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Investigating volatility spillover of energy commodities in the context of the Chinese and European stock markets

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ABSTRACT

This paper investigates spillover from energy commodities to Shanghai stock exchange and European Stock market, and identifies possible risks transmission and portfolio diversification opportunities. The study is conducted on daily spot prices of carbon (CO2) emission, natural gas and crude oil from 16 December 2010 to 29 December 2022, employing Granger causality test, dynamic conditional correlation (DCC), Diebold-Yilmaz (2012) and Barunik-Krehlic (2017) models. Results identify higher volatility and imply greater connectedness in the longer run. Additionally, natural gas is witnessed as the highest contributor of the shocks and crude oil as the highest receiver of the shocks from the network connection. Further results suggest for investment in energy commodities in shorter run rather than long run for efficient portfolio diversification. Results from this study are expected to have practical implications for portfolio managers, investors, and market regulators, given the suggestion of this study to incorporate energy stocks for efficient diversification of risk.

1. Introduction

Continuous integration of global financial markets, coupled with increasing financialization of energy commodities, has evinced interest in studies on conditional risk spillover among major security and commodity markets. In the recent times, focus on examining the diffusion of return linkages and volatility across capital markets has gained prominence (Al-Hajieh, 2023). During the market crisis, it becomes imperative for managers of portfolios and practitioners to take corrective measures against the possible transmission of risk in capital markets. Empirical research analysing spillover intensity or dynamic linkages amongst markets provides insights that enable accurate predictions of both return and volatility. Co-movement and variations between energy commodities and stock markets present bigger challenges, especially for policymakers. It is because, the interdependence in these markets not only affects the cost of production, corporate incomes and employment growth rates but also considerably impacts macroeconomic policies. It therefore becomes critical that investors comprehend the effect of change in energy commodities on the risk and return characteristics of their investment portfolios. Many contemporary studies are incorporating raw materials as an essential component of investment portfolios

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jointly with classes of stocks (Vivian and Wohar, 2012). Traders are using inferences from these studies to detect the fluctuations in both stock and commodity markets, and hence identify the trend and mutuality in the markets (Choi and Hammoudeh, 2010).

Many events between 2009 and 2019 have affected both energy and stock markets, resulting in volatility spillover amongst major world markets (Bouteska et al., 2023). Numerous studies have investigated an association among commodities and the stock market establishing economic activities of different countries. For instance, Hamilton (1983) identified that oil price shocks as the key factor that contributed to the US recession. Malik and Ewing (2009) applied the DCC approach and identified correlation between weekly WTI (West Texas Intermediate) oil prices and equity market. Chang et al. (2013) analysed the correlations among S&P500 stock indices, FTSE100, crude oil, Dow Jones and NYSE. Bastianin et al. (2016) highlighted the significance of association of crude oil prices and instability in markets as it impacts management of risk and structuring of optimum macroeconomic and energy policy. Chebbi et al. (2020) undertook a study on relationship of two energy commodities: natural gas and crude oil with QE Al Rayan Islamic index and suggested a robust relationship between returns on commodity and those of stock index. Hung, (2020) investigated the return spillover among crude oil prices and the five major equity markets in Europe, namely France, Italy, German, UK and Spain before and during the COVID-19. Likewise, Zhu et al. (2020) undertook a study on volatility spillover of carbon with electricity market in Europe. In the Chinese context, Cong and Shen (2013) found that over a longer period, energy prices explained fluctuations in equity market, with every 1% rise in energy price index, the equity market index went down by 0.54%. They concluded that higher risk is found in high frequency models than the low frequency model. Another study by Liu et al. (2019) assessed the effect of crude oil price uncertainty on three major markets of China, i.e., stock, commodity and foreign exchange. Meng et al. (2020) established the spillover effect of global crude price fluctuation on commodity market. Their study concluded the presence of asymmetric spillover effects, with downside spillover higher than the upside spillover.

In view of the mixed outcomes of extant empirical literature, this paper exhaustively explores volatility spillover of three energy commodities and investigates the resemblances and disparities of spillover in the Chinese and European stock markets. The three energy commodities which are considered in this study in light of their growing prominence in commodity markets are: crude oil, natural gas and CO2 emission. Natural gas has been gaining importance as it is cleaner and emits lesser greenhouse gas (GHG) emissions, outperforming other energy commodities in major industries like residential, industrial, power production, in terms of its utility. Crude oil is considered precious as an energy commodity that serves as a vital raw material in electricity generation and is crucial for industries worldwide. As an answer to the GHG emission problem, CO2 emission is emerging as a crucial commodity in the form of crude oil, natural gas, and coal usages (Fan et al., 2017). Import and export of these commodities are bound to have significant ramifications on equity market. On the global level, the World Population Review (2022) has revealed China, Europe and the US as the three leading energy consumers in the top-50 list of countries in the world, having intakes of 145.56EJ, 94.39EJ and 87.79EJ respectively. China has emerged as a major centre for energy trade while Europe has surpassed the US in terms of importing energy commodities, with its energy needs being fulfilled by non-EU member countries including Russia. Therefore, due to their empirical prominence, this study has chosen Shanghai stock exchange – the largest stock exchange of China, and Euronext – the pan-European stock exchange that connects European economies to global capital markets, as proxies of the Chinese and the European stock markets, respectively.

Extant literature is primarily focussed on connectedness between energy commodities and stock markets, missing to document the impact of risk transmission on investor portfolios. This study, therefore, explores connectedness of volatility in both time and frequency domains and contributes to the existing literature in three ways. First, it investigates spillovers of three prominent energy commodities in two major stock markets, using the underpinnings of Diebold-Yilmaz (2012) and Barunik-Krehlik (2017) models in one particular study. Second, it analyses spillovers between energy commodities (crude oil, natural gas and CO2 emissions) on Chinese and European indices using the Diebold-Yilmaz (2012) approach in the time domain, that enables to quantify the contribution of each asset to total market volatility, inferring the net transmitters and net receivers of volatility. Third, it additionally applies the Barunik-Krehlik (2017) model to investigate spillovers in the frequency domain and provides insights into time horizons during which the different spillovers play, proposing effective mitigation of risk by holding assets for shorter time periods against longer time durations. Moreover, given the scarce studies exploring the link between natural gas, carbon emissions and stock markets, the results of this study will provide greater understanding of energy commodities and stock market relationship to recognize the possible risks of transmissions. Also, since the integration of financial markets necessitates the portfolio managers' awareness of the diversification benefits of energy commodities, this study provides new understanding of energy commodities and their nexus with the financial markets and hence enable portfolio managers to make better comprehensions of the impact of changes in energy commodities on the risk, return characteristics of their investor's portfolios.

The remaining paper is structured as follows: Section 2 conducts a detailed review on spillover or dynamic linkages of energy commodity, stock market and other asset classes. Section 3 discusses data and the econometric model applied, while Section 4 discusses the empirical results and Section 5 outlines conclusion and policy implications.

2. Literature review

The correlation between stock markets and oil price is essential to policymakers and financial investors. The portfolio strategies of investors are associated with connectedness between financial assets and investors. In other words, diverse asset classes are expected to have cross-market influences, and this supports market participants to have different hedging strategies. Several occurrences between 2009 and 2019 have affected both energy and stock markets and numerous studies have investigated the linkage between these two markets. Further, Kling (1985) conducted a study on oil price volatility and the US stock market and exhibited a negative relationship of return on stock market with crude oil price. Likewise, Jones and Kaul (1996) evaluated the reactions of the US, the UK, Canada and

Japan to crude oil price movements and noticed some impact of the oil price variations on return of these select stock markets. Malik and Hammoudeh (2007) noticed strong connectedness of uncertainty and shock amongst crude oil, the US equity and the Gulf equity markets. Next, Choi and Hammoudeh (2010) employed multivariate DCC and observed a rise of S&P 500 index in connection with commodities (namely, gold, copper, silver, Brent oil and WTI oil) since 2003.

