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Investigating the role of metal and commodity classes in overcoming resource destabilization

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ABSTRACT

The resource destabilization and accentuated demands for sustainability across the globe have motivated the current study to examine the nexus between the classes of metals and commodities to highlight the role of various metals in reducing the carbon footprint. We employed two alternative perspectives of time and frequency connectedness between metal classes including energy metals, precious metals, and industrial metals and commodities like energy and agriculture for the period encompassing June 1, 2012 to February 11, 2022. We found that spillovers are fashioned in the similar class than across the metal classes and commodities. Energy metals are strongly disconnected revealing their diversification benefit while other metals and commodities form intra-class spillovers. The time-varying spillovers emphasized on the distressed periods with spiked spillovers and net time-varying spillovers demonstrated leading risk contribution of crude oil and fuel. Our sub-sample analysis also detected the stronger inter-class connectedness in the post-COVID time. The findings inform policymakers, environmentalists, investors seeking sustainable portfolios, and asset managers.

1. Introduction

The paramount concerns of attaining environmental sustainability through the utilization of natural and renewable resources is surfacing on various policy boards, regulatory reforms, and on the governmental fronts. The resource destabilization and ineffective use of natural resources is impeding the sustainable growth and economic development. The role of various naturally available resources in privileging the sustainable development is signposting in the view that "clear waters and green mountains are as good as mountains of gold and silver". Abdulahi et al. (2019) explain this mismatch between resources destabilization and sustainability as a paradox which has created a riddle of stagnant economic and sustainable development. This paradox is attributed to the three reasons, for instance, at first, the natural resource extraction requires various economic resources through introducing industries for promotion of long-term growth. Secondly, it is reported that prices of natural resources bear volatility and thus destabilize the economies with major export promotion. Third, the impeding sustainability through resources destabilization is faced with rents of non-inclusive governments that focus on political aspects than the sustainable development (Abdulahi et al., 2019).

Amidst these heightened challenges, the role of several metals in combating the environmental issues and reducing the carbon footprints is remarkable. Continuous efforts toward energy transitions are made to avoid the catastrophic impacts of climate change which require a transformation toward energy metals responsible for overcoming climate concerns (Appiah et al., 2022). Energy metals encapsulate the use of those metals which are recyclable, energy-efficient, and are renewable in their true spirit. It is asserted that valuable metals, preferably environmentally compatible, can help in energy transition and worldwide natural resources are sufficient to overcome the energy consumption and depletion challenges.[1] As a result of global decarbonization initiatives and several technological innovations of digitalization and smart grids, it is imperative to the investors to minimize the

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[1] Please see: https://energiesysteme-zukunft.de/en/topics/metals-for-the-energy-transition.

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carbon footprints of their companies with strong societal demand (Karim et al., 2022a, 2022b). The International Renewable Energy Agency (IRENA) states that the cost of electricity by using environmentally sustainable metals and renewable technologies can be reduced between 25% and 60% based on different technologies.[2] Thus, energy metals, often termed as energy transition metals are capable of replacing the traditional metals with those of environmentally sustainable and naturally available to achieve sustainable development. To this point, scholars are converging toward energy metals but no significant findings can be reported in this gray area of using versatile metals in the portfolio to service twofold objectives: first, to fulfill the sustainable motives of the investors, and second, to diversify their portfolios with low-risk markets. Therefore, energy metals and their use in the literature as well as in the practice remained unequivocal.

Moreover, the current study employs time and frequency connectedness approaches provided by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). The time-based spillovers are unique in investigating the network connectedness by differentiating the risk transmission and risk reception across various metals and commodities. Meanwhile, the frequency-spillovers are novel in giving insights about the connectedness mechanism over a passage of time, for example, short and long-run spillovers. Further, the time-varying attributes of both methodologies allow for assessing the spiked spillovers reflecting the intense time-periods belonging to financial, economic, and policy aspects.

Building on these arguments, the current study contributes to the existing literature in several ways. First, this is the pioneer study to examine the nexus between metal and commodities classes to identify whether both classes transmit and receive risk for various time-horizons. Second, the study employed three classes of metals namely, energy metals, precious metals, and industrial metals along with two classes of commodities such as energy and agriculture commodities. The choice of selection of metal classes and commodity classes persists in the fact that different types of metals and commodities carry versatile properties in terms of risk management and risk-bearing potential (Karim & Naeem, 2021, 2022). Therefore, a diversified set of metals and commodities offers greater outlook to select among the markets for portfolio allocation and risk mitigation. Third, we utilized the time and frequency dependent spillovers that are renowned for providing net risk transmitters and net risk recipients over a period of time. Fourth, we provide subsample analysis of COVID-19 to validate our findings of time and frequency spillovers. Finally, we stipulated significant ramifications for policymakers, regulation bodies, financial market participants, environmentalists, resource rich countries, and investors to portray the environmentally sustainable avenues through the use of various metals and combat the climate issues.

Our analysis found a classic intra-class connectedness and diminishing inter-class spillovers by applying thresholding on the dataset between metal classes and commodities implying that similar class of commodities and metals connect better with each other than the contrasting classes. the connectedness structure highlighted strong disconnection of energy metals reflecting their low-risk bearing potential as compared to other metal classes and commodities. A strong bi-directional spillover mechanism is manifested in the other metal classes and commodities. Frequency spillovers also revealed similar in-class trajectories of spillovers both in the short- and long-run. The dynamic spillovers exhibited spiked spillovers during intense time periods for instance, Shale oil revolution, the crash of Chinese stock market, Brexit, U.S interest rate hike and COVID-19.

Time-varying net spillovers indicated crude oil and fuel as net transmitters of risk while gas oil showed net risk reception. The grouped risk spillovers highlighted precious metals as net risk transmitters while agriculture commodities are net risk receivers. The closer to zero spillovers of energy metals, industrial metals and energy commodities indicated their diversification avenues for the whole sample period suggesting risk mitigation in a portfolio of versatile metals and commodities. Sub-sample analysis illustrated disconnection between metal classes and commodities in the pre-COVID period whereas markets were interconnected in the post-COVID time showcasing the investors' sentiment when crisis struck the economy. In this way, our findings provide fruitful key suggestions for policymakers, institutional and individual investors, regulatory authorities, and portfolio managers to offset their asset risk through energy metals as they are rich in renewable energy resources to service their sustainable objectives and mitigating the environmental issues.

The rest of the paper is organized as follows: Section 2 presents the methodological approach applied in the study, Section 3 elaborates data and preliminary analysis, Section 4 explains the results along with the discussion, and Section 5 concludes the study.

2. Methodology

2.1. Connectedness of energy, precious, industrial metals and commodities

To estimate the time-based series, this study employed the (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014) approach using the p order of the static VAR model as shown in equation (1):

$$\mathbf{y}_t = \mathbf{\Phi}(L)\mathbf{y}_t + \boldsymbol{\varepsilon}_t = \mathbf{\Phi}_1\mathbf{y}_{t-1} + \mathbf{\Phi}_2\mathbf{y}_{t-2} + \cdots + \mathbf{\Phi}_p\mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{1}$$

Where the vector $\mathbf{y}_t = (R_{1t}, \ldots, R_{nt})$ provides the $n \times 1$ vector which contains the connection of Australian electricity markets however the $\mathbf{\Phi}(L)$ indicates the lagged variable. $\boldsymbol{\epsilon}_t$ indicates the random error term under the mean value of zero with the matrix variance of $\mathbf{\Sigma}$. Thus, it is observed that there is no serial correlation in the error term of the equation in this research. As mentioned previously, the static VAR model provides the estimation of the time-domain, thus to indicate the moving averages process of the infinite order, equation (1) can be written as, VMA (∞), say $\mathbf{y}_t = \mathbf{\Psi}(L)\boldsymbol{\varepsilon}_t = \mathbf{\Psi}_0\boldsymbol{\varepsilon}_t + \mathbf{\Psi}_1\boldsymbol{\varepsilon}_{t-1} + \cdots + \mathbf{\Psi}_h\boldsymbol{\varepsilon}_{t-h} + \cdots$. The symbol $\mathbf{\Psi}_h$ denotes the coefficient analogous of the moving averages to its h-th lag. The $\mathbf{\Psi}_0$ adjust to $\mathbf{I}$ when h-th lag become zero. Where, the $\mathbf{I}$ shows the identity matrix in the lag time.

