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TVP-VAR based time and frequency domain food & energy commodities connectedness an analysis for financial/geopolitical turmoil episodes

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HIGHLIGHTS

- Fuel energy and crude oil prices are key transmitters of return shocks.
- Time-varying interlinkages associate with major financial/geopolitical stress events.
- The market is particularly susceptible to short-term shocks.
- Cumulative portfolio returns exhibit a sharp increase during the early phase of the COVID-19.
- Portfolio performances witnessed a significant decrease between mid-2014 and early-2016.

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ABSTRACT

Amidst the current global inflationary challenges, the concurrent rise of energy and agricultural commodity prices, which constitute the primary components of consumer prices, has emerged as a matter of significant interest among both scholars and policymakers. To this end, this study examines the dynamic interlinkages between food and energy commodity indexes from 2005:1 to 2023:3, covering turmoil episodes such as the Global Financial Crisis (GFC), the COVID-19 pandemic, and the Russia-Ukraine Conflict (RUC). Additionally, following Broadstock et al. (2022), we perform dynamic portfolio analyses to determine portfolio performances under 3 different portfolio construction approaches. The empirical results presented in this paper allow for a number of important findings. First, both the time and frequency-domain connectedness indexes associate with major financial/geopolitical stress events. Second, the fuel energy and the crude oil price indexes are the largest propagators and recipients of spillovers Third, the cumulative portfolio returns exhibit significant growth during the early phase of the COVID-19, declining during the RUC, and a notable upswing during the GFC. Finally, our findings for frequency-dependent connectedness networks indicate that the market is particularly susceptible to short-term shocks. This paper has significant ramifications for investors, market players, and policymakers.

1. Introduction

Fluctuations in global commodity prices have far-reaching implications, influencing both financial markets and macroeconomic stability, especially in terms of price stability. The effects of the co-movement of these prices have more pronounced and complex consequences. Although the co-movement between commodity prices has become an intensively discussed and researched topic since its sudden hike prior to the 2008 GFC, it has once again gained importance. In the face of the prevailing global inflationary issues, the simultaneous escalation of energy and agricultural commodity costs, which form the fundamental constituents of consumer prices, has surfaced as a topic of substantial concern to scholars and policymakers alike.

Fossil energy is the most important type of energy, which is an integral part of the production process of various fields, including agriculture. Therefore, high oil prices induce elevated costs of inputs like fertilizers and chemicals as well as an additional cost associated with the transport of products. On the other hand it also leads to an increased

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demand for biofuels, increasing demand for crops like rapeseed oil, barley, and maize, which are crucial to the production of biofuels. In addition, oil and agricultural commodities are also linked via the exchange rate, with rising oil prices leading to an increase in the current account deficit and depreciation of the national currency [28].

The motivation of this paper is to investigate how energy and food prices are linked in commodities markets using high-frequency data and network analysis, offering a novel approach to analyzing trends in commodity prices. This research aims to bridge a gap in existing literature by assessing the interconnectedness during the GFC, pandemic, and RUC periods. Understanding the coexistence and interconnectedness of sub-price groups not only helps to better comprehend the volatility in commodity markets but would also provide a deeper understanding of inflation dynamics. Increased awareness of the interrelationship and connectedness of energy and agricultural commodity prices, particularly food prices, will promote the capacity for economic and financial policy-making in areas where the social effects of these prices, such as income distribution, poverty, and social justice are evident.

The relationship between agricultural commodities and energy prices is a widely discussed subject in the literature. The pioneer studies showed that rising oil and food prices after the 1973 oil crisis affected world trade [16]. The common trends in oil and food prices have become an issue of concern for many countries over the last 15 years, especially with the GFC [48]. During the GFC, the world experienced a global crisis accompanied by the highest food prices and food insecurity in history. FAO Food Price Index for 2008 raised by 76% over 2006 prices and 40% over 2007 prices [23]. The COVID-19 outbreak, which has been a global health crisis since early 2020, directly disrupted the global food supply chain system, unlike the GFC period, and led to a global economic recession. Thus, food markets faced many months of uncertainty [13]. Against this backdrop of uncertainty, the FAO Food Price Index for May 2020 decreased by 1.5% month-on-month to 91 points. This latest decline in May 2020 reflects a fall in all sub-indices except sugar, which rose for the first time in three months [24]. In February 2022, Russia's attempted invasion of Ukraine led to worldwide food security problems. Even before the invasion, global food commodity prices were at a record-high. The increase was partly because of the state of the market, but it was also owing to the high expenses of energy, fertilizer, and various services for agriculture. The RUC has exacerbated global problems. The invasion of Ukraine by Russia after markets were squeezed during the COVID-19 pandemic and the sudden halt in exports in both countries caused global supply problems and price spikes. The FAO Food Price Index set a new record high in March 2022, rising 12.6% from February, 33.6% from the previous year, and 15.8% from its peak in February 2011 [25,26]. Food prices have declined significantly in the year since reaching record highs due to the impact of the RUC. In April 2023, the FAO Food Price Index fell to 127.2 points, down 20.35% from its historic peak in March 2022. This is the sharpest decline since the start of the pandemic. Food prices, spiked by Russia's invasion of Ukraine, have eased as the supply chain has improved, but the conflict is still ongoing and geopolitical tensions remain high [34].

It's important to highlight that there is a strong linkage between energy demand and food supply. On the demand side, buildings show significant promise for cost-effective emission reduction. This, in turn, indirectly contributes to decreasing food supply and subsequently helps in lowering food prices. In this context, Hirvonen et al. [32] investigated cost-effective energy retrofit strategies for detached houses in Finland and suggested that enhancing the structural envelope of the building as an efficient method for emissions reduction. Similarly, Hu et al. [33] examined energy usage and carbon emissions of public buildings in China and formulated a multi-objective optimization model to investigate economically efficient strategies for reducing emissions. Their results indicated that should focus on the utilization of renewable energy sources like photovoltaic (PV) and ground source heat pump (GSHP) systems to maintain an equilibrium in energy consumption, enabling dynamic adjustments as needed.

This research adds to previous studies in a variety of ways. First off as stated earlier, a major contribution of this work stems from offering a novel approach to analyzing trends in commodity prices. We examine the time-varying and frequency-dynamics of interlinkages between fossil energy and food products. It is worth noting that the initial methodology analyzes the time-varying nature of linkages among financial assets, while the second approach examines the frequency dynamics of interdependencies, which are vital for market participants, traders, and policymakers. Furthermore, we focus on the frequency of connectedness in the short, medium, and long term. This approach is essential because investor heterogeneity is evident in their changing choices, risk appetites, and expectations over time, emphasizing the importance of considering the time-investment element when analyzing connectedness. This suggests that time-frequency analysis is appropriate. While similar approaches have been employed in prior studies [29,64], this study introduces further contributions. It begins by exploring the abrupt fluctuations in food prices during all three crisis periods, emphasizing their sudden shifts. Furthermore, it delves into the intersections between fossil fuels and agricultural products within the contexts of the GFC and the pandemic and the pandemic and the RUC. By examining these dynamics, this study seeks to fill a void in the current body of research by examining the interconnections during these periods. Additionally, this study broadens the scope beyond agricultural products to encompass various food items, such as meat, milk, dairy products, cereals, vegetable oil, and sugar, which experienced significant price fluctuations during tumultuous times. Moreover, it employs Caldara & Iacoviello [14] Geopolitical Risk Index (GPR) to provide a quantitative evaluation of the relationship between fossil energy and the GPR. Finally, we carry out dynamic portfolio exercises and estimate hedging effectiveness under different portfolio construction approaches.