While historical literature establishes the interdependence of crude oil and stock market, recent literature focuses on their correlation in the volatility phase as fluctuations in the oil price and the equity market are significant factors in the assessment of the financial risk of the market and asset pricing. Bastianin et al. (2016) highlighted the significance of the cohesive relationship of financial volatility with crude oil prices due to impact of risk management and the design of suitable macroeconomic policies related to energy. Due to its ability to influence a company's bottom line and its inadvertent bearing on the business cycles, crude oil also contributes to stock market volatility, hence raising an associated question whether crude oil price is exogenous *vis a vis* fluctuation in equity market. Bastianin et al. (2016) proposed that initial studies might have unsuccessfully represented the nexus between the two variables because crude oil was deemed exogenic in these studies. Conversely, latest studies (e.g., Economou, 2016; Arezki et al., 2017) have acknowledged that the price of crude oil is ascertained by demand and supply components, and it is more appropriate to consider them as endogenic.

Various studies across the world have examined the relationship and effects of stock markets on energy prices and vice versa. In the earlier stage, Sadorsky (1999) applied VAR to examine linkage between S&P 500 index and monthly oil prices. The empirical proof implies that oil price shock propels S&P 500 equity return. Sadorsky (2003) used monthly and daily data from July 1986 to December 2000 and discovered that conditional volatility of oil price had a major influence on technology prices. Onour and Sergi (2010) emphasized that the volatility in oil price affects stock price and found the connectedness of S&P 500 index with the GCC stock markets. Filis et al. (2011) applied time varying approach to analyse the association of stock market shock with oil price and found robust correlation between these two markets. Similarly, Zhang and Asche (2015) identified a linkage of oil price with the Nordic stock exchange. Ma et.al. (2020) established the linkage structure model of China's energy market, capital market and carbon emission trading market by applying the DCC-MVGARCH model to investigate the linkage mechanism of the three markets. Lin and Chen (2019) explored the association and volatility spillovers amongst stock market of NEC, Beijing CET market and coal market by applying VAR (1)-DCC-GARCH(1,1) model and VAR(1)-BEKK-AGARCH(1,1) model. Further, Chebbi et al. (2020) studied the dynamic association between the Islamic index and energy commodities, and recommended robust association between the stock index and commodity returns, signifying financialization of commodity markets. Xiao and Wang (2020) however observed that there are nonlinear bidirectional causative exchanges and consequential knowledge transfers of equity market with crude oil price.

There are existing studies on association of energy commodities between equity market of South-East Asian economies. For instance, Hussin et al. (2012) found that the EMAS Islamic law index and FTSE Bursa Malaysia move positively with oil market. Ghorbel et al. (2014) observed positive temporal relationship between oil, Malaysian and Indonesian stock markets through the financial crisis of 2008–09. Lou and Chen (2015) examined realised volatility forecasts for various time periods on the China Stock Index 300 using HAR model and found the model performing best in mid-term and long term. Chen and Lv (2015) investigated the asymptotic reliance among the Chinese stock market and the world crude oil market centred on the Extreme Value Theory (EVT) and observed a positive extremal reliance. EVT adequately encapsulates the Chinese special oil price adjustment process. Fang et al. (2018) examined the cross-correlations among CO2 emission allowance and stock series by applying multifractal detrended cross-correlation analysis (MF-DCCA), thereby observing that the cross-correlation is multifractal in Chinese and European markets. Liu et al. (2019) assessed the dynamic linkage of risk and expressed that in a number of major events, China's macro-financial risks were significantly plagued by international fossil fuel movements. Yousaf and Hassan (2019) assessed volatility spillover and returns among emergent Asian stock markets and crude oil in the course of the Chinese stock market collapse of 2015. The empirical results showed a certain underlying impact from crude oil price shifts to the widely held stock markets. Wei et al. (2019) disclosed effects of future oil stock on the Chinese equity market significantly. Likewise, Zhu et al. (2020) investigated the volatility spillover impact of carbon and electricity markets, and pointed out more risk in high frequency models than those in medium and low frequency models. More recently, Wu et al. (2022) used the Diebold-Yilmaz and Barunik-Krehlik approaches to methodically scrutinise the dynamic frequency spillovers amid carbon emission trading (CET), fossil energy and sectoral stock markets in China. The findings reveal that the short-term (no more than 30 days) spillovers dictate both the total spillover and the net spillovers of the CET markets. Also, the net pairwise spillovers of CET with the stock markets and the same with the fossil energy markets are negative or nearly negative, and the former is recorded to be weaker than the latter.

Some studies on volatility spillover have also explored the European financial markets and energy commodities. For instance, Arouri et al. (2011) employed VAR-GARCH model to explore the sector-level propagation of fluctuations between the European and the US oil prices and financial markets. Unidirectional association is witnessed from oil market to the European financial market while bidirectional spillover is found from oil to the US financial market. On the other hand, Arouri et al. (2012) analyzed the volatility spillover of oil prices with the European financial markets, using the data spanning from January 1998 to December 2009 of both cumulative and sectoral indices. Their study exhibited volatility connectedness in these markets and indicated that improved insight into these relationships is crucial for portfolio management. Khalfaoui et al. (2015) undertook a study on the nexus of WTI with return on stock market using various GARCH models in G7 countries, and observed a significant level of connectedness. More recently, Tan et al. (2020) used modified error variance decomposition and network diagrams to hold a methodical analysis of the way information from other markets affects the European carbon market, and stressed that the type of information spillover varies over the time horizons. Many other authors such as Huang et al. (1996), Sadorsky (1999), Park and Ratti (2008), Apergis and Miller (2009), Wang and Liu (2016), Ashok et al. (2022), Goodell et al. (2022), Yadav et al. (2022), among others, studied oil stocks and emphasised it as a crucial portfolio component.

To the best of our awareness, limited literature is available on exploring the dynamic linkages between oil price movements and stock indices in the European and the Chinese markets together. Although many researchers have explored the links between crude oil and stock markets in the last two decades, studies on dynamic linkage of natural gas and CO2 emissions with stock markets are scarce. Owing to the integration of financial markets, diversification benefits of energy commodities should be known to portfolio managers. Most of the existing literature is focussed on association between energy commodities and stock markets, disregarding the impact of risk transmission on investor portfolios. Therefore, a new understanding of energy commodities and their relationship with financial markets need to be developed. In consideration of these gap areas, this study intends to enrich the literature and assist portfolio managers in making better comprehensions of the impact of changes in energy commodities on the risk, return characteristics of their investor's portfolios.

3. Data and econometric model

3.1. Data

The study examines the dynamic linkages from energy commodities to Chinese and European stock exchanges, selecting Shanghai stock exchange – the largest stock exchange of China, and Euronext – the pan-European stock exchange connecting European economies to global capital markets as proxies, respectively. The World Population Review (2022) has revealed China, Europe and the US as the three-leading energy consumers in the top-50 list of countries in the world. China has emerged as a major centre for energy trade while Europe has surpassed US in terms of importing energy commodities. China is currently the world's largest carbon emitter (30.7% of global emissions), fuelled by its growing demand for fossil fuels for electricity generation and manufacturing and exceeding consumption by the US (13.8%) (Jiang and Chen, 2022). The energy commodities are proxied by crude oil index, natural gas index and carbon emissions index (spot prices), as highlighted in Table 1.