2.1.1. Time-dependent connectedness

To analyze the time-dependent connectedness and a generalized forecast error variance decomposition (FEVD), the investigation of Pesaran and Shin (1998) have been used to estimate the VMA (∞) as discussed in equation (1). To further proceed with the H-step analysis, the j-th realized daily returns has been taken into account to the i-th variable of the estimated realized returns under the error variance that can be seen from equation below:

$$\theta_{ij} = \frac{\sum_{h=0}^{H-1}\left(\mathbf{e}_i'\mathbf{\Psi}_h\mathbf{\Sigma}\mathbf{e}_j\right)^2}{\mathbf{e}_j'\mathbf{\Sigma}\mathbf{e}_j \times \sum_{h=0}^{H-1}\mathbf{e}_i'(\mathbf{\Psi}_h\mathbf{\Sigma}\mathbf{\Psi}_h')\mathbf{e}_i} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{H-1}\left((\mathbf{\Psi}_h\mathbf{\Sigma})_{ij}\right)^2}{\sum_{h=0}^{H-1}(\mathbf{\Psi}_h\mathbf{\Sigma}\mathbf{\Psi}_h')_{ii}} \tag{2}$$

Where, the ij-th term of the $\mathbf{\Sigma}$ that is denoted as σ_{ij} and the diagonal item represents as σ_{jj} of the j-th term. The $\mathbf{e}_j$ represents zero with the condition that when j-th item is one in the equation. The results are standardized equally for the contribution in the variables in terms of the ($j = 1, 2, \ldots, n$), where the forecast horizon (H) of 100 days chosen for this study provides the estimation of the connectedness in the Australian electricity market. This connectedness of the Australian electricity markets are computed with the approaches from the literature of (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014) in order to support our results.

[2] Please see: https://www.ifpenergiesnouvelles.com/issues-and-foresight/decoding-keys/climate-environment-and-circular-economy/metals-energy-transition.

2.1.2. Time scale (Frequency)-Dependent connectedness

To further support the estimation process of the VMA p-order model from equation (1), this study obtains the estimation with the frequency-dependent connectedness to analyze the time-scale variation in our model. The Fourier transform has been applied on the lagged coefficients under the illustration of VMA (∞) where, $\mathbf{y}_t = \mathbf{\Psi}(L)\boldsymbol{\varepsilon}_t$. Moreover, $\mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega}) = \sum_{h=0}^{\infty}\mathrm{e}^{-\mathrm{i}\omega h}\mathbf{\Psi}_h$ has been obtained where the ω shows the frequency at particular degree. Furthermore, this study also analyzed the power spectrum of $\mathbf{y}_t$ as $\mathscr{S}_y(\omega) = \sum_{h=-\infty}^{\infty}E[\mathbf{y}_t\mathbf{y}_{t-h}^{'}]\mathrm{e}^{-\mathrm{i}\omega h} = \mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega})\mathbf{\Sigma}\mathbf{\Psi}(\mathrm{e}^{\mathrm{i}\omega})$ which provides the j-th variable connectedness to the i-th variable of forecast error variance (both of the variable provides the connectedness to its j-th and i-th term in the equation). On the basis of the illustrations, the equation is as follows:

$$\vartheta_{ij}(\omega) = \frac{1}{\sigma_{jj}} \times \frac{\left|(\mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega})\mathbf{\Sigma})_{ij}\right|^2}{(\mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega})\mathbf{\Sigma}\mathbf{\Psi}'(\mathrm{e}^{\mathrm{i}\omega}))_{ii}} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{\infty}(\mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega h})\mathbf{\Sigma})_{ij}^2}{\sum_{h=0}^{\infty}(\mathbf{\Psi}(\mathrm{e}^{-\mathrm{i}\omega h})\mathbf{\Sigma}\mathbf{\Psi}'(\mathrm{e}^{\mathrm{i}\omega h}))_{ii}} \tag{3}$$

2.1.3. Time-dependent connectedness vs. frequency-dependent connectedness

Table 1 provides the definitions and measurements of the time-dependent connectedness taken from the research of (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014), the frequency-dependent connectedness measurement used by (Baruník and Křehlík, 2018). From the definitions, it can be observed that the variation comes from the variables j which is related to its i-th term that are forecast error variance in the measurement of time and frequency.

This research investigated domains of time and frequency simultaneously with the follow-up studies of Balli et al. (2020) Caporin et al. (2021). The benefit of using time-frequency involves firstly, the short and long term horizons components in the frequency dependence. Secondly, in context to the network structure of markets, the directional spillovers can be obtained for the analysis of variation in the time-frequency domains.

3. Data and preliminary statistics

3.1. Data

To test the connectedness of Energy, Precious, Industrial Metals and Commodities various group of metals are taken. Energy, Metals includes, Germanium (GER), Gallium (GAL), Indium (IND), Tellurium (TEL), Lithium (LIT) and Vanadium (VAN). Precious Metals contains Gold (GLD), Silver (SLV), Platinum (PLT), Palladium (PLD), Industrial Metals covers Aluminium (ALM), Cobalt (COB), Copper (CPR), Nickel (NKL), Energy Commodities covers Crude oil WTI(WTI), Crude oil Brent (BRNT), Natural gas (NTS), Coal (COAL), Fuel oil (FUEL), Gas oil (GOL), Gasoline (GSL), Agriculture Commodities comprises of Wheat (WHT), Corn (CRN), Soybean (SYBN), Cocoa (COC), Coffee (COF), Sugar (SGR). Data has been sourced from Datastream spanning the period June 1, 2012 to February 11, 2022.

Table 1
Connectedness measurements.

Connectedness Type	Time-Dependent	Frequency-Dependent
Connectedness (j to i)	$\widetilde{\theta}_{ij} = \frac{\theta_{ij}}{\sum_{j=1}^{n}\theta_{ij}}$	$\widetilde{\vartheta}_{ij}(\omega) = \frac{\vartheta_{ij}(\omega)}{\sum_{j=1}^{n}\vartheta_{ij}(\omega)}$
Total spillover index	$C = \frac{1}{n}\sum_{i\neq j}^{n}\sum_{j=1}^{n}\widetilde{\theta}_{ij}$	$C(\omega) = \frac{1}{n}\sum_{i\neq j}^{n}\sum_{j=1}^{n}\widetilde{\vartheta}_{ij}(\omega)$
Net pairwise	$C_{ij,net} = \widetilde{\theta}_{ij} - \widetilde{\theta}_{ji}$	$C_{ij,net}(\omega) = \widetilde{\vartheta}_{ij}(\omega) - \widetilde{\vartheta}_{ji}(\omega)$
From connectedness	$C_{i\leftarrow\cdot} = \frac{1}{n}\sum_{j\neq i}^{n}\widetilde{\theta}_{ij}$	$C_{i\leftarrow\cdot}(\omega) = \sum_{j\neq i}^{n}\widetilde{\vartheta}_{ij}(\omega)$
To connectedness	$C_{i\rightarrow\cdot} = \frac{1}{n}\sum_{j\neq i}^{n}\widetilde{\theta}_{ji}$	$C_{i\rightarrow\cdot}(\omega) = \sum_{j\neq i}^{n}\widetilde{\vartheta}_{ji}(\omega)$
Total connectedness	$C_{i,net} = \frac{1}{n}\sum_{j\neq i}^{n}\widetilde{\theta}_{ji} - \frac{1}{n}\sum_{j\neq i}^{n}\widetilde{\theta}_{ij}$	$C_{i,net}(\omega) = \sum_{j\neq i}^{n}\widetilde{\vartheta}_{ji}(\omega) - \sum_{j\neq i}^{n}\widetilde{\vartheta}_{ij}(\omega)$

Note: all of the classifications are sourced from Diebold and Yilmaz (2012,2014) and Baruník and Křehlík (2018).