Several significant findings emerge when considering the main results of this study. Firstly, the Total Connectedness Index (TCI) noticeable upswings in response to major financial and geopolitical events. This highlights the susceptibility of commodity prices to external shocks. Additionally, the study identifies fuel energy and crude oil price indices as key transmitters and recipients of return shocks, emphasizing the significant influence of fuel energy prices on other commodity indices over time. Furthermore, the study emphasizes the difference in connections over different term structures, offering insights into the temporal dynamics. These findings hold crucial policy implications, indicating that policymakers should carefully oversee spillover effects between energy and food indices amidst significant financial and geopolitical events.

The rest of the article is organized as follows: Section 2 provides the literature review. The data and methodology are described in Section 3. Section 4 presents and discusses the empirical findings and Section 5 concludes.

2. Literature review

In recent years, the commodities market has undergone significant changes, driven by financialization, increased price volatility, and heightened connectivity. This literature survey delves into three central themes: the financialization of commodity markets, research on notable price movements in energy and food markets, and the emergence of connectedness analysis. The co-development of these main themes is not coincidental but rather a result of a theoretical discussion expanded through observed phenomena, leading to the development of applied tools and novel approaches.

Financialization of commodity markets, as per Tang and Xiong [58], is the process characterized by the integration of commodity futures markets with broader financial markets, wherein portfolio rebalancing by index investors may lead to the transmission of volatility from external financial realms to commodity markets. This is commonly referred to as the "financialization of commodity markets". This concept also has drawn the concern of policymakers, who have attributed the superfluous increase in energy and food prices to the activities of commodity index traders.

The financialization hypothesis suggests that as financial markets become increasingly interconnected and progressively more complex, there is a concurrent rise in the correlation of market prices over time.

This phenomenon can be ascribed to significant institutional transformations occurring in conjunction with the deregulation of financial markets. The pronounced and widespread deregulation of financial sectors stimulated a wave of financial innovations. These innovations not only introduced novel financial instruments, such as portfolios, funds etc. including commodity investments, but also facilitated the emergence of opportunities for investors to assume highly-leveraged positions.

There has been a substantial surge of capital, particularly index funds, flowing into commodity markets since early 2000s [44,49,55]. This occurrence can be ascribed to the stock market crash in the early 2000s due to the market bubble. This bubble alerted investors to the inverse relationship between commodity returns and stock returns, leading to a significant influx of capital into commodity markets since commodities are viewed as an asset capable of mitigating stock portfolio risk [3]. Fund companies, particularly the index funds play a significant role in allocating assets to commodities, a phenomenon known as the financialization of commodities [21].

Cheng and Xiong [15] critically review academic studies to analyze the impact of financial investors on risk sharing and information discovery in commodity markets. They emphasize how financialization has substantially altered these markets through mechanisms that include increased capital inflow, changes in risk profiles, and enhanced information transmission among market participants.

The rapid rise and subsequent plummet of oil prices in 2007–2008 sparked a discussion about whether financialization, which involves using commodities solely as investment assets, has distorted their market pricing [47]. Subsequently, scholarly inquiries have delved into the phenomenon of financialization. Challenges in pinpointing commodity investors and understanding their approaches with the accessible data, as well as the absence of a shared perspective on what constitutes speculation, have resulted in varying outcomes and divergent opinions within academic circles [11,31,36,63]. Moreover, amid the COVID-19 pandemic, the discussion regarding the involvement of financial investors in commodities experienced a resurgence [7,40,50]. These studies reported prevalent speculation and herding behaviors during the pandemic.

Prior to the 2008 GFC, the simultaneous and drastic fluctuations in energy and food prices led many researchers to focus on the relationship between them and a literature has proliferated. More recently, researchers have scrutinized the impacts of turmoil times such as the SARS-CoV-2 and the RUC on price dynamics of food and energy commodity markets. Therefore, there is an abundant literature on the relationship between energy and food prices.

The empirical literature on the energy-agricultural commodities nexus can be split into three categories. The first category covers research from the GFC period. For example, Nazlioglu [41] discovered a unidirectional non-linear causal relationship between oil prices and corn and soybean prices employing the Diks-Panchenko non-linear causality method. Nazlioglu et al. [42] implemented the Variance Causality test to determine the transmission of volatility. Prior to the GFC, there was no risk transmission between oil and agricultural commodity markets, but during the crisis, oil price volatility spilt over to maize, wheat, and soybean prices. Utilizing structural VAR analysis, Wang et al. [61] found that oil shocks explained agricultural commodity prices rather marginally before the 2006 food crisis, but that their explanatory power was substantially stronger after the crisis. Jebabli et al. [43] applied a time-varying parameter vector autoregression (TVP-VAR) model to examine the volatility spillovers. They found that crude oil is a net risk taker during and after the crisis period and that it had a short-term and sudden impact on food prices during the crisis period. Al-Maadid et al. [2] employed a VAR-GARCH model and find that volatility spillovers in energy and food prices are highest during the GFC period. Using deviated cross-correlation analysis (DCCA), Pal and Mitra [53] found that the association between food and energy prices was initially minimal but strengthened during the crisis. To examine regimes and volatility spillovers, Yip et al. [67] implemented the Fractional Integrated VAR (FIVAR) model and the Markov Switching model. Their results showed that when crude oil prices display high-volatility, the net volatility spillover effect is likely to grow. Han et al. [68] examined volatility spillovers using the VARMA-BEKK-GARCH model. The findings revealed the existence of a reciprocal volatility link between crude oil and agricultural commodity returns and suggest that temporary volatility transmission can be explained during the GFC period. Tiwari et al. [59] utilized copula-based approaches to investigate the link between oil and selected agricultural commodities taking geopolitical risks into account. The findings indicated that agricultural commodity and oil fluctuations are strong and synchronized, but geopolitical threats have a detrimental influence on these movements.

The second group includes studies covering the GFC and the COVID-19 period. For example, Cao & Cheng [13] investigated the spillover effects using the Baruník and Křehlík [8] frequency domain spillover index approach. Their findings suggested that the highest degree of spillovers between oil and food markets occurred in the short term, during the GFC, but the situation during COVID-19 was weaker than during the GFC period. Sun et al. [56] employed the entire bootstrap sample and causality tests to determine the long-term relationship and causality. The findings suggested that there is a reciprocal causal link between crude oil and agricultural commodities and that both are affected by each other.