The daily closing prices of constituent series is collected from 16 December 2010–29 December 2022. This is followed by conversion of the raw series into return (log) series, calculating the log differences between prices of two consecutive days (Khera et al., 2022). The conversion is done by using the following formula:

$$R_{i,t} = \log\left(\frac{Y_{i,t}}{(Y_{i,t-1})}\right)$$

Where R_{it} is representative of return(log) series at time t, whereas Y_{it-1} and Y_{it} represents the daily observation value(closing) of i^{th} fund on consecutive days. The data description of these constituent markets is presented in Table 1 as follows:

3.2. Econometric model

Our methodology follows a three-step framework. Firstly, we employ granger causality test to identify the direction of causality among the variables. Secondly, we apply the Dynamic Conditional Correlation (DCC) model to identify time varying correlations of asset returns to ascertain the behaviour of asset prices and their co-movements. Such associations have important implications in portfolio diversification and risk management. We eventually apply the Diebold-Yilmaz (2012) model to quantify the connectedness and to identify directional and net spillovers, followed by Barunik-Krehlik (2017) frequency domain spillover index that decomposes contribution of each asset to global volatility at different frequencies. Further details of these models are provided below:

3.2.1. Granger causality method

Granger causality (GC), one of the most significant tools of analysis to assess the causal linkages between variables (Roebroeck, 2015). It helps to identify the direction of causality in a time series data, determining whether shift in one series influences other or not (unidirectional, bidirectional and none). If X Granger causes Y, it suggests that the past value of X contains important information that helps to predict Y (Friston et al., 2003). GC estimates variations in the model error in case of inclusion of a new series, to focus on valuing the dependent signal (Granger, 1969). GC test influences without the requirement of any priori hypothesis. This is centred on assumptions that: (a) cause occurs before its effect, and (b) cause can lead to distinctive knowledge of future values. The series must be stationary to employ this method; if the series is not stationary, we have to convert series into stationary series either by detrending or differencing prior to applying this test. The GC equation can be presented as follows:

Table 1
Data description of constituent series.

Market	Asset	Acronyms	Source
Energy commodity	Crude oil	RCO	Bloomberg
Energy commodity	Natural Gas	RNG	Bloomberg
Energy commodity	Carbon emissions	RCE	Bloomberg
Chinese stock exchange	Shanghai Stock Exchange	RSSE	Bloomberg
European stock exchange	Euronext	XLE	Bloomberg

Source: Authors' own presentation

$$X_{(t)} = \sum_{j=1}^{p} A_{11,j}; X_{(t-j)} + \sum_{j=1}^{p} A_{12,j}; Y_{(t-j)} + \varepsilon_{1(t)} \tag{1}$$

$$Y_{(t)} = \sum_{j=1}^{p} A_{21,j}; X_{(t-j)} + \sum_{j=1}^{p} A_{22,j}; Y_{(t-j)} + \varepsilon_{2(t)} \tag{2}$$

Where, p signifies the lag of variables considered in this paper.

3.2.2. Dynamic conditional correlation

Dynamic Conditional Correlation (DCC) is one of the bivariate or multivariate models that assists in complex financial decisions like risk management, hedging and portfolio optimization and asset pricing after getting the dynamic linkages or spillover from one market to another market or one series into another series. It is a measure of the degree of volatility, as developed by Engle (2002). It captures the time varying correlations of asset returns. This model is applied in two different stages: the first stage consists of determining the parameters of GARCH and the residuals derived from GARCH are used in DCC model to determine the correlation in the second stage. To apply DCC model, conditions like presence of volatility clustering and ARCH effect must be satisfied. Further, the value of both ARCH and GARCH terms should be significant, with their sum less than one. The model is depicted as $H_t = D_t\ R_t\ D_t$, where, H_t is the estimator of conditional correlation, D_t signifies conditional standard deviation while R_t denotes conditional correlation. The equation can be shown as follows:

$$R_t = Q_t^* - 1Q_t\ Q_t^* - 1 \tag{3}$$

Where, $Qt = (1 - a - b)Q + a\varepsilon t - 1\ \varepsilon tT - 1 + b\ Qt - 1$ in which Q depicts an unconditional covariance matrix obtained from error, i.e., expressed as $\mathrm{Cov}[\varepsilon_t\varepsilon tT]$. Qt^* denotes diagonal matrix which is represented as diag ($q1/211t$, $q1/222t$,.,$q1/2mnt$). In this equation, a and b denote DCC parameters in form of short and long run spillover respectively.

3.2.3. Diebold and Yilmaz (2012)

In this study, after investigating the spillover effect, Diebold and Yilmaz (2012) and Barunik and Krehlik (2017) are employed to analyze dynamic connectedness among variables. Diebold and Yilmaz (2012) is a model for quantifying connectedness, measuring forecast error variance breakdown. This method focusses on variance composition and captures both directional and net spillovers between markets. The forecasted error variance of i^{th} series is disintegrated and is attributed to other variables examined in the system. A vector autoregressive model is fitted initially for a multivariate series, then H period forecast is created followed by breakdown of the forecast error variance with respect to each variable for shocks from similar or other constituent series at time t. d^H is used to denote the ij^{th} H-step forecast error variance, i.e d^H is representative of the *ijij*.

fraction of variable i's H-step, due to the forecast error variance in variable j. It is to be noted that $d^H, i, j = 1, \cdots N$, $if = j$, while $if = j$, emphasize that the connectedness measured in the study are “non-own” or “cross”.

3.2.4. Barunik and Krehlik (2017)

We employ spillover index methodology of Barunik and Krehlik (2017) to identify time–frequency dynamics of return connectedness. This method is an extension of the spillover.

index of Diebold and Yilmaz (2012) since it assesses directional spillovers at multiple frequencies. It helps to identify the largest contributor/receiver of spillovers and recognizes the source of contagion to enhance investment decisions. Using Barunik and Krehlik method, this study explains the frequency dynamics of spillover and decomposition of variance during short, medium and long-run. enabling decomposition of the contribution of each asset to total volatility at varying frequencies. Connectedness present at high frequencies is suggestive of instant information transmission by stock markets, with movement in one asset having an impact in the short term. Connectedness present at lower frequencies, suggests continuing shocks transferred for longer periods. Barunik and Krehlik model measures the frequency dynamics of connectedness, describing the spectral formulation of variance decomposing; hence, we consider a frequency response function, $\Psi\ e{-}i\omega = \sum e{-}i\omega h\Psi h$, which is obtained as a Fourier transform of the coefficients shown as below:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1} \sum_{h=0}^{\infty} \left(\left| \Psi(e^{-iw})\Sigma)_{j,k} \right|^2 \right)}{\sum_{h=0}^{\infty} (\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw}))_{jj}} \tag{4}$$

where, $\Psi\ e{-}i\omega = \sum h\ e{-}i\omega h\Psi h$ are the Fourier transform of the impulse response function Ψ and $(f(\omega))j,k$ denotes the portion of the spectrum of the j-th variable under frequency ω due to shocks in the kth variable. As the denominator holds the spectrum of the j-th variable under frequency ω, we can interpret the above Equation as the quantity within the frequency causation. To obtain the generalized decomposition of variance decompositions under frequency ω, we weigh the function $(f(\omega))j,k$ by the frequency share of the variance of the j-th variable. We define weighting function as in form of following equation:

$$\Gamma_j(\omega) = \frac{\left(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw})\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi(\omega^{-iw})\Sigma\Psi'(e^{+iw})\right)_{jj}d\lambda'} \tag{5}$$

The above equation shows the power of the j-th ums of the frequencies to a constant value of 2π. We should note that although the Fourier transform of the impulse response is a complex number value, the generalized factor spectrum is the squared coefficients of the weighted complex numbers.