3.2. Preliminary statistics

Table 2 exhibits the descriptive statistics together with diagnostics check through JB test of normality, ARCH LM test of heteroskedasticity and Q-Stat at 20th lag to test autocorrelation among the energy metals, precious metals, industrial metals, energy commodities and agriculture commodities. From energy metals the GAL, IND, TEL yield negative average returns whereas GER, LIT and VAN generate positive mean returns. Among precious metals, SLV and PLT shows negative while GLD and PLD realized positive returns with negative skewness depicting recurrent small gains and infrequent smaller losses. Industrial metals including ALM, COB, CPR and NKL produce comparable average returns. Among energy commodities, NTS generate higher averages together with higher variability whereas GOL, GSL and BRNT manifested negative average returns although a similar amount variability is observed among COAL, FUEL and GOL. WHT exhibit the highest variability in agricultural commodities followed CRN, COF and SGR. Also, the considerably higher values of Jarque-Bera (J.B.) test of normality reflects the abnormal return patterns among time. ARCH Lagrange multiplier test manifests the rejection of null hypothesis of no ARCH effects in all commodities. Q-Stat signifies the evidence of non-randomness at lag 20 through the statistically significant test values in all commodities.

Fig. 1 displays the correlation matrix among metals and commodities. The larger correlation magnitude is presented by the stronger colour display and blue colour shows positive correlation while red colour exhibits negative relationship. The varying strength of correlation is represented by diverse colour intensity among the metals and commodities. Now looking at the figure, a positive and moderate correlation between GLD and SLV followed by slightly declined degree of correlation with GLD and SLV to PLT. Although, PLT showed a greater degree of correlation with PLT together with a decreasing tendency of association with GLD and SLV. Also, industrial metals including COB, CPR, NKL display a bit lower positive correlation with ALT, GLD and SLV. While a high negative correlation between the pair of CRN-SYB of agricultural commodities is observed besides a lower negative correlation between WTI and FUEL with a downtrend in WTI and GOL. As a whole, a significant pattern of correlation is ascertained amongst the similar group of commodities; whereas, no significant correlation is found between the dissimilar commodities.

4. Empirical results

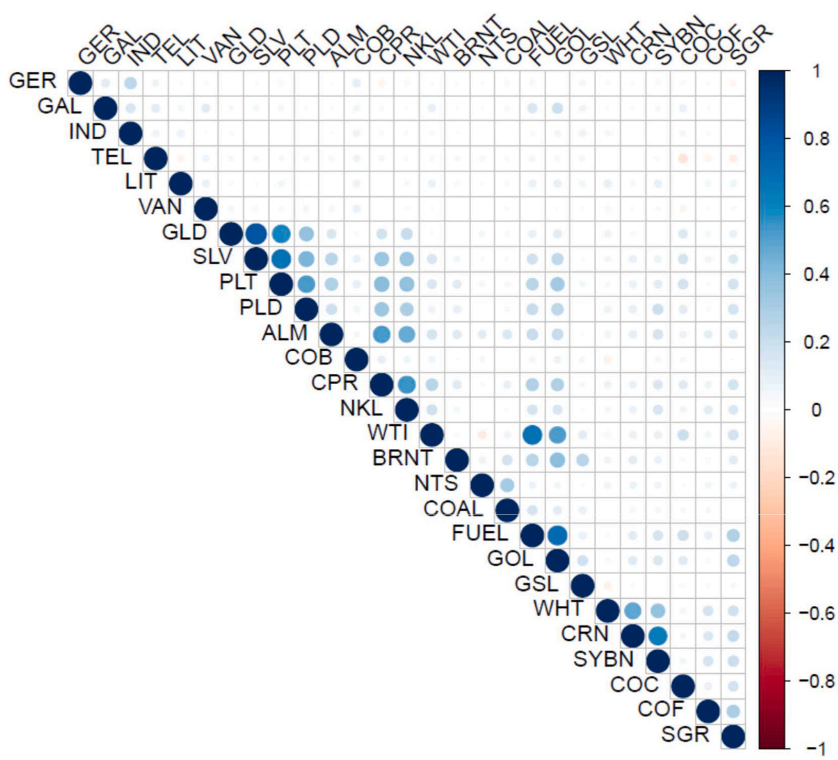
4.1. Connectedness of metal classes and commodities

Following Diebold and Yilmaz (2012) methodology, Fig. 2 shows the connectedness of metals and commodities. It comprises of Fig. 1(a) without thresholding, displaying a complex network of the connectedness of metal classes and commodities. Fig. 1(a) is not so visible owing to large pairwise connections. Hence, thresholding (the values below the average of initial 100 highest fractional metals and commodities are defined to be 0s) is used to highlight the connectedness presented in Fig. 1(b). The figure demonstrated a clear understanding of the network connectedness showing that all metals and commodities are heavily connected within the similar group and no spillovers formation is observed among inter-class commodities. From precious metal group, SLV and GLD are showing strong intra-connectedness. Similarly, among agriculture commodities CRN and SYBN expresses the similar behaviour. An identical within same class connectedness of commodities responses are ascertained by Naeem et al. (2022a) and Caporin et al.

Table 2
Descriptive statistics.

	Markets	Symbol	Mean	Std. Dev.	Skewness	Kurtosis	JB	ARCH	Q(20)
Energy Metals	Germanium	GER	0.009	3.200	0.904	65.542	91390.400 [a]	47.743 [a]	57.472 [a]
	Gallium	GAL	−0.004	3.540	−0.043	21.777	10088.661 [a]	13.338 [a]	24.491 [a]
	Indium	IND	−0.125	4.061	−2.904	40.572	35716.128 [a]	40.445 [a]	24.780 [a]
	Tellurium	TEL	−0.161	2.347	2.589	20.674	9661.856 [a]	35.485 [a]	365.373 [a]
	Lithium	LIT	0.319	2.111	3.951	25.372	15016.566 [a]	61.588 [a]	293.830 [a]
	Vanadium	VAN	0.056	5.713	−0.620	30.505	19822.978 [a]	15.494 [a]	23.896 [a]
Precious Metals	Gold	GLD	0.026	2.038	−0.248	1.735	70.071 [a]	45.271 [a]	11.322 [a]
	Silver	SLV	−0.041	3.607	−0.209	3.548	273.022 [a]	103.733 [a]	17.693 [a]
	Platinum	PLT	−0.063	3.375	−0.357	7.296	1145.650 [a]	149.626 [a]	27.835 [a]
	Palladium	PLD	0.257	4.391	−0.719	17.280	6398.064 [a]	102.982 [a]	49.033 [a]
Industrial Metals	Aluminum	ALM	0.094	2.577	0.189	1.591	91390.400 [a]	47.743 [a]	57.472 [a]
	Cobalt	COB	0.173	3.551	−0.232	4.011	10088.661 [a]	13.338 [a]	24.491 [a]
	Copper	CPR	0.058	2.586	0.062	1.775	35716.128 [a]	40.445 [a]	24.780 [a]
	Nickel	NKL	0.073	3.727	0.113	0.231	9661.856 [a]	35.485 [a]	365.373 [a]
Energy Commodities	Crude oil WTI	WTI	0.022	6.198	0.695	22.976	15016.566 [a]	61.588 [a]	293.830 [a]
	Crude oil Brent	BRNT	−0.024	5.786	−4.618	73.334	19822.978 [a]	15.494 [a]	23.896 [a]
	Natural gas	NTS	0.246	6.721	−0.429	19.316	70.071 [a]	45.271 [a]	11.322 [a]
	Coal	COAL	0.151	4.318	−1.320	29.668	273.022 [a]	103.733 [a]	17.693 [a]
	Fuel oil	FUEL	0.016	4.516	−1.260	9.039	1145.650 [a]	149.626 [a]	27.835 [a]
	Gas oil	GOL	−0.011	4.648	0.134	9.863	6398.064 [a]	102.982 [a]	49.033 [a]
	Gasoline	GSL	−0.010	1.798	0.396	3.409	91390.400 [a]	47.743 [a]	57.472 [a]
Agriculture Commodities	Wheat	WHT	0.053	4.088	0.426	2.561	10088.661 [a]	13.338 [a]	24.491 [a]
	Corn	CRN	0.019	3.522	−0.358	2.162	35716.128 [a]	40.445 [a]	24.780 [a]
	Soybean	SYBN	0.032	2.997	−0.574	2.142	9661.856 [a]	35.485 [a]	365.373 [a]
	Cocoa	COC	0.041	2.953	0.153	0.650	15016.566 [a]	61.588 [a]	293.830 [a]
	Coffee	COF	0.076	3.201	0.298	1.321	19822.978 [a]	15.494 [a]	23.896 [a]
	Sugar	SGR	−0.019	3.341	0.401	1.157	70.071 [a]	45.271 [a]	11.322 [a]

Note.
[a] indicates a 1% level of significance.