Umar et al. [57] investigated return and volatility shocks using TVP-VAR and Diebold and Yilmaz [18,19] methods. Their findings showed that the net return link between variables and the total return and volatility linkages change over time and increase significantly, especially during crises. To determine the causality of and volatility spillovers between the sub-indices of food and oil prices, Raza et al. [52] employed the time-frequency causality and correlation approaches. They discovered a causal relationship in both directions between the sub-indices of food and oil prices, indicating that oil price shocks are the primary transmitters of volatility. Yoon [66] examined the cointegration and causality relationship among ethanol and corn and crude oil prices employing Quantile Johansen and Quantile Granger tests. They detected a short-run causality between variables, whereas they did not find a long-run cointegration.

The third group covers studies that examine the COVID-19 and RUC period. Cui & Maghyereh [17] analyzed the connectedness and dynamic correlations using DCC-GARCH t-Copula and TVP-VAR models. Their findings showed that the dynamic connectedness between oil and agricultural commodities are time-varying, positive, and intensify during crises. Using a frequency TVP-VAR model, Furuoka et al. [29] showed the link between natural gas, oil and agricultural commodity prices is stronger during the RUC period. On the contrary, Wu et al. [64] showed that the connectedness increases in both periods, but the transmission of connectedness is stronger in the COVID-19 period.

As noted earlier, an important theme in the literature this study is based on is connectivity. With the deregulation of markets and financialization through financial innovation, the risks of market spillover have become increasingly apparent. As a result, there has been a increasing body of applied literature exploring the topic focusing on connectedness. Diebold and Yilmaz [20] highlight their initial discussions surrounding this concept being the Asian Crisis as their main intellectual curiosity. Their core objective was empirical description of connectedness and its evolution with minimal assumptions. They have deliberately avoided delving into complex underlying structures, making their approach adaptable to various economic and financial contexts. We should note that they have initially used terms like “contagion”

Table 1
Summary statistics.

	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(20)	Q2(20)
FEI	0.58	64.83***	−0.49***	2.09***	48.64***	−5.27***	32.65***	61.80***
COPI	0.75	81.37***	−0.60***	2.86***	88.12***	−6.15***	32.10***	96.29***
NGPI	0.87	146.50***	0.40**	3.69***	130.34***	−4.48***	51.63***	229.36***
MEPI	0.25	5.29***	−0.31*	1.08***	14.35***	−5.56***	157.04***	80.04***
DPI	0.30	15.07***	0.34**	1.41***	22.39***	−4.48***	170.77***	53.30***
CPI	0.47	18.79***	0.70***	3.56***	133.11***	−5.03***	52.03***	15.26
VOPI	0.51	34.89***	−0.13	2.43***	54.45***	−4.93***	47.46***	34.31***
SPI	0.64	50.06***	0.15	1.21***	14.27***	−4.54***	32.54***	30.52***
GPR	1.96	437.98***	1.40***	4.06***	221.73***	−6.90***	23.02***	3.70

Notes: J-B indicates the Jarque Bera results, and ***, **, and * show significance levels at the 1%, 5%, and 10% confidence levels, respectively. ERS refers to the unit root test as proposed by Stock et al. [51], while Q (20) and Q2 (20) indicate the Ljung–Box statistics to investigate serial correlation.

and "spillovers" instead of "connectedness."

The extant literature has thoroughly studied the connections between agricultural and energy commodities. The current specific knowledge gap in the research landscape pertains to the limited temporal and frequency domain analysis of the connections between energy and agricultural commodities, as well as missing out current crises. This research, however, is focused on the GFC period, as well as the COVID-19 and RUC periods. Furthermore, previous research has only used a limited number of agricultural items. In order to address this void, our research examines the temporal and frequency domain association between various food price sub-indices across these three turbulent eras. Consequently, our research seeks to provide a more thorough understanding of the link between agricultural commodities and energy. Furthermore, we enhance current energy-food commodity analyses by using the frequency and time domain connectedness techniques based on TVP-VAR.

It should be noted that frequency-dependent connectedness among the energy and agricultural commodities has been examined by other econometric approaches (e.g., the wavelet methodology) by recent studies in the extant literature [10,27,46,65]. This methodology is distinguished by its focus on time and frequency domains, thereby enabling the assessment of the degree of correlation between two time series over the observation period across various time intervals (e.g., short-term versus long-term). On the other hand, Barunik and Ellington [9] employs the spectral decomposition of time-varying variance matrices. The Bayesian structure of this framework includes prior shrinkage and imparts knowledge regarding estimation uncertainty through the posterior distribution of the connectedness metrics. This differs markedly from traditional studies that solely furnish single-point estimates and depend on bootstrapping for confidence intervals.

This study carries several important implications. Firstly, it aims to ensure a comprehensive analysis of recent phases of distress concerning energy and food prices, encompassing a broader range of sub-price indices. This broader perspective can offer a more nuanced understanding of the dynamics between energy and food prices during turbulent times, which can be valuable for policymakers and researchers. Secondly, the study considers a period of rising global inflationary pressures, which have led to significant policy responses from major economies. By examining the impact of these policy measures on headline and core inflation rates, the study can shed light on the effectiveness of various strategies in managing inflation, especially when driven by complex behaviors in energy, food, and service prices. Lastly, the study addresses the interaction between the three stress periods and the recent global inflationary episode, potentially revealing interconnections and common trends that could inform future policy decisions and market strategies. Overall, this research has the potential to inform economic and policy discussions by providing a holistic perspective on energy and food prices, inflation, and their interplay in