4. Empirical estimation and discussion

In this section, we document the results of preliminary analysis, GC, DCC, Diebold and Yilmaz (2012), and Barunik and Krehlik (2017) as below:

4.1. Preliminary analysis and Granger causality (GC)

The descriptive statistics of the energy commodities (i.e., crude oil, natural gas and CO2 emissions), Shanghai stock exchange and Euronext is exhibited in Table 2. We notice that each series is spotted with positive average return except the return of carbon emissions (RCE) which is negative (−0.3268). It is evident that RCE is the most volatile (in terms of riskiness) due to its high standard deviation (0.055), followed by return on natural gas (RNG) and crude oil (RCO). Based on skewness, the results show that except for CO2 emissions, the return on all the variables are left-skewed. This indicates an asymmetric tail that expands to negative value. Each series is right-skewed that denotes each series is higher peaked and contains fatter tails. Thus, skewness and kurtosis represents that examined series are not normally distributed, and the same has been verified by the result obtained from Jarque–Bera test. Since the presence of stationarity is required to check the dynamic connectedness, Augmented Dickey Fuller (ADF) test is applied to confirm the same. As evident in Table 2, the P-value of ADF test is less than 0.05 of each return series, confirming that series is integrated at I(0). Additionally, Phillips Perron (PP) test is employed to check the stationarity which is also in the similar line of ADF test. Next, GC test is used to examine the cause-and-effect relationship amongst the return series.

Table 3 provides GC results of the constituent series. GC is employed to analyze the direction of information between variables (Gupta and Guidi, 2012). It can be observed from the Table that neither crude oil (RCO) nor Shanghai Stock Exchange (RSSE) Granger causes each other. Similarly, natural gas (RNG) does not Granger cause Shanghai Stock Exchange (RSSE) and RSSE also does not Granger cause RNG. The causality between carbon emissions (RCE) and Shanghai Stock Exchange (RSSE) is unidirectional as RCE Granger causes RSSE while RSSE does not Granger cause RCE. The causality between crude oil (RCO) and European stock exchange (REN) is also found to be unidirectional, i.e., RCO Granger causes REN but REN does not Granger cause RCO. There is no cause and effect between Natural Gas (RNG) and European Stock market (REN). Similarly, there is no cause and effect between Carbon Emissions (RCE) and European Stock market (REN).

In sum, we find that none of the energy commodities have bidirectional causality with either of the two stock exchanges (RSSE and REN). Crude oil (RCO) and Carbon emissions (RCE) are the only two energy commodities that exhibit unidirectional impact on the European Stock exchange (REN) and Shanghai Stock Exchange (SSE) respectively.

Fig. 1 presents the raw price series of crude oil, natural gas, carbon emission, Chinese stock exchange and European stock exchange respectively. These series follow stochastic trend based on data from December 16, 2010 to December 29, 2022 as there is no constant change. We notice that energy markets (crude oil, natural gas and carbon emission) are witnessed with high fluctuation during Russia-Ukraine invasion. Further, these raw series have been converted into log difference to remove the stochastic trend which is log return series presented in Fig. 2. It seems that each series is mean reverting.

Next, we apply DCC-GARCH to investigate the spillover effect from energy commodities to European and Chinese stock exchanges which is presented in Table 4. Referring to the result of Table 4, 'Mean' denotes overall mean whereas 'Constant' signifies the intercept term. Further, ARCH effect (shown as a1) denotes the effect of the previous disturbance while GARCH (b1) signifies the effect of

Table 2
Descriptive Statistics of constituent variables.

	RCO	RNG	RCE	RSSE	REN
Mean	-0.3268	-0.4571	-0.5573	-0.1160	-0.1275
Minimum	0.2822	0.1805	0.6306	0.0771	0.0988
Maximum	-0.0001	0.0002	0.0003	0.0000	0.0002
Std. Dev.	0.0277	0.0338	0.0550	0.0137	0.0119
Skewness	-0.9074	-1.1621	0.8836	-1.0762	-0.6760
Ex. Kurtosis	30.1592	14.1564	35.6932	9.1963	9.8366
Jarque-Bera Test	111157 (0.0000)* **	25081 (0.0000)* **	155615 (0.0000)* **	10873 (0.0000)* **	12016 (0.0000)* **
ADF Test	-12.45 (0.0100)* *	-14.08 (0.0000)* **	-14.82 (0.0100)* *	-13.97 (0.0100)* **	-14.06 (0.0000)* **
PP Test	0.0000 * **	0.0000 * **	0.0000 * **	0.0000 * **	0.0000 * **

Source: Authors' own presentation.
Notes: * * and * ** denotes the significance level at 1% and 0.1% respectively.

Table 3
Results of Granger causality.

Ho	F-value	P-value
RCO does not → RSSE	0.8100	0.4025
RSSE does not → RCO	1.6129	0.1852
RNG does not → RSSE	2.3068	0.0559
RSSE does not → RNG	0.6141	0.6525
RCE does not → RSSE	2.578	0.0357 *
RSSE does not → RCE	0.2214	0.9266
RCO does not →REN	3.1643	0.0132 *
REN does not →RCO	0.9570	0.4300
RNG does not → REN	0.3875	0.8177
REN does not → RNG	2.2638	0.0600
RCE does not → REN	0.9805	0.4397
REN does not → RCE	0.2930	0.8702

Source: Authors' own presentation.
Notes: → indicates Granger causing, * indicates significant level at 5% level.

previous variance. As regards with the result of DCC from return on crude oil (RCO) to return on Shanghai Stock Exchange (RSSE) shown in Table 4(A), ARCH and GARCH parameters of the RCO are significant, indicating the persistence of volatility. Further, GARCH term of Shanghai Stock exchange is significant while ARCH is not significant, implying the volatility persistence in the long term but absence in short term. It is noticed that the summation of a1 and b1 is less than 1 which signifies that stationarity and decay in volatility persistence over the time exist. Further, Chinese stock exchange is witnessed with least sum of alpha 1 and beta 1 (0.9793) that indicates the fast decay in volatility persistence while crude oil has slow decay in volatility persistence as it is backed by 0.9883 sum of a1 and b1. The reason for the volatility persistence could be due to the equity market determinants and decrease in the variability of economic information. The dcc a1 is insignificant while dcc b1 is significant. The result reveals that there is no spillover from RCO to RSSE in short run while the spillover exists in long run.

With reference to results of DCC from return on natural gas (RNG) to return on Shanghai Stock Exchange (RSSE) presented in Table 4(B), GARCH terms of both return on natural gas (RNG) and RSSE are significant, while ARCH terms are not significant, implying the volatility persistence in long run but absent in the short term. We notice that the summation of alpha 1 and beta 1 is less than 1 that signifies the presence of stationarity and decay in volatility persistence. RNG has less decay in volatility persistence whereas Chinese stock market has fast decay. The dcc a1 is significant while dcc b1 is insignificant. It indicates that there is spillover effect from RNG to RSSE in short run only. Moreover, the results of DCC from return on carbon emissions (RCE) to return on Shanghai Stock Exchange (RSSE) is presented in Table 4(C). ARCH and GARCH parameters of RCE are significant, implying persistence in volatility both over the shorter and the longer term. GARCH term of RSSE is only significant that indicates volatility persistence over the long run but absent in the short run. Sum of alpha 1 and beta 1 is less than 1, signifying the stationarity and decay in volatility persistence. Further, RCE and Chinese stock market are witnessed with slow and fast decay in volatility persistence because of its summation of alpha 1 and beta 1 respectively. It is evident from the table that dcc a1 is insignificant while dcc b1 is significant, the spillover or dynamic linkage is present from RCE to RSSE only in long run not in short run.

The result of DCC from return on crude oil (RCO) to return on European stock exchange (REN) is presented in Table 4(D). ARCH and GARCH terms of both RCO and REN are significant, implying volatility persistence over the longer as well as shorter time span. As summation of alpha 1 and beta 1 is less than 1, it can be said that there is stationarity and decay in volatility persistence. On this note, it is noticed that European stock has slow decay while RCO has fast decay in volatility persistence. The reason for the volatility persistence could be due to the equity markets determinants and decrease in the variability of economic information. The dcc a1 is insignificant while dcc b1 is significant indicating absence of spillover effect from crude oil to REN in short term while presence in the long term.