Note: This figure indicates the correlation matrix among the energy, precious, and industrial metals and other commodities from 1/06/2012 to 11/02/2022.

Fig. 1. Correlation matrix
Note: This figure indicates the correlation matrix among the energy, precious, and industrial metals and other commodities from June 1, 2012 to February 11, 2022.

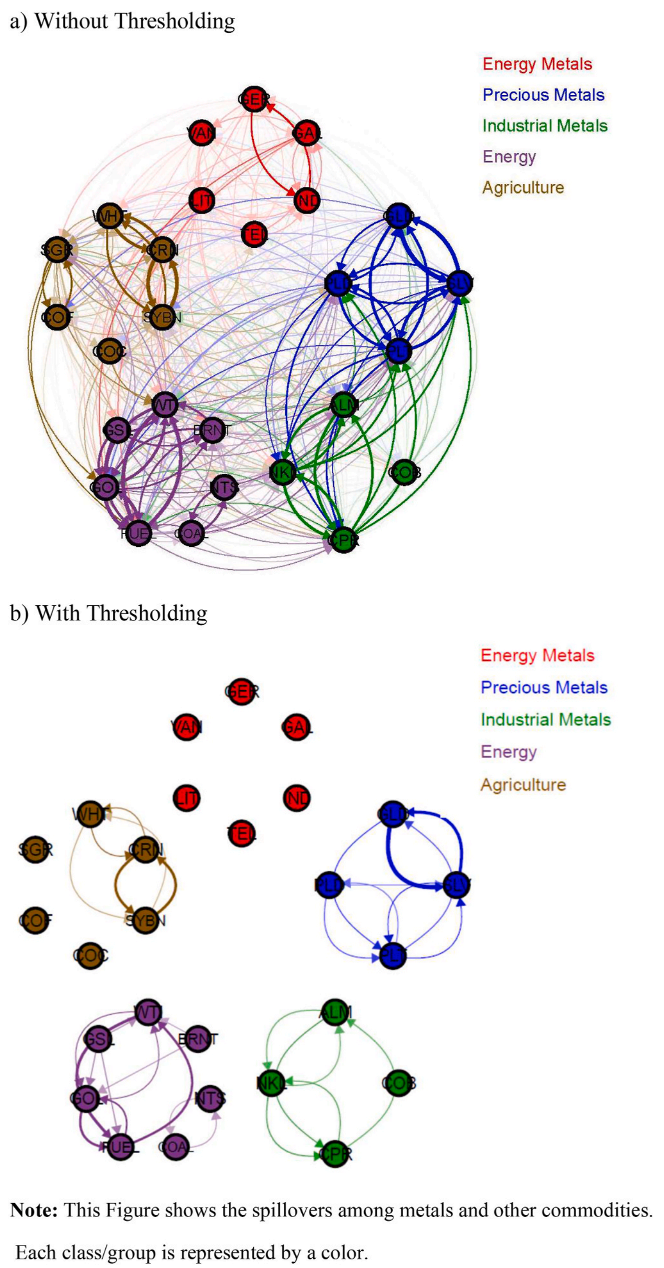


Fig. 2. Spillovers based on Diebold and Yilmaz (2012)
Note: This Figure shows the spillovers among metals and other commodities. Each class/group is represented by a color.

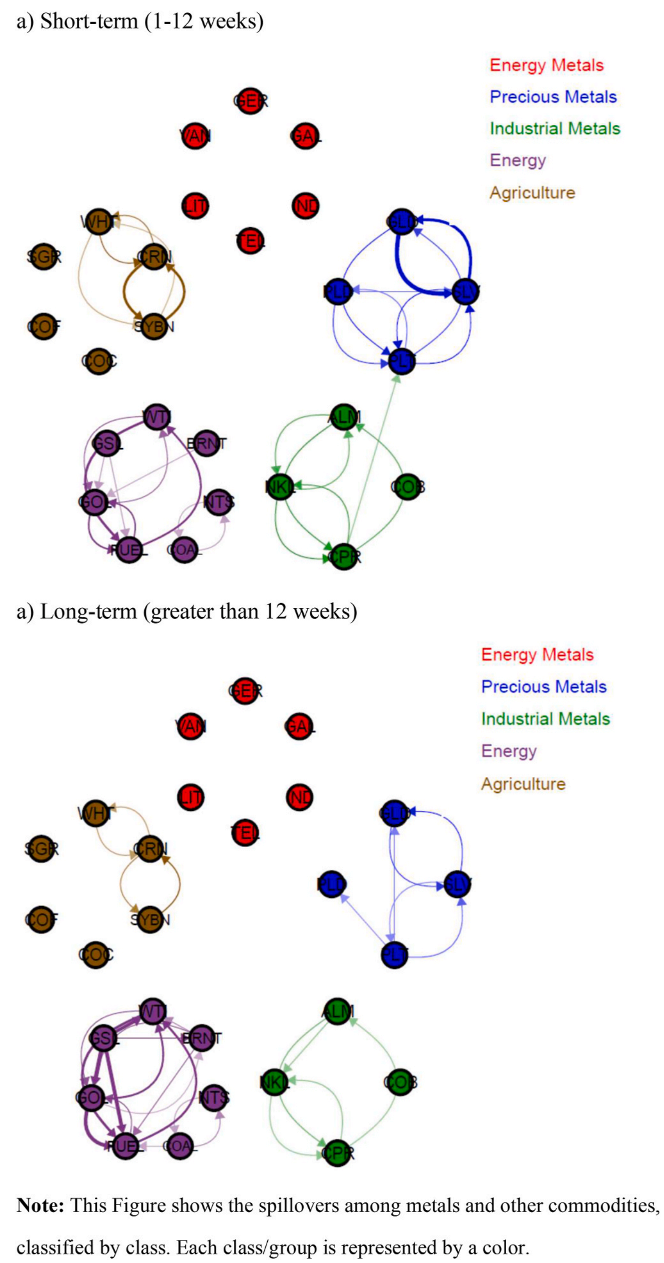


Fig. 3. Spillovers based on Baruník and Křehlík (2018)
Note: This Figure shows the spillovers among metals and other commodities, classified by class. Each class/group is represented by a color.

(2021). Despite that, energy metals show strong disconnection across the commodities and from the network as well. Further, among agricultural commodities; SGR COF and COC exhibit analogous results. This strong disconnection confirms the diversification potential of these commodities. As proposed by Yoon et al. (2019), investors may integrate commodities to their portfolios to control the negative returns spillover shocks. Thus, assets selection from commodity market results in an optimal portfolio strategy.

Fig. 3 exhibits the connectedness of metal classes and commodities based on Baruník and Křehlík (2018) for short- (Fig. 3(a)) and long-term (Fig. 3(b)) sample analysis. Our results in Fig. 1(b) reaffirm the connectedness configuration within energy metals, precious metals, industrial metals together with energy and agricultural commodities through uniform group patterns of persistent in-class connectedness. CPR is the only commodity displaying risk transmission to the PLT in short term. While the Long-term spillovers effects are recurring strong disconnection throughout the groups in the whole network. The precious metals display a cross connectedness among GLD, SLV and PLT, where PLT is the net risk receiver and GLD and SLV both are coupled with the feature of being net risk receivers and transmitter. Energy metals remained disconnected from the system-wide connectedness which suggests diversification benefits in the long-run.