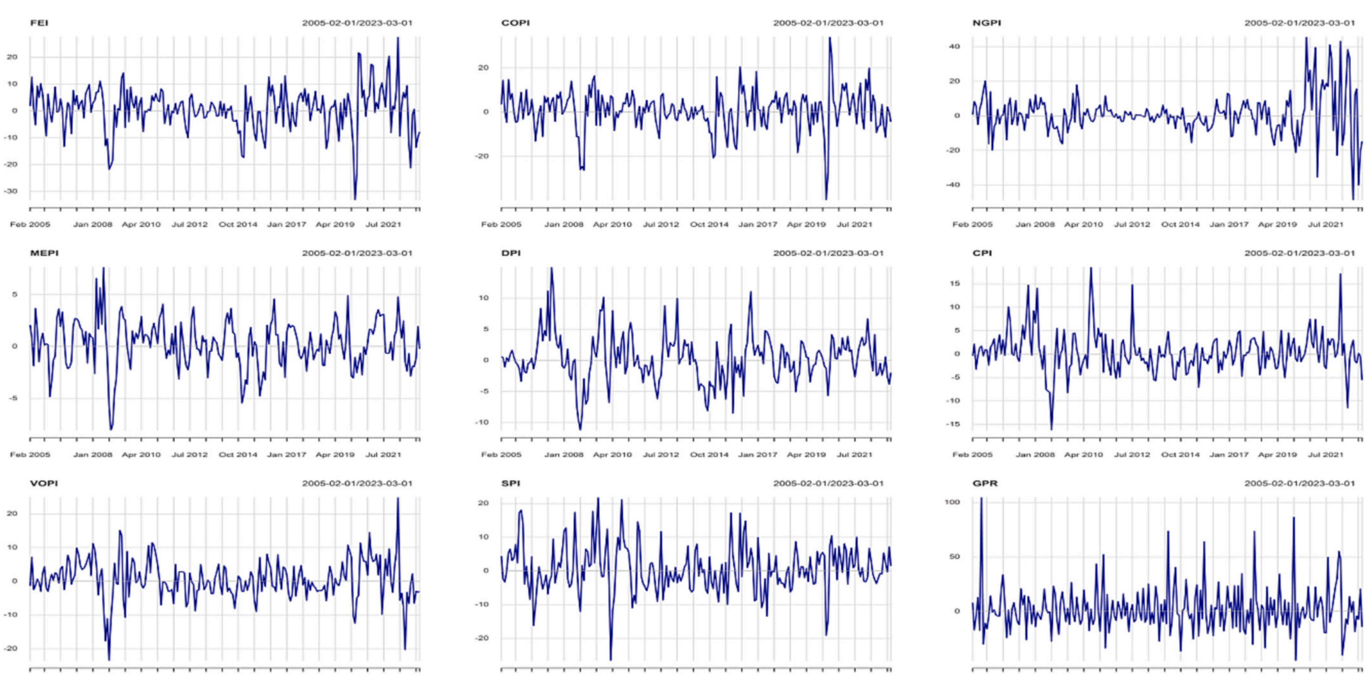

Fig. 1. Trends in the return series.

the global economy.

3. Data and methodology

3.1. Data

Our data set consists of the monthly fuel energy index (FEI), crude oil price index (COPI), natural gas price index (NGPI), dairy price index (DPI), meat price index (MEPI), sugar price index (SPI), cereals price index (CPI), vegetable oil price index (VOPI), and GPR between 2005:1 and 2023:3. FEI, COPI, and NGPI data were collected from the World Bank Commodity Markets Pink Sheet database. We gathered MEPI, DPI, CPI, VOPI, and SPI from the FAO. We sourced the GPR from the EPU [14]. The descriptive statistics and plots of returns are presented in Table 1 and Fig. 1, respectively.

Among the returns, natural gas, and cereals have the highest mean and volatility values, respectively, which aligns with the risk-return trade-off notion. Except for FEI, COPI, MEPI, and VOPI, all returns have a right-tailed distribution. Moreover, all return series are leptokurtic and the high JB values signify that they are abnormally distributed. Furthermore, the returns exhibit significant autocorrelations and ARCH/GARCH errors.

Fig. 1 exhibits prominent fluctuations around geopolitical/financial stress incidents, i.e., the 2005 London bombings on July 7, 2005,[1] the 2008 oil price spike in July 2008 [37], the proclamation of the SARS-CoV-2 on 2020/03/11, and the start of RUC on 2022/02/24. It is worthwhile noting that return series display notable spikes towards the end of the episode.

3.2. Methodology

3.2.1. TVP-VAR connectedness

Antonakakis et al. [4] defined a TVP-VAR interconnectedness approach, which serves as an extension of the Diebold and Yilmaz [19] approach. Within this approach, the variance-covariance matrix fluctuates through Kalman filter estimation, incorporating the concept of forgetting factors, as inspired by Koop and Korobilis [38].

$TVP-VAR(p)$ model is defined as follows:

$$y_t = B_t x_{t-1} + \varepsilon_t \ \varepsilon_t | \ \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + \varrho_t \ \varrho_t | \ \Omega_{t-1} \sim N(0, \Xi_t) \tag{2}$$

with

$$x_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} B_t^{'} = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{pt} \end{pmatrix} \tag{3}$$

wherein Ω_{t-1} denotes all available information until $t-1$; y_t and x_{t-1} denote $n \times 1$ and $np \times 1$ vectors, respectively. B_t and B_{it} are $n \times np$ and $n \times n$ matrices, respectively. ε_t and ϱ_t are $n \times 1$ and $n^2 p \times 1$ dimensional vectors, respectively. Σ_t and Ξ_t are $n \times n$ and $n^2 p \times n^2 p$ dimensional matrices, respectively. $vec(B_t)$ is the vectorization of B_t and is an $n^2 p \times 1$ dimensional vector.

TVP-VAR is transformed to its vector moving average (VMA) structure in the spirit of Wold representation theorem, hence the Generalized IRF (GIRF) and generalized forecast error variance decompositions (GFEVD) are estimated. Accordingly, the VMA representation of y_t is introduced as $\sum_{j=0}^{\infty} A_{jt} \varepsilon_{t-j}$, where A_{jt} is the $n \times n$ matrix.

The $GIRF(\Psi_{ij,t}(H))$ represents the responses of all variables j, following a shock in i computed with an H-step ahead of forecast. $GIRF(\Psi_{ij,t}(H))$ is given as follows:

$$GIRF_t(H, \rho_{j,t}, \Omega_{t-1}) = E(y_t + H | e_j = \rho_{j,t}, \Omega_{t-1}) - E(y_{t+j} | \Omega_{t-1}) \tag{4}$$

$$\Psi_{j,t}(H) = \frac{A_{H,t} \Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\rho_{j,t}}{\sqrt{\Sigma_{jj,t}}} \ \rho_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{5}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}^{-1/2} A_{H,t} \Sigma_t e_j \tag{6}$$

where e_j is an $n \times 1$ vector which is 1 with the selection of the jth element, and 0 o.w. Therefore, the $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ is estimated based on $\widetilde{\Phi}_{ij,t}(H)$ as follows:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{7}$$

with $\sum_{j=1}^{n} \widetilde{\Phi}_{ij,t}(H) = 1$, and $\sum_{i,j=1}^{n} \widetilde{\Phi}_{ij,t}(H) = n$.

TCI:

$$C_t(H) = \frac{\sum_{i,j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{n} * 100 \tag{8}$$

Total directional connectedness (TDC) to others:

$$C_{i \to j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ji,t}(H)} * 100 \tag{9}$$

TDC from others:

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100 \tag{10}$$

Net TDC:

$$C_{i,t}(H) = C_{i \to j,t}(H) - C_{i \leftarrow j,t}(H) \tag{11}$$

3.2.2. TVP-VAR frequency-domains connectedness network

Barunik and Ellington [9] intoduced a dynamic network form, that shows the effects of persistent and transitory shocks from j on the future variance of k as follows:

Define $(X_{t,T})_{1 \leq t \leq T, T \epsilon N}$ with $X_{t,T} = \left(X_{t,T}^1, \ldots, X_{t,T}^N\right)^T$, where t represents the time index and T as the "*sharpness of the local approximation of the time series* $(X_{t,T})_{1 \leq t \leq T, T \epsilon N}$ *by a stationary one*" [9].