With reference to the result of DCC from return on natural gas (RNG) to return on European Stock Exchange (REN) in Table 4(E), GARCH terms of RNG are significant, while ARCH term is insignificant, which imply the volatility persistence over the long time span but absent in the short span. The sum of alpha 1 and beta 1 is less than one, signifying stationarity and decay in volatility persistence. RNG and REN have high and low summation of alpha 1 and beta 1; the same denotes that RNG is slow and REN is fast in capturing the decay in their volatility persistence. The reason for the volatility persistence could be due to the equity markets determinants and decrease in the variability of economic information. The dcc a1 is insignificant while dcc b1 is significant implying spillover effect from RNG to REN in long run and no spillover effect in the short run.

The results obtained from the DCC of return on carbon emissions (RCE) to return on European Stock Exchange (REN) is displayed in Table 4(F). The RCE and REN are spotted with significant ARCH and GARCH term ensuring the presence of volatility persistence. Additionally these two markets have less than one summation of alpha 1 and beta 1 which signifies stationarity and decay in volatility persistence. The dcc a1 is insignificant while dcc b1 is significant implying spillover effect from RCE to REN in the long term and no spillover effect in the short term.

Further, Table 5 presents an average spillover amongst energy markets, Chinese stock exchange and European Stock Exchange (REN) employing Diebold and Yilmaz (2012) model. In this table, within and cross-market spillovers are represented by diagonal and off-diagonal elements of the matrix respectively. 'From' in last column signifies the mean spillover derived from the network connections considered under examination while values in the sixth row "To" depicts the average spillover contributed to constituent

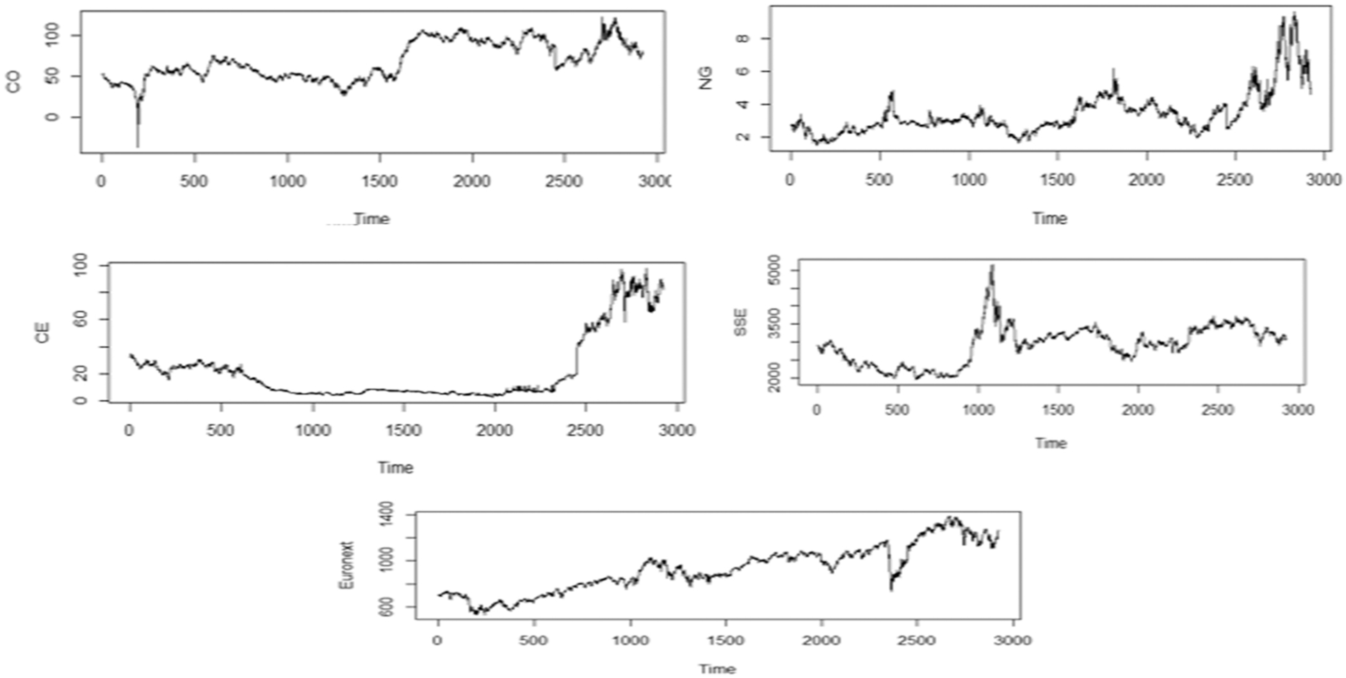

Fig. 1. Graphical display of raw series.

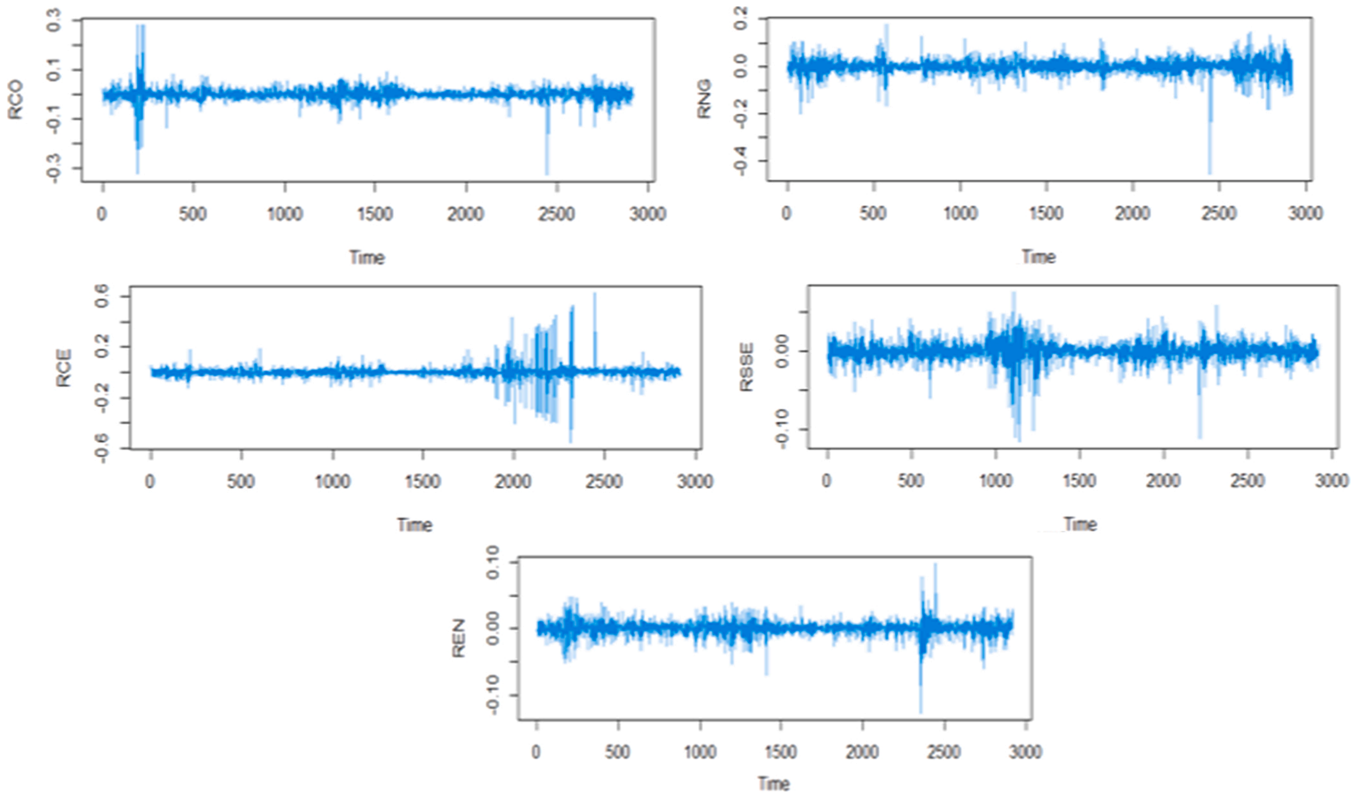

Fig. 2. Graphical presentation of log return series.

