (2020), "Covid-19 and global capital flows", July, 1–11, available at: https://read.oecd-ilibrary.org/view/?ref=134_134881-twep75dnkt&title=COVID-19-and-global-capital-flows

Ozili, P.K. (2022), "Global economic consequence of Russian invasion of Ukraine", *SSRN Electronic Journal*, doi: 10.2139/ssrn.4064770.

Ozturk, M. and Cavdar, S.C. (2021), "The contagion of the Covid-19 pandemic on the volatilities of international crude oil prices, gold, exchange rates and bitcoin", *The Journal of Asian Finance, Economics and Business*, Vol. 8 No. 3, pp. 171-179.

Panas, E. and Ninni, V. (2000), "Are oil markets chaotic? A non-linear dynamic analysis", *Energy Economics*, Vol. 22 No. 5, pp. 549-568, doi: 10.1016/S0140-9883(00)00049-9.

Qiang, W., Lin, A., Zhao, C., Liu, Z., Liu, M. and Wang, X. (2019), "The impact of international crude oil price fluctuation on the exchange rate of petroleum-importing countries: a summary of recent studies", *Natural Hazards*, Vol. 95 Nos 1/2, pp. 227-239.

Schmidhuber, J. (2020), "COVID-19: from a global health crisis to a global food crisis?", Food Outlook, June, pp. 63-71, available at: www.fao.org/3/ca9509en/CA9509EN.pdf, available at: http://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=caba6&AN=

20203258929, available at: http://sfx.library.cdc.gov/cdc?sid=OVID:cabadb&id=pmid:&id=10.4060%2Fca9509e&issn=0251-1959&isbn=&volume=&issue=June&spage

Singh, V.K., Nishant, S. and Kumar, P. (2018), "Dynamic and directional network connectedness of crude oil and currencies: evidence from implied volatility", *Energy Economics*, Vol. 76, pp. 48-63, doi: 10.1016/j.eneco.2018.09.018.

Singleton, K.J. (2014), "Investor flows and the 2008 boom/bust in oil prices", *Management Science*, Vol. 60 No. 2, pp. 300-318, doi: 10.1287/mnsc.2013.1756.

Tabassum, S., Kaur, L., Yadav, M.P., Khan, K. and Zulphikar, Z. (2024a), "Demystifying the time varying linkage among ESG compliant, fintech and artificial intelligence stocks", *Journal of Accounting and Organizational Change*, doi: 10.1108/JAOC-01-2024-0041.

Tabassum, S., Rashid, U., Rabbani, M.R., *et al.* (2024b), "Quantifying the quantile connectedness among memecoin, halal ETF and ESG index", *Journal of Islamic Marketing*, doi: 10.1108/JIMA-01-2024-0048.

Tank, A. and Ospanova, A. (2022), "Economic impact of Russia -Ukraine war", *International Journal of Innovative Research in Science Engineering and Technology*, Vol. 11 No. 4, pp. 3345-3349, doi: 10.15680/IJIRSET.2022.1104025.

Tiwari, A.K., Cunado, J., Gupta, R. and Wohar, M.E. (2018), "Volatility spillovers across global asset classes: evidence from time and frequency domains", *The Quarterly Review of Economics and Finance*, Vol. 70, pp. 194-202, doi: 10.1016/j.qref.2018.05.001.

Toyoshima, Y. and Hamori, S. (2018), "Measuring the time-frequency dynamics of return and volatility connectedness in global crude oil markets", *Energies*, Vol. 11 No. 11, doi: 10.3390/en11112893.

Turhan, M.I., Sensoy, A. and Hacihasanoglu, E. (2014), "A comparative analysis of the dynamic relationship between oil prices and exchange rates", *Journal of International Financial Markets, Institutions and Money*, Vol. 32 No. 1, pp. 397-414, doi: 10.1016/j.intfin.2014.07.003.

Umar, Z., Nasreen, S., Solarin, S.A. and Tiwari, A.K. (2019), "Exploring the time and frequency domain connectedness of oil prices and metal prices", *Resources Policy*, Vol. 64, p. 101516, doi: 10.1016/j.resourpol.2019.101516.

Wen, T. and Wang, G.J. (2020), "Volatility connectedness in global foreign exchange markets", *Journal of Multinational Financial Management*, Vol. 54, p. 100617, doi: 10.1016/j.mulfin.2020.100617.

Wu, C.C., Chung, H. and Chang, Y.H. (2012), "The economic value of co-movement between oil price and exchange rate using copula-based GARCH models", *Energy Economics*, Vol. 34 No. 1, pp. 270-282, doi: 10.1016/j.eneco.2011.07.007.

Yadav, M.P., Abedin, M., Sinha, N. and Arya, V. (2024), "Uncovering dynamic connectedness of artificial intelligence stocks with agri-commodity market in wake of COVID-19 and Russia-Ukraine invasion", *Research in International Business*, doi: 10.1016/j.ribaf.2023.102146.

Zhang, D. (2017), "Oil shocks and stock markets revisited: measuring connectedness from a global perspective", *Energy Economics*, Vol. 62, pp. 323-333, doi: 10.1016/j.eneco.2017.01.009.

Zhang, W. and Hamori, S. (2021), "Crude oil market and stock markets during the COVID-19 pandemic: evidence from the US, Japan, and Germany", *International Review of Financial Analysis*, Vol. 74, p. 101702, doi: 10.1016/j.irfa.2021.101702.

Further reading

Baruník, J., Kočenda, E. and Vácha, L. (2017), "Asymmetric volatility connectedness on the forex market", *Journal of International Money and Finance*, Vol. 77, pp. 39-56, doi: 10.1016/j.jimonfin.2017.06.003.

Barunik, J., Krehlik, T. and Vacha, L. (2016), "Modeling and forecasting exchange rate volatility in time-frequency domain", *European Journal of Operational Research*, Vol. 251 No. 1, pp. 329-340, doi: 10.1016/j.ejor.2015.12.010.

Diebold, F.X. and Yilmaz, K. (2015), "Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004-2014", *Journal of Financial Econometrics*, Vol. 14 No. 1, pp. 81-127, doi: 10.1093/jjfinec/nbv021.

Wongbangpo, P. and Sharma, S.C. (2002), "Stock market and macroeconomic fundamental dynamic interactions: ASEAN-5 countries", *Journal of Asian Economics*, Vol. 13 No. 1, pp. 27-51, doi: 10.1016/S1049-0078(01)00111-7.

Xiao, X. and Huang, J. (2018), "Dynamic connectedness of international crude oil prices: the Diebold-Yilmaz approach", *Sustainability*, Vol. 10 No. 9, doi: 10.3390/su10093298.

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