$(X_{t,T})_{1 \leq t \leq T, T \epsilon N}$ is structured as follows:

$$X_{t,T} = \varphi_1(t/T) X_{t-1,T} + \ldots + \varphi_p(t/T) X_{t-p,T} + \Sigma_{t,T} \tag{12}$$

where $\Sigma_{t,T} = \Sigma^{-\frac{1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,T} \sim NID(0, I_N)$, and $\varphi(t/T) = (\varphi_1(t/T), \ldots, \varphi_p(t/T))^T$ are time-varying autoregressive coefficients. In fixed time neighbourhood of $\mu_0 = t_0/T$, a stationary process $\widetilde{X}_t(\mu_0)$ approximates the process $X_{t,T}$ as

$$\widetilde{X}_t(\mu_0) = \varnothing_1(\mu_0) \widetilde{X}_{t-1}(\mu_0) + \ldots + \varnothing_p(\mu_0) \widetilde{X}_{t-p}(\mu_0) + \Sigma_t \tag{13}$$

with $t \in \mathbb{Z}$, satisfying the suitable regularity conditions $\left| X_{t,T} - \widetilde{X}_t(t_0) \right| = O_P(|t/T - \mu_0| + 1/T)$. Time-varying $VMA(\infty)$is shown:

$$X_{t,T} = \sum_{\mathrm{h}=-\infty}^{\infty} \psi_{t,T}(\mathrm{h}) \Sigma_{t-\mathrm{h}} \tag{14}$$

Here, $\psi_{t,T} \approx \psi(t/T, h)$ and $sup_l \|\psi_t - \psi_l\|^2 = O_p(h/t)$ for $1 \leq h \leq t$ as $t \to \infty$. "*The spectral density of* $X_{t,T}$ *at frequency d is defined as*" [9]:

$$S_X(\mu, \varpi) = \sum_{h=-\infty}^{\infty} E\left[\widetilde{X}_{t+h}(\mu) \widetilde{X}_t^T(\mu)\right] e^{-i\varpi h}$$
$$= \left\{\psi(\mu) e^{-i\varpi}\right\} \Sigma(\mu) \left\{\psi(\mu) e^{+i\varpi}\right\}^T \tag{15}$$

[1] https://www.reuters.com/article/feature-london-bombing-idUKNOA32614320070713.

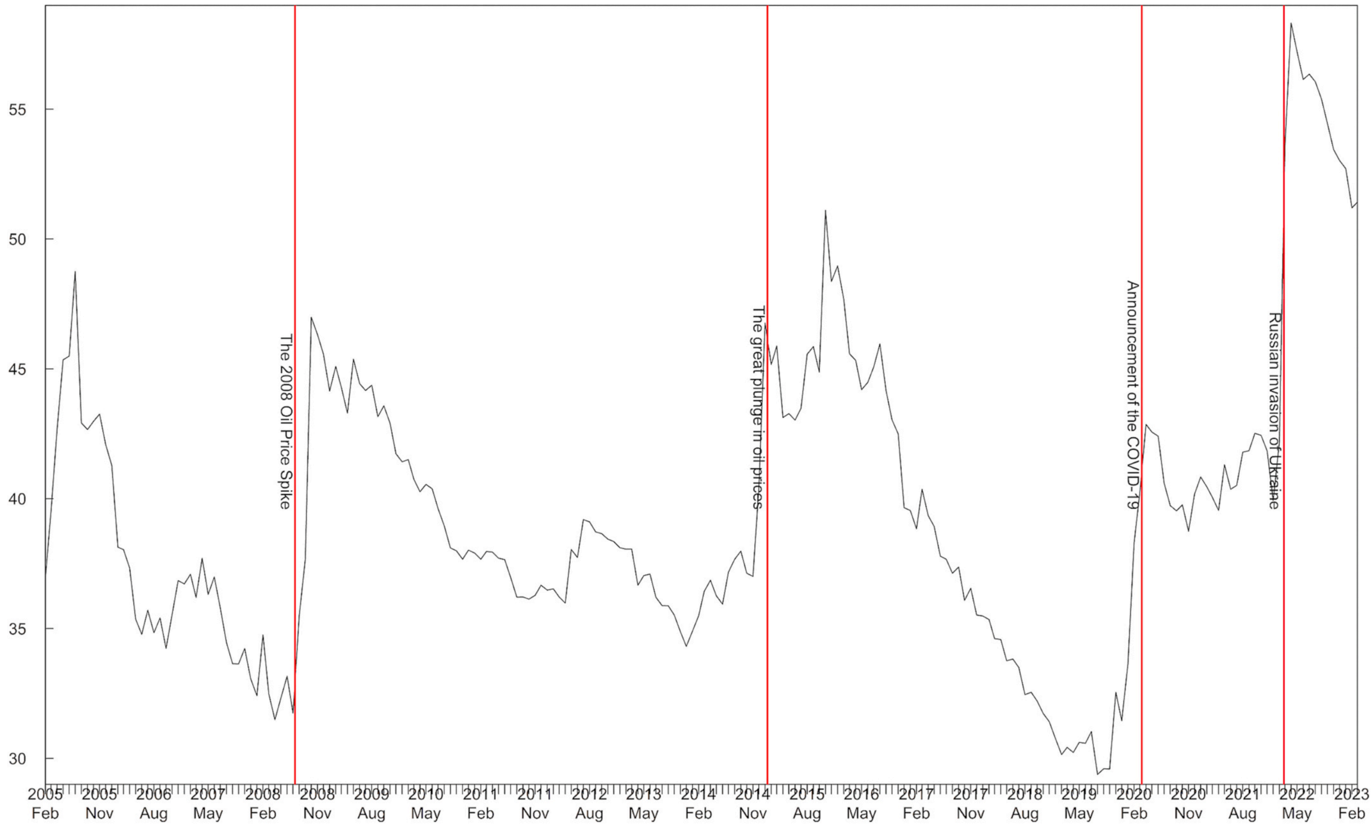

Fig. 2. TCI for returns.

The dynamic adjacency matrix is defined as:

$$[\theta(\mu,d)]_{j,k} = \frac{\sigma_{kk}^{-1}\int_a^b \left|[\psi(\mu)e^{-i\varpi}\epsilon(\mu)]_{j,k}\right|^2 d\varpi}{\int_{-\pi}^{\pi}\left[\{\psi(\mu)e^{-i\varpi}\}\Sigma(\mu)\{\psi(\mu)e^{+i\varpi}\}^T\right]_{j,j} d\varpi} \tag{16}$$

where $d = \{(a,b) : a, b\epsilon(-\pi,\pi), a < b\}$.

The 'local network connectedness':

$$C(\mu,d) = 100 \times \sum_{\substack{j,k=1\\ j\neq k}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{j,k}. \tag{17}$$

Here,

$$\left[\widetilde{\theta}(\mu,d)\right]_{j,k} = [\theta(\mu,d)]_{j,k} \Big/ \sum_{k=1}^{N} [\theta(\mu)]_{j,k} \tag{18}$$

FROM connectedness for $k \neq j$, is defined as:

$$C_{j\leftarrow\bullet}(\mu,d) = 100 \times \sum_{\substack{k=1\\ k\neq j}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{j,k} \Big/ \sum_{j,k=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{j,k} \tag{19}$$

TO connectedness for $k \neq j$, is defined as:

$$C_{j\rightarrow\bullet}(\mu,d) = 100 \times \sum_{\substack{k=1\\ k\neq j}}^{N} \left[\widetilde{\theta}(\mu,d)\right]_{k,j} \Big/ \sum_{k,j=1}^{N}\left[\widetilde{\theta}(\mu)\right]_{k,j} \tag{20}$$

3.2.3. Time-varying portfolio technique

We follow the methodology outlined by Broadstock et al. [12], we apply various multivariate portfolio development techniques and assess their hedging effectiveness.