Table 4
Dynamic Conditional Correlation Results.

4 (A) DCC GARCH from RCO to RSSE				
Variables	Coefficient	Std. Error	t-statistics	p-value
[RCO]. Mean	-0.0001	0.0003	-0.4169	0.6768
[RCO]. Constant	0.0000	0.0000	0.6556	0.5121
[RCO]. a1a1	0.1242	0.0265	4.6808	0.0000 * **
[RCO]. b1b1	0.8641	0.0318	27.1983	0.0000 * **
[RSSE]. Mean	0.0002	0.0004	0.5413	0.5883
[RSSE]. Constant	0.0000	0.0000	0.1244	0.9010
[RSSE]. a1	0.0848	0.1681	0.5045	0.6139
[RSSE]. b1	0.8945	0.0350	25.5876	0.0000 * **
dcca1	0.0059	0.0096	0.6208	0.5347
dccb1	0.9270	0.0691	13.4130	0.0000 * **
4(B) DCC GARCH of RNG with RSSE				
[RCO]. Mean	0.0001	0.0006	0.1946	0.8457
[RCO]. Constant	0.0000	0.0001	0.0898	0.9285
[RCO]. a1	0.0853	0.2554	0.3339	0.7384
[RCO]. b1	0.9051	0.0280	32.2750	0.0000 * **
[RSSE]. Mean	0.0002	0.0004	0.5608	0.5750
[RSSE]. Constant	0.0000	0.0000	0.1347	0.8929
[RSSE]. a1	0.0846	0.1542	0.5488	0.5831
[RSSE]. b1	0.8948	0.0322	27.7529	0.0000 * **
dcca1	0.0512	0.0243	2.1041	0.0354 *
dccb1	0.3021	0.1673	1.8062	0.0709
4(C) DCC GARCH of RCE with RSSE				
[RCO]. Mean	0.0007	0.0006	-1.3468	0.1781
[RCO]. Constant	0.0000	0.0000	1.0283	0.3038
[RCO]. a1	0.0954	0.0116	8.2556	0.0000 * **
[RCO]. b1	0.9036	0.0175	51.5825	0.0000 * **
[RSSE]. Mean	0.0002	0.0004	0.5609	0.5749
[RSSE]. Constant	0.0000	0.0000	0.1346	0.8929
[RSSE]. a1	0.0846	0.1542	0.5487	0.5832
[RSSE]. b1	0.8948	0.0322	27.7474	0.0000 * **
dcca1	0.0045	0.0090	0.4995	0.6174
dccb1	0.8611	0.0989	8.7022	0.0000 * **
4(D) DCC GARCH of RCO with REN				
[RCO]. Mean	-0.0001	0.0003	-0.4185	0.6756
[RCO]. Constant	0.0000	0.0000	0.6554	0.5122
[RCO]. a1	0.1242	0.0266	4.6756	0.0000 * **
[RCO]. b1	0.8641	0.0317	27.2258	0.0000 * **
[RSSE]. Mean	0.0006	0.0002	3.0910	0.0020 * **
[RSSE]. Constant	0.0000	0.0000	0.6974	0.4855
[RSSE]. a1	0.1468	0.0270	5.4367	0.0000 * **
[RSSE]. b1	0.8303	0.0490	16.9367	0.0000 * **
dcca1	0.0000	0.0001	0.0004	0.9997
dccb1	0.9256	0.0907	10.2033	0.0000 * **
4(E) DCC GARCH of RNG with REN				
[RCO]. Mean	0.0001	0.0006	0.1946	0.8457
[RCO]. Constant	0.0000	0.0001	0.0898	0.9285
[RCO]. a1	0.0853	0.2554	0.3339	0.7385
[RCO]. b1	0.9051	0.0280	32.2693	0.0000 * **
[RSSE]. Mean	0.0006	0.0002	3.0820	0.0021 * **
[RSSE]. Constant	0.0000	0.0000	0.7034	0.4818
[RSSE]. a1	0.1464	0.0269	5.4409	0.0000 * **
[RSSE]. b1	0.8307	0.0486	17.0859	0.0000 * **
dcca1	0.0000	0.0003	0.0001	0.9999
dccb1	0.9279	0.2832	3.2769	0.0010 * **
4(F) DCC GARCH of RCE with REN				
[RCO]. Mean	-0.0007	0.0006	-1.3461	0.1783
[RCO]. Constant	0.0000	0.0000	1.0286	0.3037
[RCO]. a1	0.0954	0.0116	8.2558	0.0000 * **
[RCO]. b1	0.9036	0.0175	51.5796	0.0000 * **
[RSSE]. Mean	0.0006	0.0002	3.0825	0.0021 * **
[RSSE]. Constant	0.0000	0.0000	0.7034	0.4818
[RSSE]. a1	0.1464	0.0269	5.4413	0.0000 * **
[RSSE]. b1	0.8307	0.0486	17.0862	0.0000 * **
dcca1	0.0071	0.0088	0.8071	0.4196
dccb1	0.8679	0.1544	5.6209	0.0000 * **

Source: Author's own calculation.,
Notes: * and * ** denote the significance level at 5% and 0.1% respectively.

Table 5
Diebold-Yilmaz (2012) results of Frequency Connectedness.

	RCO	RNG	RCE	RSSE	REN	FROM
RCO	91.96	3.64	2.28	0.79	1.33	8.04
RNG	3.11	92.07	2.23	1.33	1.27	7.93
RCE	2.51	2.05	93.15	1.38	0.90	6.85
RSSE	1.06	1.31	1.19	95.78	0.66	4.22
REN	1.28	1.80	1.37	0.70	94.85	5.15
TO	7.96	8.80	7.07	4.20	4.16	32.19
NET	-0.08	0.86	0.22	-0.02	-0.98	

Source: Authors' own presentation

markets. As regards with this table, we notice that crude oil (RCO) is the highest receiver of the shocks with 8.04% followed by Natural gas (RNG). On the other hand, Chinese stock exchange (RSSE) is the least receiver of the shock.

Turning to the contribution of shocks, it is noticed that Natural gas (RNG) is witnessed with highest contributor (8.80) followed by crude oil (RCO) while European stock exchange (REN) is least contributor (4.16) of the shocks to network connection. Further, both stock exchanges (Chinese and European) are net receiver of the shocks as they receive more shocks than they contribute. In energy market, crude oil is net receiver (−0.8) while natural gas (RNG) and carbon emission (RCE) are net contributors of the shocks with 0.86 and 0.22 respectively. As regards with its own contribution of shocks, 91. 96% of RCO, 92.07% of RNG, 93.15% of RCE, 95.78% of RSSE and 94.85% of REN is attributed by their own shocks. Next, graphical representation of total shocks, received and contributed shocks are displayed in Figs. 3, 4 and 5 respectively. We notice that shock is high in each case (total, contribution and recipient) at the end of 2021 (COVID-19) and beginning of Russia- Ukraine invasion. However, there is no high connectedness during this invasion. It infers that Russia-Ukraine invasion does not push towards these examined markets towards large connectedness.

Additionally, to examine the spillover in two different frequency domains; one is from day 1 to day 4 (short term frequency connectedness) and other is from 4 days to infinity (long term frequency connectedness), we apply Barunik and Krehlic (2017) method, presented in Table 6(A) and 6(B). As regards with the table, "WTH" signifies within, "ABS" denotes the absolute, "From" refers to the spillover obtained from other series and "To" depicts the spillover contributed to other respective assets class or markets.