4.2. Time-varying connectedness

Fig. 4 represents time-varying dynamic total spillover among energy metals and commodities employing the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methodology. The whole sample period is analyzed by using 104 days rolling window to inspect the time-varying characteristics and captured various trends in the spillover. The total spillover showing an initial bounce in the graph (2014–2016) indicates the emergence of Shale oil revolution in addition to the Chinese financial

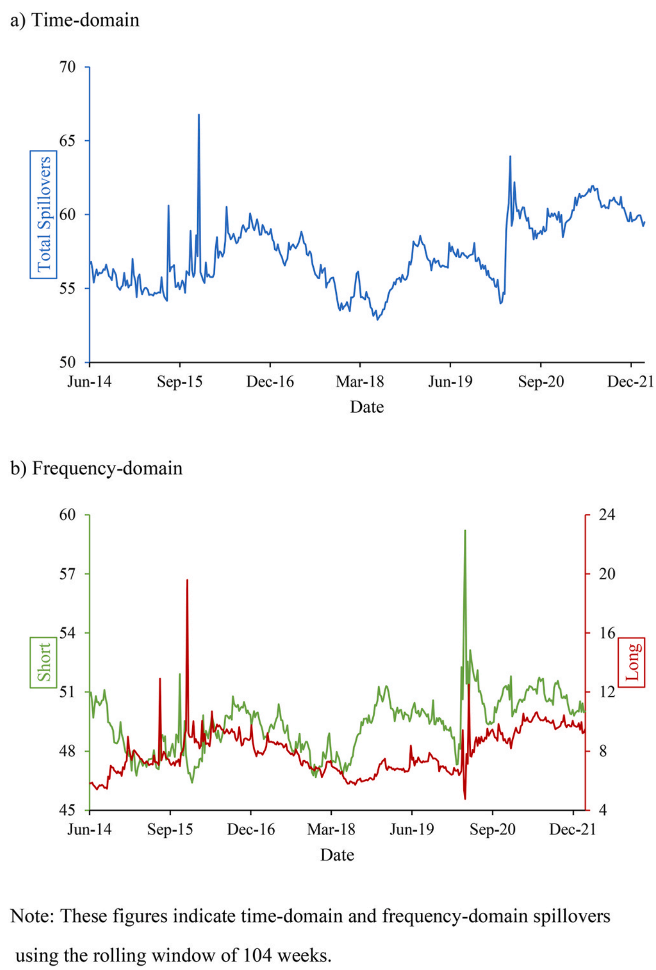


Fig. 4. Dynamic total spillovers
Note: These figures indicate time-domain and frequency-domain spillovers using the rolling window of 104 weeks.

market crisis considering that the high connectedness between metals and commodities is representing the effect of this prominent event, and Chinese stock market crash illustrates the stock market sell-off during 2015–2016 (Anwer et al., 2022). As a consequence of abnormal market conditions, the stronger risk spillovers are originated during this period (Nguyen and Le, 2021). In the similar manner, during 2016–2017 the rapid growth in the connectedness of metals and commodities depicts the well-known event of Brexit referendum (Karim and Naeem, 2022; Xiao et al., 2020), upon which strong risk spillovers were attributable to the departure of U.K. from the European Union. In succession, rise in U. S. interest rate in 2017–2018 symbolizes a shift of integration in metals and commodities contemplating the distressed market conditions (Elsayed et al., 2020). And finally, 2019–2020 represents the COVID outbreak which brought health emergency raising severe economic unrest to regulators, market participants and investors (Alawi et al., 2022; Karim et al., 2022c). By and large time-varying spillovers between metals and commodities are sensitive to the global financial catastrophes, thus the declining economic events originate financial markets connectedness. In the view of these tendencies, high connectedness results in to system-wide spillover whereas low connectedness is featured during a stable period.

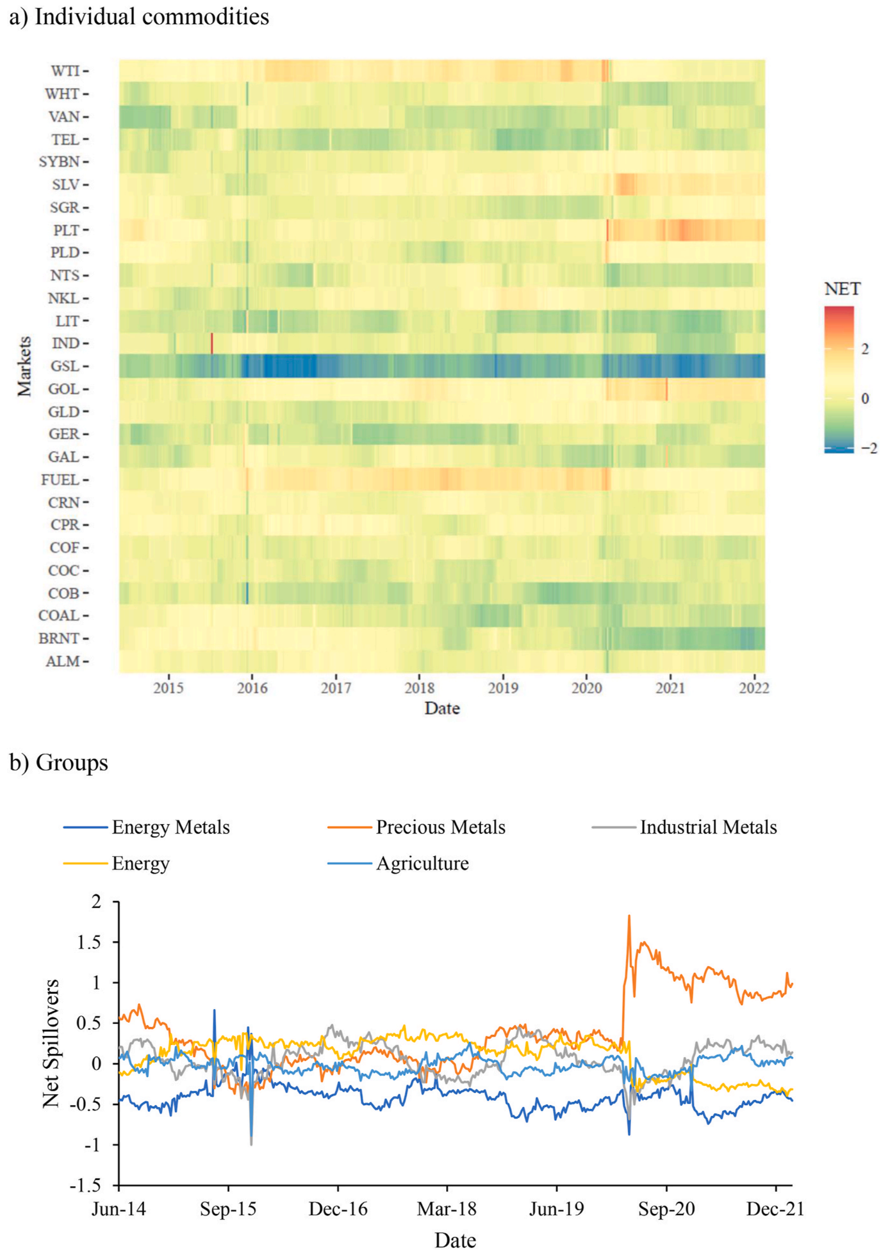
Fig. 4(b) manifests frequency connectedness in which a breakdown of total spillovers in the form of long-run (red) and short-run (green) connectedness is displayed. The short-run spillovers dominance over the long-run spillovers can be clearly seen in the figure where total connectedness reaches above 65% during 2014–2016 where market experienced heightened spikes of 57% in long run and just 51% in short run frequency spillovers. Thereafter, notable ups and downs captured the distressing events of Chinese market crash, Shale Oil Revolution (SOR), upsurge of U.S. Fed interest rates and Brexit referendum when markets endured turbulent short-run frequency spillovers. Similarly, the steady movement of returns manifests a stable period by a gradual frequency downturn back to the normal market conditions. During 2019, a steep rise in the spillovers reflects the COVID-19 pandemic period where prominent rise in connectedness between metals and commodities is configured in the short-run. Overall, the results accentuate that distressing periods are described by strong spillovers, that mainly justify the short-run connectedness. Alternatively, a comparatively stable spillover behaviour in long-run connectedness between metals and commodities is ascertained, given the markets uncertainty. Since, the short-run spillovers are marked by sensitive market circumstances like abnormal economic incidents or uncertain global business conditions (Rehman et al., 2022; Yang et al., 2021; Naeem and Karim, 2021). Our findings enumerate paramount frequency spillovers in the short-run than in the long-run. Short-run spillovers perform a crucial part in the total frequency spillovers determination and this is validated by Naeem et al. (2021), and Hasan et al. (2021)., despite the fact that long-run spillovers indicate stable market settings.