3.2.3.1. Minimum variance portfolio (MVP). This approach enhances the anticipated portfolio yield while concurrently reducing portfolio risk. The Minimum Variance Portfolio (MVP) represents an ideal balance between return and risk, as articulated by Markowitz [39]. The portfolio allotments are computed as follows:

$$w_t = \frac{\sum I}{I\sum_t^{-1} I} \tag{21}$$

Here, w_t is $m \times 1$ portfolio weight vector, I is a unit vector with n-dimension, and $\sum_t$ is an $n \times n$ conditional variance-covariance matrix.

3.2.3.2. Minimum correlation portfolio (MCP). The correlation matrix is given as:

$$R_t = diag\left(\sum_t\right)^{-0.5} H_t diag\left(\sum_t\right)^{-0.5} \tag{22}$$

R_t is an $n \times n$ matrix. The weights are estimated as:

$$w_{Rt} = \frac{R_t^{-1} I}{IR_t^{-1} I} \tag{23}$$

3.2.3.3. Minimum connectedness portfolio (MCoP). The MCoP is defined by the pairwise connectedness indices [12]. The portfolio weights are computed as follows:

$$w_{Ct} = \frac{PCI_t^{-1} I}{IPCI_t^{-1} I} \tag{24}$$

where PCI_t is the pairwise connectedness index matrix.

Table 2
Average connectedness table.

	FEI	COPI	NGPI	MEPI	DPI	CPI	VOPI	SPI	GPR	FROM
FEI	36.84	31.46	6.76	3.92	3.96	3.42	9.13	3.19	1.32	63.16
COPI	34.74	40.74	0.95	3.98	2.80	2.92	8.98	3.61	1.28	59.26
NGPI	14.60	2.56	70.78	2.04	2.35	2.02	2.11	1.70	1.84	29.22
MEPI	12.25	13.16	1.36	55.91	2.90	5.27	4.36	3.16	1.63	44.09
DPI	6.43	4.92	1.66	2.48	65.36	4.77	11.75	0.94	1.69	34.64
CPI	3.24	2.59	3.35	1.31	2.72	63.28	16.40	4.44	2.68	36.72
VOPI	9.38	8.26	1.53	1.49	6.63	14.30	53.19	3.30	1.91	46.81
SPI	6.47	5.87	1.79	0.74	1.07	5.77	6.41	70.77	1.11	29.23
GPR	0.97	0.85	1.35	1.51	1.59	3.33	2.18	1.27	86.94	13.06
TO	88.09	69.67	18.75	17.47	24.02	41.81	61.32	21.60	13.45	356.18
NET	24.93	10.42	−10.47	−26.61	−10.63	5.09	14.52	−7.63	0.39	TCI = 39.58

Notes: Findings are computed by TVP-VAR model.

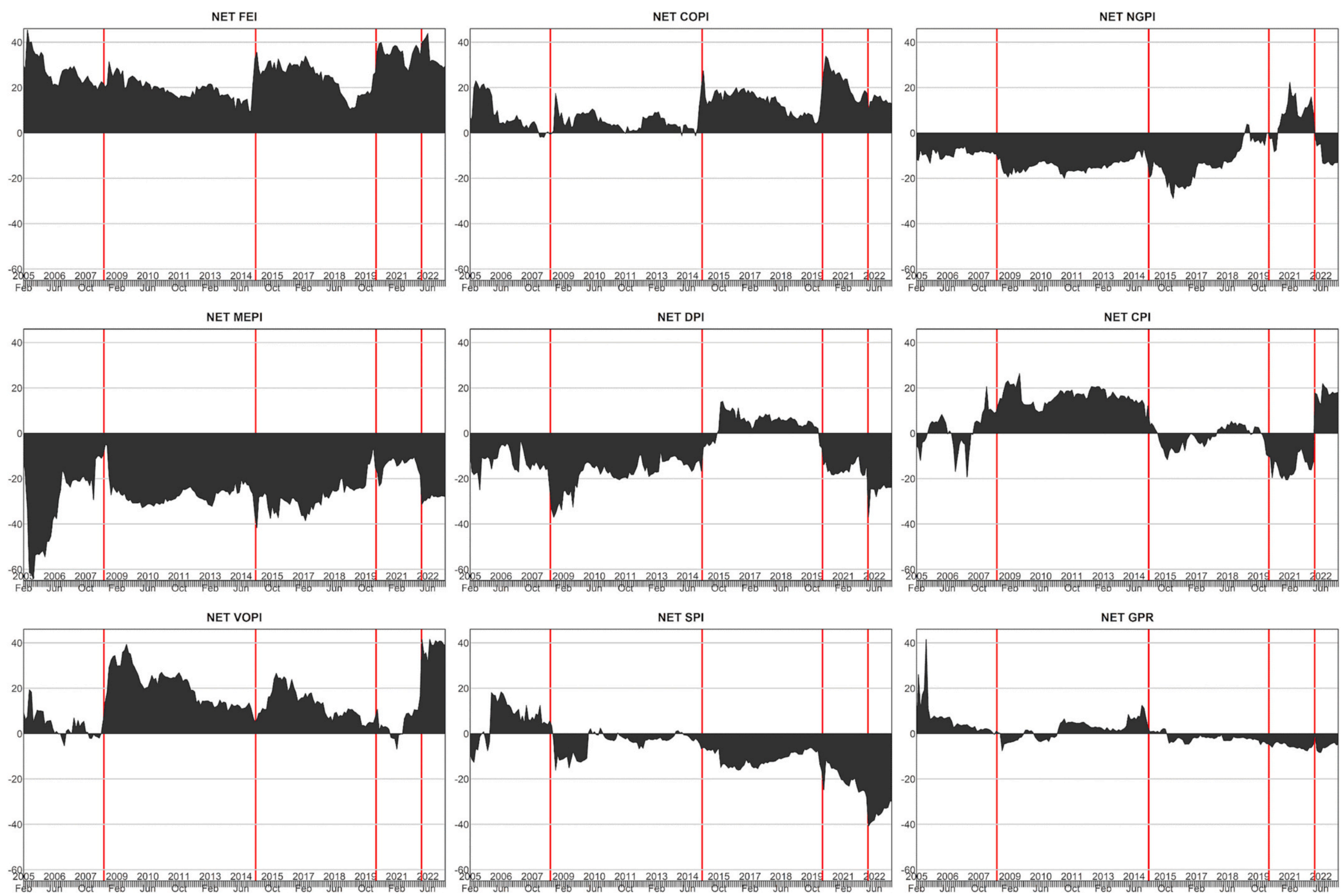

Fig. 3. NDS for the returns.
Notes: Vertical red lines show the following incidents over the episode: The 2008 oil price spike on July 11, 2008, the great plunge in oil prices on January 14, 2015, the announcement of the SARS-CoV-2 outbreak on 11 March 2020, and the RUC on 24 February 2022, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Results

4.1. *Dynamic interlinkages*

In the first phase of the research, the study is centered on examining the dynamic connectedness between the return series and prominent financial or geopolitical occurrences, with the representation of the TCI provided in Fig. 2.