Referring to Table 6(A), it is observed that return on Euronext (REN) has highest return spillover (2.26%) derived from other series followed by return on natural gas (RNG) which is 1.13% in the short run. Clearly, return on crude oil (RCO) is contributing the maximum to the other series.

Further, return on Euronext (REN) has high frequency connectedness (4.34%) obtained from other series while return on crude oil (RCO) contributes more to the volatility spill over (7.21%) in the long run. From Barunik and Krehlic (2017) frequency-domain result, total connectedness of the five series is observed to be higher in long-run than in the short run suggesting reduced diversification opportunities in the long run.

5. Conclusions and policy implications

Commodities have emerged as a significant financial asset with distinguishable properties from the traditional asset classes. Several studies have incorporated raw materials in investment portfolios with other asset classes (Vivian and Wohar, 2012). Commodities are significant not only due to their usage but also since they are increasingly used as an asset class in form of investment alternatives. For

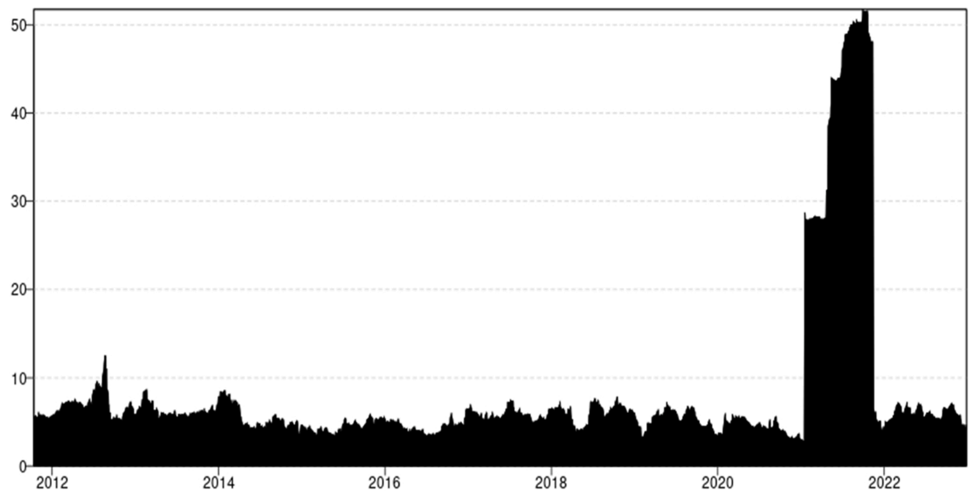

Fig. 3. Graphical representation of total connectedness.

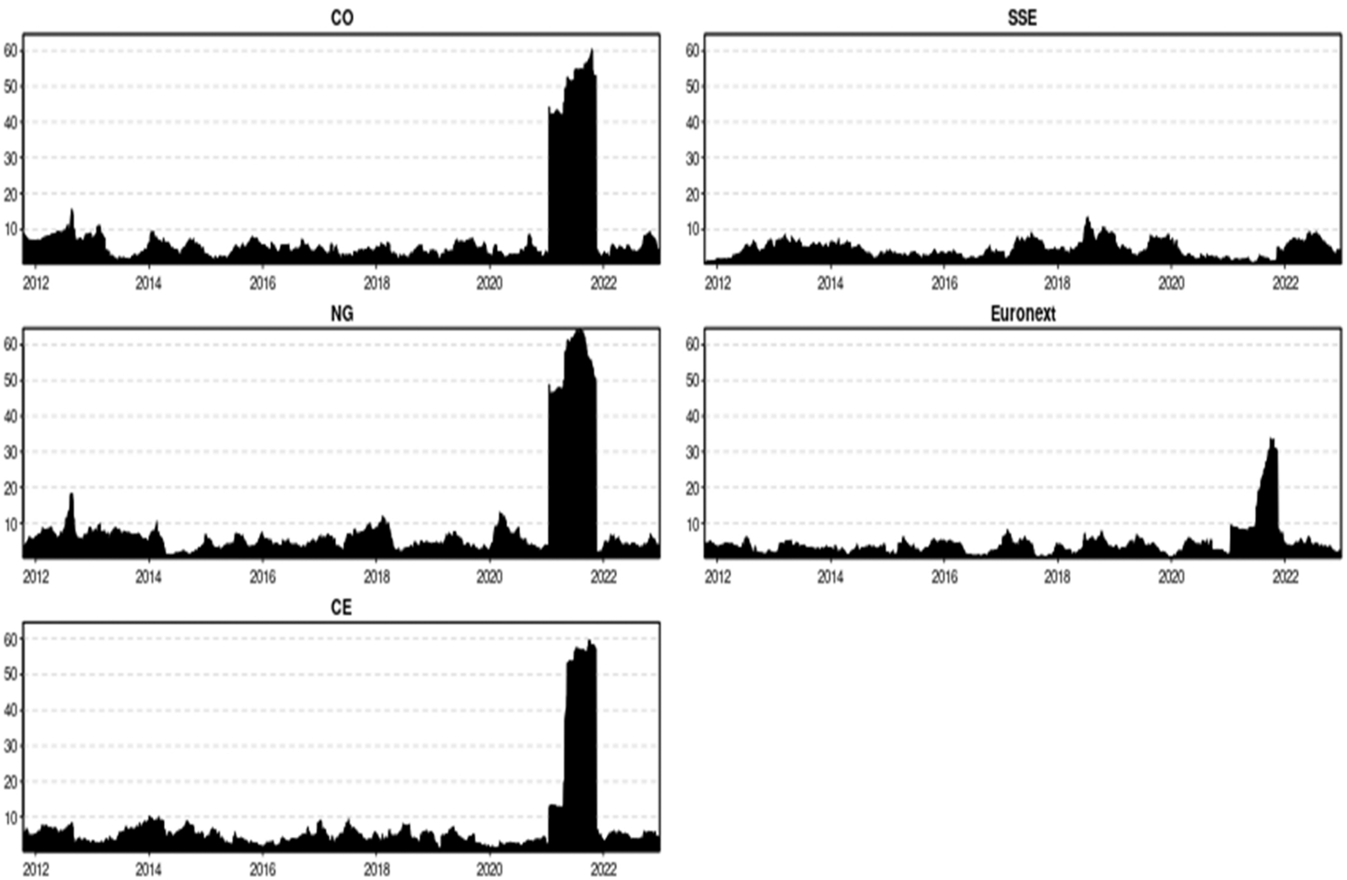

Fig. 4. Graphical representation of connectedness received from network connection.