4.3. *Time-varying net spillovers*

Fig. 5 shows time varying net spillovers in individual as well as group of metals and commodities. These figures indicate net spillovers using the rolling window of 104 weeks on the basis of time-domain. In Fig. 5 (a), orange colour heat-plots represent positive values depicting net risk transmitters and negative heatmaps are net risk receivers. Overall, WTI crude oil is net risk transmitter because its market integration is greater than rest of the commodities due to increased oil dependence (Kang et al., 2017; Naeem et al., 2022c, 2022d; Karim et al., 2022c). It is evident from the figure that almost all energy commodities are diversifiers showing the value near to 0 (yellow colour). GSL is net risk receptor and it is a highly used energy commodity. SLV and PLT with GOL are also risk transmitter in post-COVID period. Except for the FUEL that has prominently shown risk transmission before COVID period. When inflation is resulted from economic growth, gold prices increase rapidly. In addition, our findings highlight the role of precious metal markets as a transient asset during market turmoil, similar to the studies including, (Baur and McDermott, 2010; Farid et al., 2021; Billah et al., 2022) (see Fig. 6).

Fig. 6-I shows frequency-domain net spillovers employing Baruník and Křehlík (2018) taking 1–12 weeks period as a short term for individual (Fig. 6-Ia) and group (Fig. 6-Ib) of metals and commodities. As experienced earlier, WTI and FUEL are net risk transmitters while GSL is net risk receiver. Now, in relation to WTI and FUEL we note that before the outbreak they were the net transmitter of volatility (Jebabli et al., 2022; Naeem et al., 2022c, 2022d) as during this period prices strikes to record lows in the three years. It is considered to be the turbulent times in US natural gas industry. As mentioned by Mezghani et al. (2021), The crude oil is most risky and vulnerable that it is greatly impacted by crisis period; especially when it comes to the portfolio allocation and hedging strategies.

Fig. 6-IIa (individual) and 6-IIb (groups) show long-term (more than 12 weeks) net spillovers from which GSL has not changed the status of being net risk receiver in short as well as in long run. Once again, WTI shows the behaviour of risk transmitter in long run. The justification behind this behaviour is that WTI is generally volatile because of different shocks. As crude oil is still the most traded and consumed commodity around the globe, resulting in expanded worldwide integration in last few years. Hence, the substantial development of industrialization in many countries originate the thriving demand for crude oil. In Fig. 6-IIb precious metals group shows an upsurge whereas rest of the commodities a downturn in COVID period. The upsurge in the



Note: These figures indicate time-domain net spillovers using the rolling window of 104 weeks.

Fig. 5. Time-varying net spillovers using Diebold and Yilmaz (2012)
Note: These figures indicate time-domain net spillovers using the rolling window of 104 weeks.

precious metals also reflect their stronger market integration and their capability to absorb the shocks when faced with the crisis. Similarly, net spillovers for each group identified the role of being diversifier to improve the structure of portfolio.

4.4. Subsample analysis

Fig. 7 displays the subsample network analysis of return connectedness estimation employing Diebold and Yilmaz (2012) approach. It is clear that energy metals are completely disconnected and there is a strong intra-group connectedness among each class of commodities. Before COVID crisis, PLD is the only net transmitter from the class of energy metals to CPR in industrial metal group. Meanwhile, in post-COVID period, energy metals (those were totally disconnected earlier), transmitted net volatility spillovers to NTS and GOL in energy sector and to SGR in agricultural commodities. While CPR is the risk receiver from PLT out of the industrial metal group. The results of this study are in line with prior studies, (Antonakakis et al., 2017; Naeem et al., 2022a, 2022b, 2022c; Karim et al., 2022d; Pham et al., 2022). Once again, our sub sample period results indicate that spillovers among different commodity groups do not persist in short run. On the contrary, we observed only intra-group volatility spillovers among commodities. As the results illustrate that return connectedness only prevails within commodity groups, highlighting strongest return connectedness within each class of commodities.