The TCI oscillated between 29% and 59% and peaked on April 2022 (58.31%), shortly after the RUC. It is worthwhile remarking that the TCI significantly surged around prominent incidents of the episode. The index sharply rose in the 2008 July–October period and reached 46.98%. It should be noted that oil prices culminated in an all-time high of $147.98 on July 11, 2008. Moreover, this period coincides with the 2008 GFC and covers the collapse of Lehman Brothers on September 15, 2008. Afterward, the TCI gradually plummeted until December 2013 and skyrocketed between 2014:11 and 2015:01 triggered by the great plunge in oil prices [6]. The index experienced a moderate drop and hit its trough in August 2019 (29.38%). Subsequently, the TCI skyrocketed starting in late 2019 with the pandemic. The index dramatically amplified owing to the Russia and Ukraine conflict and hit its apex in April 2022. Table 2 provides average connectedness findings.

With reference to the average connectedness findings, the widest transmitters/recipients of shocks are the fuel energy index and the crude

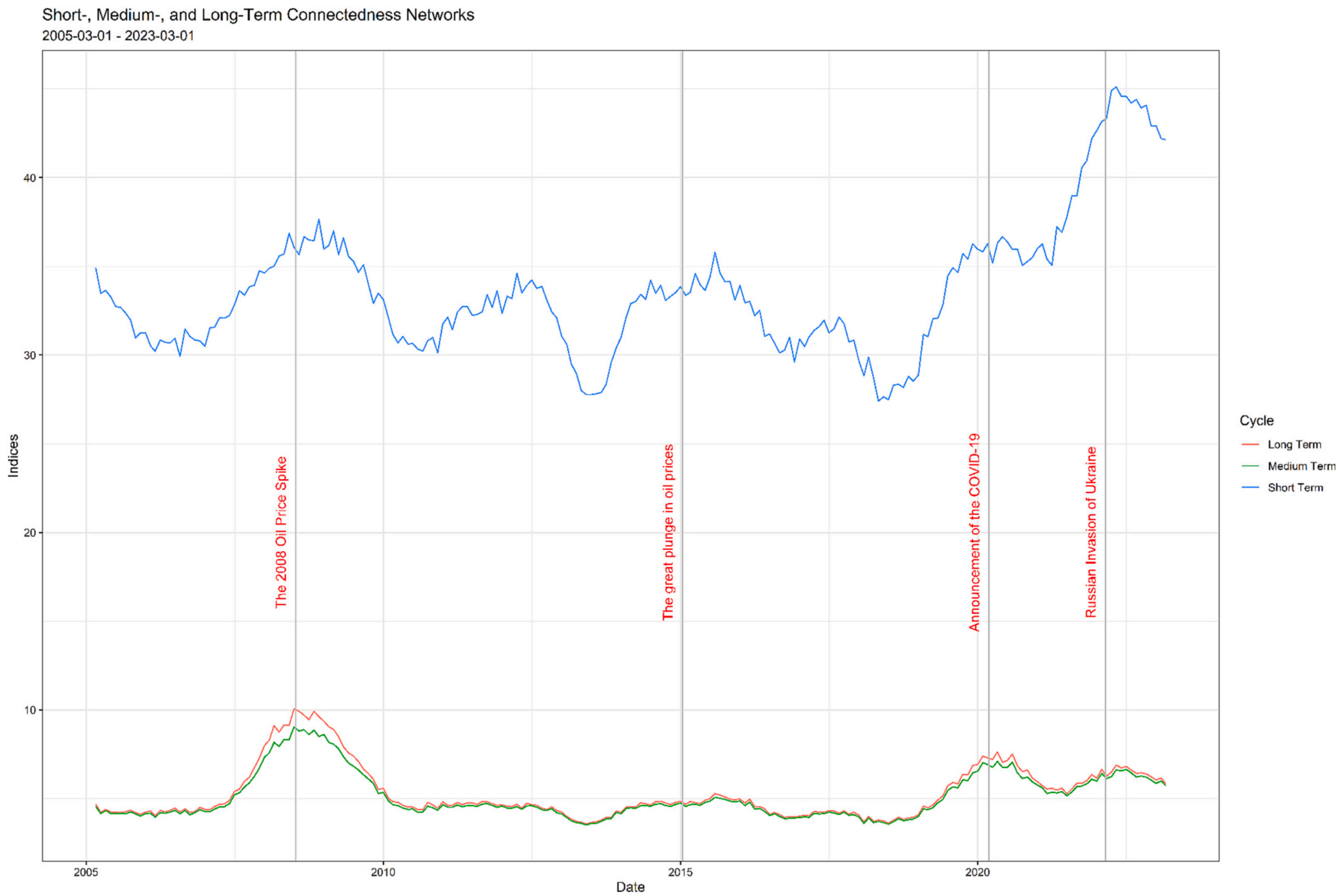

Fig. 4. Frequency-dependent return connectedness networks.

oil price index, whereas the GPR spreads/receives the fewest of the shocks. This aligns with Gong et al. [30], and underpins the prominent role of fuel energy in transmitting return shocks to the other indexes over the episode. FEI, COPI, CPI, VOPI, and GPR are found to be the net transmitter of return shocks on average, while the remaining indexes are the net recipients. The TCI is 39.58%. Next, we analyze the net directional spillovers (NDS) among the indexes and illustrate them in Fig. 3.

Based on the findings, first, corroborating our previous findings fuel energy, crude oil, and vegetable oil price indexes are persistent net transmitters of return shocks, whereas the meat price index is the persistent net recipient of shocks. Other indexes shift between roles of a net transmitting or a net receiving position over the episode. Second, the net spillovers accurately capture the well-known incidents of the period. Third, the GPR has the lowest net spillovers within the system.

4.2. Frequency-dependent interlinkages

Examining the frequency-dependent connectedness network of returns, we follow Kang et al. [35] and estimate temporary-, medium-, and persistent-term (1 month to 6 months, 6 months to 12 months, and more than 12 months, respectively) returns connectedness networks. We plot them with significant geopolitical/financial incidents in Fig. 4.

Frequency-dependent connectedness networks indicate that the temporary interdependence is stronger than the medium- and persistent interdependencies, which is consistent with the existing literature [35,45,60]. In particular, the frequency-dependent connectedness indexes create proper signs to the major stress events of the period. Furthermore, the medium- and the long-term connectedness indexes display very similar motifs over the episode.

Due to the dominance of the transitory (short-term) linkages over the medium- and long-term (persistent) interdependencies and aiming to compare the transitory connectedness network for the 2008 oil price spike, the COVID-19 announcement, and the RUC, we plot the topologies of short-term connectedness in Fig. 5.[2]

Our findings in Fig. 5 reveal that, first, sharing a common feature crude oil and cereals are the largest nodes in the transitory connectedness networks. This finding is unsurprising since these stress episodes are characterized with heightened geopolitical risk and hence its noteworthy impacts on oil and agricultural commodities [1,59,62]. In particular, the RUC disrupted the production of agricultural commodities and consequently unfavorably influenced the capacity of cereal exports. Second, CPI and VOPI, and COPI and FEI, COPI and FEI, and NGPI and FEI have the strongest connectedness in the connectedness networks, respectively.