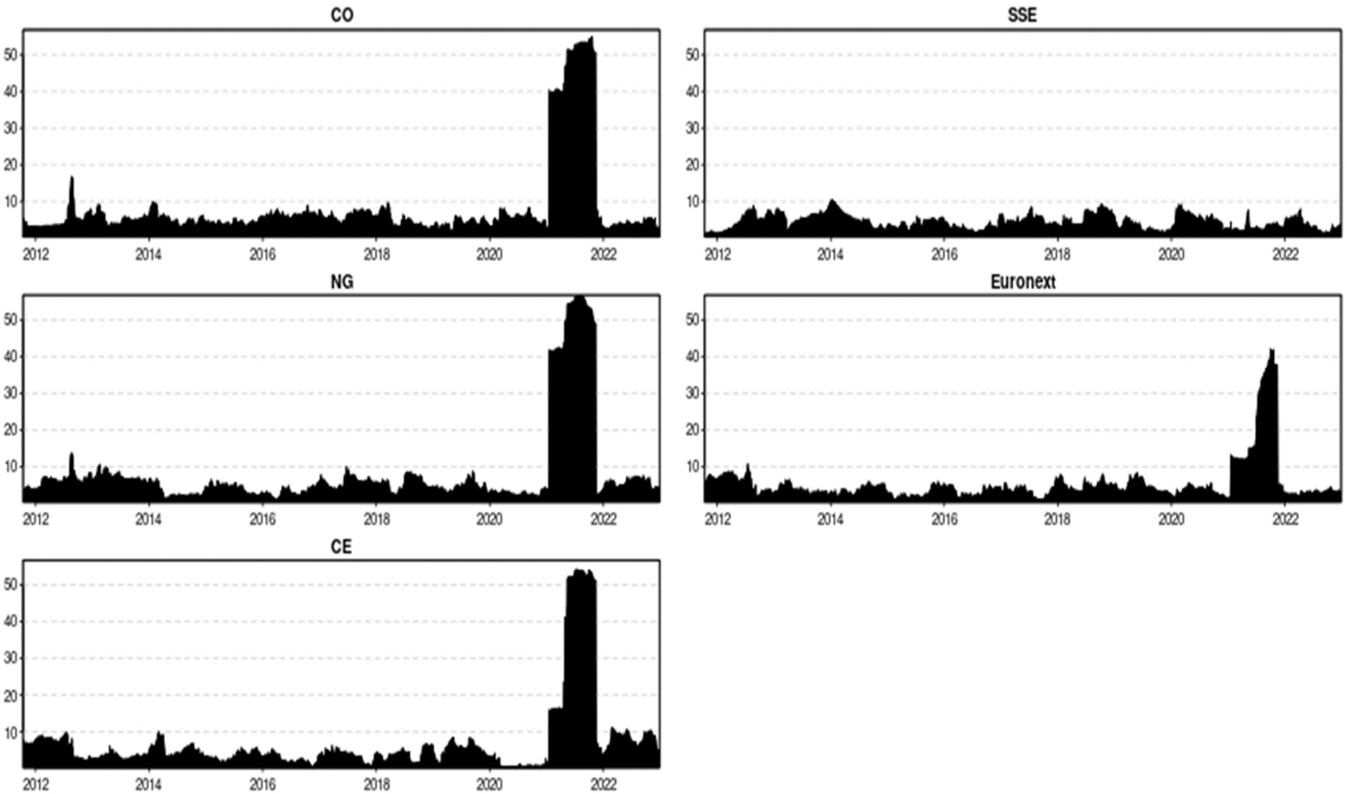

Fig. 5. Graphical representation of connectedness contributed to network connection.

Table 6 (A)
Frequency: Short term frequency connectedness (1–4 days).

	RCO	RNG	RCE	RSSE	REN	FROM_ABS	FROM_WITH
RCO	54.97	0.03	1.49	0.16	0.02	0.34	0.49
RNG	3.20	72.32	0.72	0.01	0.00	0.78	1.13
RCE	2.42	0.85	66.09	0.08	0.00	0.67	0.97
RSSE	0.03	0.94	0.24	70.80	0.00	0.24	0.35
REN	4.56	2.13	0.72	0.42	63.67	1.56	2.26
TO_ABS	2.04	0.79	0.63	0.13	0.00	3.60	
TO_WTH	2.95	1.14	0.92	0.19	0.01		5.21

Source: Authors' own presentation

Table 6(B)
Frequency: 4 days to infinity, long term frequency connectedness.

	RCO	RNG	RCE	RSSE	REN	TO_ABS	TO_WITH
RCO	41.73	0.03	1.39	0.16	0.01	0.32	1.04
RNG	1.30	22.22	0.24	0.00	0.00	0.31	1.00
RCE	4.38	0.32	25.78	0.08	0.00	0.96	3.10
RSSE	0.00	0.06	0.08	27.85	0.00	0.03	0.09
REN	5.44	0.71	0.50	0.04	21.81	1.34	4.34
TO_ABS	2.22	0.23	0.44	0.06	0.00	2.95	
TO_WITH	7.21	0.73	1.43	0.18	0.01		9.57

Source: Authors' own presentation

efficient risk measurement and management, understanding the connectedness of commodities on stock markets become imminent. A study of Wang and Wang (2019) have documented impact of energy commodities like crude oil (RCO), natural gas (RNG) and others on financial markets across the world. In this paper, we examine portfolio diversification opportunities by exploring spillover from energy commodities to the Chinese and European stock exchanges, in consideration of the negligible attempts that researchers have made so far to explore the link between natural gas (RNG), carbon emissions (RCE) and stock markets in understanding the nexus of equity market with energy market and recognising the possible risks of transmission.

We apply Granger causality, dynamic conditional correlation (DCC), Diebold-Yilmaz (2012) and Barunik-Krehlic (2017) test to scrutinise the dynamic linkages. As regards with Granger causality test, the return on carbon emission (RCE) Granger causes return on Shanghai stock exchange (RSSE) and return on crude oil (RCO) Granger causes return on Euronext (REN). DCC results exhibit dynamic linkages from return on natural gas (RNG) to return on Shanghai stock exchange (RSSE) in the short run while there are dynamic linkages from return on crude oil (RCO) and return on carbon emission (RCE) to return on Shanghai stock exchange (RSSE) in the long run. Similarly, the study establishes dynamic linkages from return of crude oil (RCO), natural gas (RNG), and carbon emission (RCE) to return on Euronext (REN), indicating increased probability of simultaneous loss in the long run than in the short run. Referring to the results of Diebold-Yielmaz (2012), we notice that crude oil (RCO) is the highest receiver of the shocks with 8.04% followed by Natural gas (RNG). On the other hand, Chinese stock exchange (RSSE) is the least receiver of the shock. Natural gas (RNG) is witnessed with highest contributor (8.80) followed by crude oil (RCO) while European stock exchange (REN) is least contributor (4.16) of the shocks to network connection. At last, Barunik and Krehlic (2017) implies that the total connectedness of constituent series is high in the longer run (9.57) than in the shorter run (5.21). Hence, for effective risk transmission, hedging and arbitrage opportunities, the study advocates investment for the shorter term than longer time periods.

The findings in this paper postulate some valuable inferences for portfolio managers, policy makers, financial managers, and investors in particular. Firstly, both carbon emissions (RCE) and crude oil (RCO) display significant connectedness with Shanghai Stock Exchange (RSSE) and European stock exchange (REN) respectively. This presents effective diversification and hedging opportunity to Chinese and European investors and advocates that these investors should focus on energy commodities to escape severe investment risks. Secondly, dynamic conditional correlation and volatility spillover results suggest that investors should diversify their portfolio in short run using stocks of RCE, RCO and RNG, as there is greater likelihood of losses in the longer run. Thirdly, results from the Diebold-Yilmaz (2012) identify crude oil (RCO) to be the highest volatility contributor to stock indices, hence it is advised that investors prudently invest in it especially during turbulent times. Lastly, findings from Barunik and Krehlic (2017) highlight greater connectedness in the longer periods, indicating higher volatility in the longer run. For effective risk transmission, this research paper thus advocates investors to hold carbon emission, crude oil and natural gas for relativelyshorter time periods only. It is because, the connectedness among these assets class is low and the same has been confirmed from dynamic conditional correlation.

Given that the focus of this study has been to examine the volatility spillover of commodities with select stock markets by applying a novel combination of dynamic conditional correlation (DCC), Diebold-Yilmaz (2012) and Brunik-Krehlik (2017), we had a negligible scope of gauging the out-of-sample forecasting. We therefore emphasise to revisit the findings of this study by employing various stochastic volatility (SV) models to analyse the forecasting. To validate these findings, we propose future research on scrutinising the spillover impacts between commodities and stock markets by using not only Copula and BEKK (Baba, Engle, Kraft and Kroner) model, but more contemporary approaches such as wavelet analysis and quantile spillover models can be used further.

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Data Availability

Data will be made available on request.

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