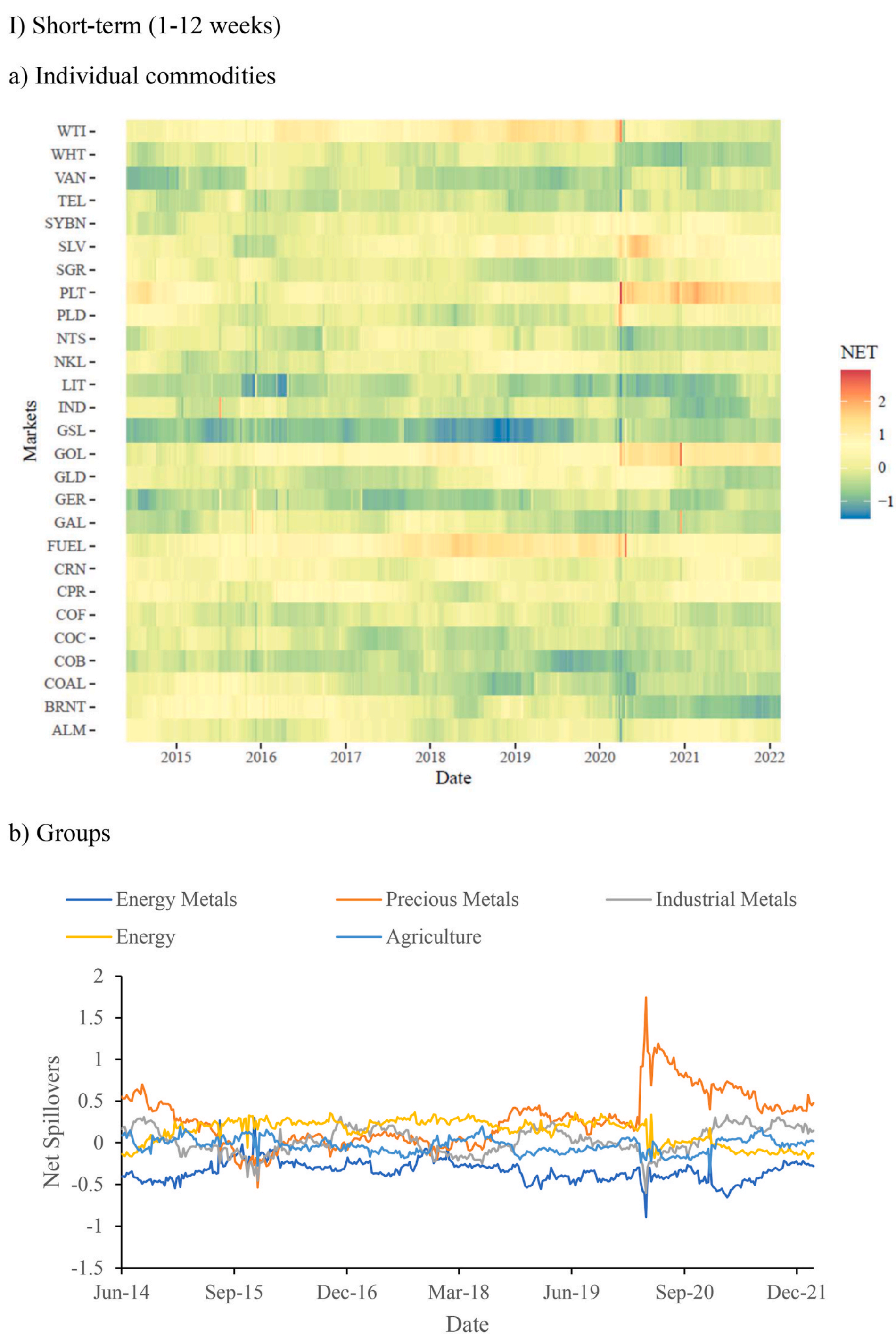


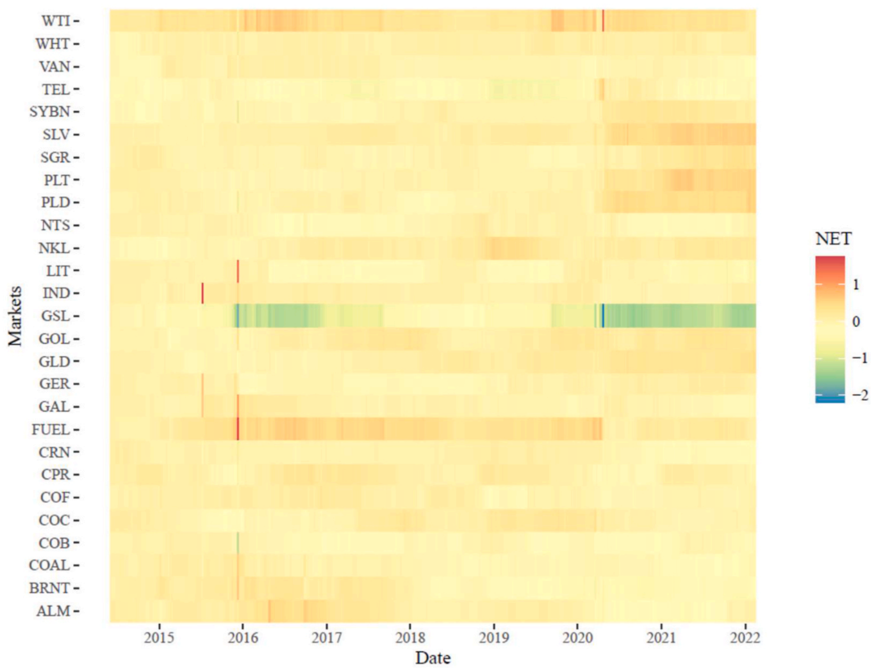
Fig. 6. Frequency-domain net spillovers using Baruník and Křehlík (2018)
Note: These figures indicate time-domain net spillovers using the rolling window of 104 weeks.

5. Conclusion

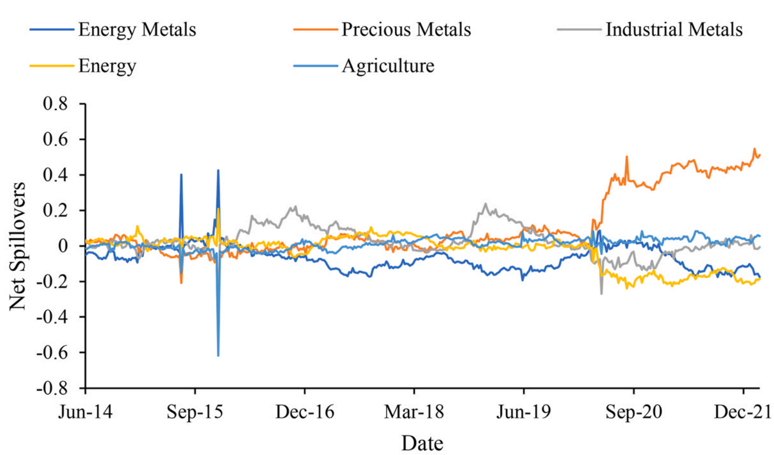
Amidst uplifted concerns of environmental sustainability and the role of natural resources to achieve eco-friendly mechanism on the globe motivates the current study to investigate the nexus between metal and commodities classes to overcome the environmental degradation. The metal classes chosen in the study are energy metals, precious metals, and industrial metals to provide a comprehensive outlook of how their spillovers over the passage of time connect with each other to diversify the risk of a portfolio and achieve a complete utilization of naturally available resources. Moreover, we included energy and agriculture commodities to manifest their significant role among various metal classes. We utilized time and frequency connectedness approaches to determine network alignment of metals and commodities over the period of time and frequency spillovers for short- and long-time horizons. Our findings highlighted strong intra-class connectedness and disappearing inter-class spillovers by applying thresholding on the dataset between metal classes and commodities. The connectedness structure highlighted strong disconnection of energy metals reflecting their low-risk bearing potential as compared to other metal classes and

II) Long-term (more than 12 weeks)

a) Individual commodities



b) Groups



Note: These figures indicate time-domain net spillovers using the rolling window of 104 weeks.

Fig. 6. (*continued*).

commodities. A strong bi-directional spillover mechanism is manifested in the other metal classes and commodities. Frequency spillovers also revealed similar in-class trajectories of spillovers both in the short- and long-run. The dynamic spillovers exhibited spiked spillovers during intense time periods for instance, Shale oil revolution, the crash of Chinese stock market, Brexit, U.S interest rate hike and COVID-19.

In addition, the time-varying net spillovers indicated crude oil and fuel as net transmitters of risk while gas oil showed net risk reception. The grouped risk spillovers highlighted precious metals as net risk transmitters while agriculture commodities are net risk receivers. The closer to zero spillovers of energy metals, industrial metals and energy commodities indicated their diversification avenues for the whole sample period suggesting risk mitigation in a portfolio of versatile metals and commodities. Sub-sample analysis illustrated disconnection between metal classes and commodities in the pre-COVID period whereas markets were interconnected in the post-COVID time showcasing the investors' sentiment when crisis struck the economy.

The results of our findings provide fruitful implications for policymakers, institutional and individual investors, regulatory authorities, and portfolio managers. The useful ramifications for policymakers entail the use of energy metals as they are rich in renewable energy resources and their use in the effective solar panels, batteries, construction, and building to reduce the carbon footprint. In this way, policymakers and regulators can issue guidelines and policies adjacent with the environmental regulations prevailing across the globe and issued by the authorities. For individual and institutional investors, the study brings

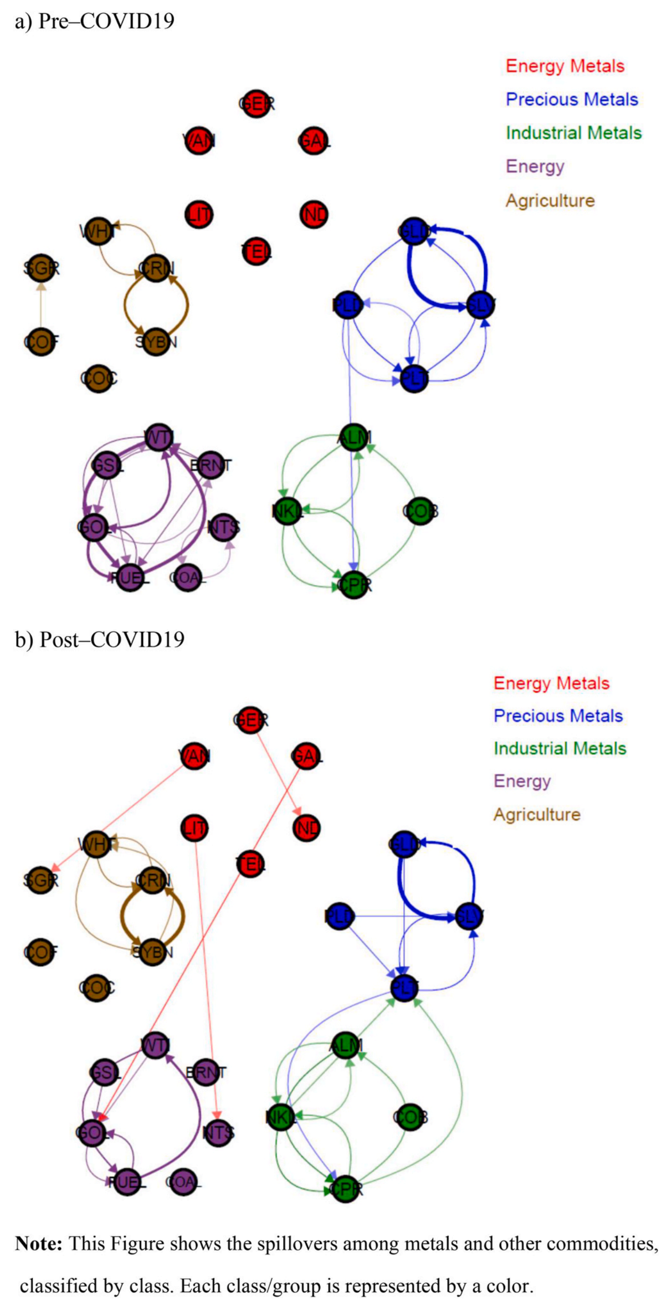


Fig. 7. Sub-sample network analysis using Diebold and Yilmaz (2012)
Note: This Figure shows the spillovers among metals and other commodities, classified by class. Each class/group is represented by a color.

insightful suggestions by unveiling the potential of energy metals to offset the risk as they carry lower risk and provide diversification benefits when economic times are unfavourable. Given the other classes of precious metals and industrial metals, the diversification potential diminishes as precious metals behave strongly against the turmoil periods by staying firm in terms of their price and volatility. Therefore, for investors, the study draws important trajectories by highlighting the diversifiers and addressing the environmentally sustainable concerns of investors by weighing alternative metals and commodities. For portfolio managers, the study provides implications for offsetting the asset risk through energy metals as they are rich in renewable energy resources to service their sustainable objectives and mitigating the environmental issues.

Author statement

Md. Abubakar Siddique; Conceptualization; Methodology; Writing - Original Draft; Writing - Review & Editing; Project Administration, Haitham Nobanee; Conceptualization; Methodology; Software; Formal analysis; Visualization; Writing - Original Draft; Writing - Review & Editing, Sitara Karim; Conceptualization; Data Curation; Methodology; Software; Formal analysis; Visualization; Writing - Original Draft; Writing - Review & Editing, Farah Naz; Conceptualization; Methodology; Writing - Original Draft; Writing - Review & Editing.

Data availability

Data will be made available on request.

References

Abdulahi, M.E., Shu, Y., Khan, M.A., 2019. Resource rents, economic growth, and the role of institutional quality: a panel threshold analysis. Resour. Pol. 61, 293–303.
Alawi, S.M., Karim, S., Meero, A.A., Rabbani, M.R., Naeem, M.A., 2022. Information transmission in regional energy stock markets. Environ. Sci. Pollut. Control Ser. 1–13.
Antonakakis, N., Chatziantoniou, I., Filis, G., 2017. Oil shocks and stock markets: dynamic connectedness under the prism of recent geopolitical and economic unrest. Int. Rev. Financ. Anal. 50, 1–26.
Anwer, Z., Naeem, M.A., Hassan, M.K., Karim, S., 2022. Asymmetric connectedness across Asia-Pacific currencies: evidence from time-frequency domain analysis. Finance Res. Lett., 102782
Appiah, M., Karim, S., Naeem, M.A., Lucey, B.M., 2022. Do institutional affiliation affect the renewable energy-growth nexus in the Sub-Saharan Africa: evidence from a multi-quantitative approach. Renew. Energy 191, 785–795.
Balli, F., de Bruin, A., Chowdhury, M.I.H., Naeem, M.A., 2020. Connectedness of cryptocurrencies and prevailing uncertainties. Appl. Econ. Lett. 27 (16), 1316–1322.
Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16 (2), 271–296.
Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Finance 34 (8), 1886–1898.
Billah, M., Karim, S., Naeem, M.A., Vigne, S.A., 2022. Return and volatility spillovers between energy and BRIC markets: evidence from quantile connectedness. Res. Int. Bus. Finance, 101680.
Caporin, M., Naeem, M.A., Arif, M., Hasan, M., Vo, X.V., Shahzad, S.J.H., 2021. Asymmetric and time-frequency spillovers among commodities using high-frequency data. Resour. Pol. 70, 101958.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182 (1), 119–134.
Elsayed, A.H., Nasreen, S., Tiwari, A.K., 2020. Time-varying co-movements between energy market and global financial markets: implication for portfolio diversification and hedging strategies. Energy Econ. 90, 104847.
Farid, S., Kayani, G.M., Naeem, M.A., Shahzad, S.J.H., 2021. Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. Resour. Pol. 72, 102101.
Hasan, M., Arif, M., Naeem, M.A., Ngo, Q.-T., Taghizadeh–Hesary, F., 2021. Time-frequency connectedness between Asian electricity sectors. Econ. Anal. Pol. 69, 208–224.
Jebabli, I., Kouaissah, N., Arouri, M., 2022. Volatility spillovers between stock and energy markets during crises: a comparative assessment between the 2008 global financial crisis and the COVID-19 pandemic crisis. Finance Res. Lett. 46, 102363.
Kang, S.H., McIver, R., Yoon, S.M., 2017. Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. Energy Econ. 62, 19–32.
Karim, S., Lucey, B.M., Naeem, M.A., Uddin, G.S., 2022a. Examining the Interrelatedness of NFTs, DeFi Tokens and Cryptocurrencies. Finance Research Letters, 102696.
Karim, S., Lucey, B.M., Naeem, M.A., Vigne, S.A., 2022b. The dark side of Bitcoin: do Emerging Asian Islamic markets help subdue the ethical risk? Emerg. Mark. Rev., 100921
Karim, S., Khan, S., Mirza, N., Alawi, S.M., Taghizadeh-Hesary, F., 2022c. Climate finance in the wake of COVID-19: connectedness of clean energy with conventional energy and regional stock markets. Climate Change Economics, 2240008.
Karim, S., Naeem, M.A., Mirza, N., Paule-Vianez, J., 2022d. Quantifying the hedge and safe-haven properties of bond markets for cryptocurrency indices. J. Risk Finance 23 (2), 191–205.
Karim, S., Naeem, M.A., 2022. Do global factors drive the interconnectedness among green, Islamic and conventional financial markets? Int. J. Manag. Finance 18 (4), 639–660.
Karim, S., Naeem, M.A., 2021. Clean energy, Australian electricity markets, and information transmission. Energy RESEARCH LETTERS 3, 29973 (Early View).
Mezghani, T., Hamadou, F.B., Abbes, M.B., 2021. The dynamic network connectedness and hedging strategies across stock markets and commodities: COVID-19 pandemic effect. Asia-Pacific Journal of Business Administration 13 (4), 520–552.

Naeem, M.A., Rabbani, M.R., Karim, S., Billah, S.M., 2021. Religion vs ethics: hedge and safe haven properties of Sukuk and green bonds for stock markets pre-and during COVID-19. Int. J. Islam. Middle E Finance Manag. https://doi.org/10.1108/IMEFM-06-2021-0252.
Naeem, M.A., Karim, S., Jamasb, T., Nepal, R., 2022a. Risk Transmission between Green Markets and Commodities. *Available at*: *SSRN*.
Naeem, M.A., Pham, L., Senthilkumar, A., Karim, S., 2022b. Oil shocks and BRIC markets: evidence from extreme quantile approach. Energy Econ., 105932
Naeem, M.A., Karim, S., Hasan, M., Lucey, B.M., Kang, S.H., 2022c. Nexus between oil shocks and agriculture commodities: evidence from time and frequency domain. Energy Econ. 112, 106148.
Naeem, M.A., Karim, S., Uddin, G.S., Junttila, J., 2022d. Small fish in big ponds: connections of green finance assets to commodity and sectoral stock markets. Int. Rev. Financ. Anal. 83, 102283.
Naeem, M.A., Karim, S., 2021. Tail dependence between bitcoin and green financial assets. Econ. Lett. 208, 110068.
Nguyen, M.K., Le, D.N., 2021. Return Spillover from the US and Japanese stock markets to the Vietnamese stock market: a frequency-domain approach. Emerg. Mark. Finance Trade 57 (1), 47–58.
Pham, L., Karim, S., Naeem, M.A., Long, C., 2022. A tale of two tails among carbon prices, green and non-green cryptocurrencies. Int. Rev. Financ. Anal. 82, 102139.
Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29.
Rehman, M.U., Vo, X.V., McIver, R., Kang, S.H., 2022. Sensitivity of US sectoral returns to energy commodities under different investment horizons and market conditions. Energy Econ. 108, 105878.
Xiao, B., Yu, H., Fang, L., Ding, S., 2020. Estimating the connectedness of commodity futures using a network approach. J. Futures Mark. 40 (4), 598–616.
Yang, K., Wei, Y., Li, S., He, J., 2021. Geopolitical risk and renewable energy stock markets: an insight from multiscale dynamic risk spillover. J. Clean. Prod. 279, 123429.
Yoon, S.M., Al Mamun, M., Uddin, G.S., Kang, S.H., 2019. Network connectedness and net spillover between financial and commodity markets. N. Am. J. Econ. Finance 48, 801–818.