4.3. Dynamic portfolio analysis

We proceed with our examination, focusing on the dynamic portfolio allocations of returns (except for the GPR) derived from the MVP, MCP, and MCoP methodologies. We compute the portfolio performances (cumulative portfolio returns) under these portfolio construction techniques and plot them in Fig. 6.

In line with Broadstock et al. [12], and Polat [69] the trend of all series exhibit similar patterns, particularly sustained a significant growth starting between early 2020 and early 2022 under the MCP and the MCoP. This growth period coincided with the onset of the COVID

[2] The transitory connectedness of returns sharply escalate around these geopolitical stress times.

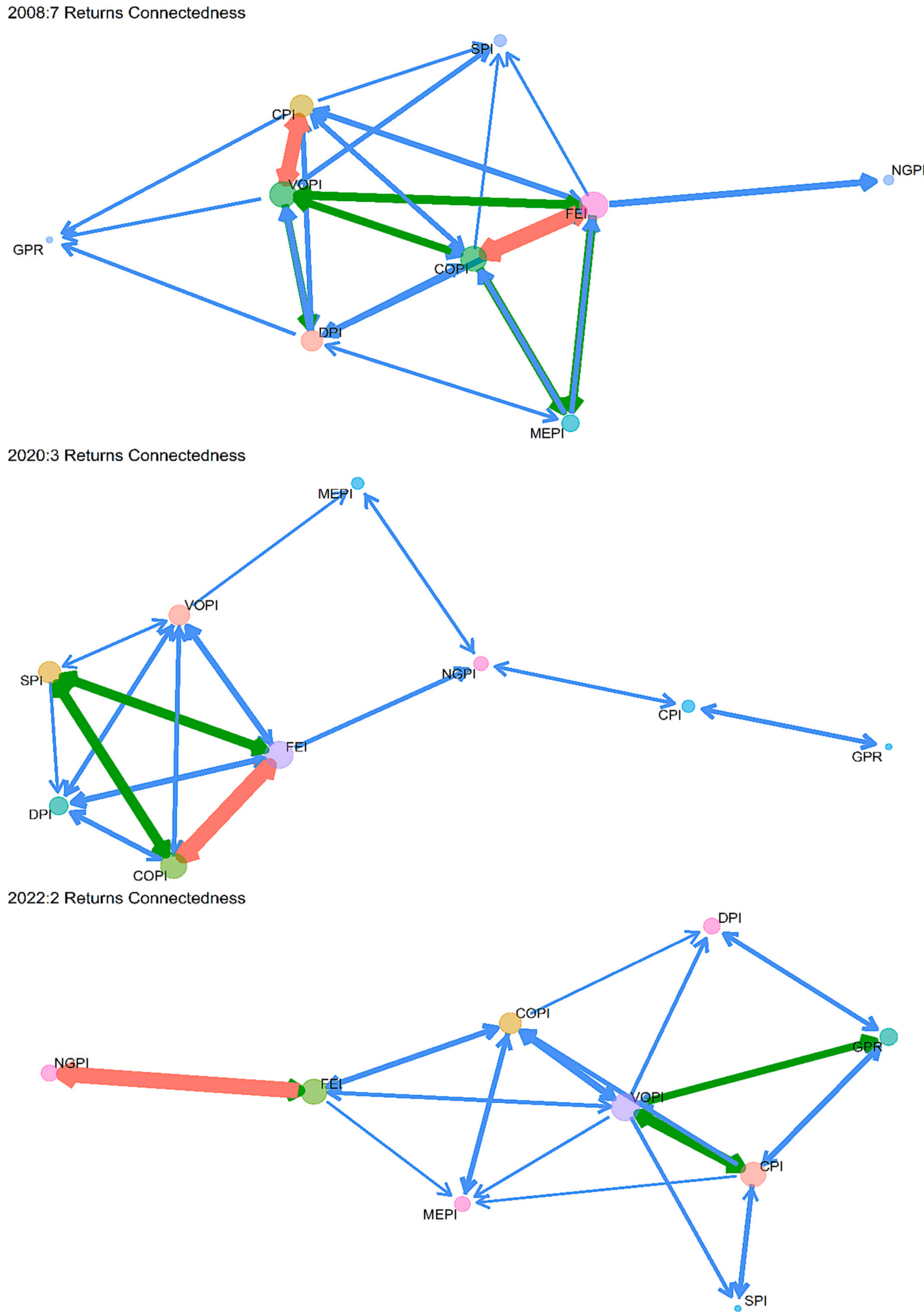

Fig. 5. Transitory connectedness networks for prominent incidents.
Notes: Arrows indicate the direction of connectedness; thickness and color (red, green, and blue, respectively) indicate magnitude of linkages (i.e., the directional connectedness reflected by red color is stronger than the connectedness represented by green, and blue colors, respectively). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 6. Portfolio Performances under MVP, MCP, and MCoP.

pandemic, and cumulative returns significantly increased under these two portfolio construction techniques. Notably, the indexes experienced a decline starting from early 2022, which might be attributed to the RUC. Additionally, the portfolio performances demonstrated a substantial upswing during the GFC, while they remained relatively lower compared with the COVID-19 episode. It is important to highlight that the portfolio performances under the three portfolio construction techniques witnessed a significant drop between mid-2014 and early-2016, potentially linked to the substantial oil price downturn during that period.

Next, we analyze the hedging effectiveness of each portfolio construction approach (MVP, MCP, and MCoP) average and present them in Table 3.

The results in Table 3 suggest that if, on average, we invest 0% in FEI, 14% in COPI, 7% in NGPI, 50% in MEPI, 15% in DPI, 10% in CPI, 0% in VOPI, and 4% in SPI, then the weights of volatilities in the portfolio will be significant decreasing by 89% for FEI, 91% for COPI, 95% for NGPI, −31% for MEPI, 54% for DPI, 63% for CPI, 0% for VOPI, 6% for SPI, and 50% for RE. A negative MEPI value signifies that investing in this asset would lead to an elevation in the volatility of each stock within the portfolio.

Average portfolio weights under the MCP, and MCoP are close and significant except for the vegetable oil price. Furthermore, HE values are negative for MEPI, DPI, CPI, and VOPI under the MCP, and MEPI, DPI, and CPI under the MCoP.

5. Concluding remarks

The purpose of this research is to look at the time and frequency-dependent returns interlinkages among nine food and energy commodity indexes in 2005:1 and 2023:3. To our knowledge, our study is the first to implement time and frequency-dependent connectedness methods to focus on the dynamic interlinkages between food and energy indexes covering the GFC, COVID-19 pandemic and RUC periods. Additionally, we carry out a dynamic portfolio analysis in the spirit of Broadstock et al. [12] and determine time-varying portfolio allocations of the commodity indexes under different portfolio construction approaches.

First, the TCI creates appropriate responses to major financial and geopolitical incidents over the episode, oscillating between 29% and 59%. The TCI reaches considerably high levels around the major events, which is consistent with earlier studies [5,54].

Second, the fuel energy and the crude oil price indexes are the largest transmitters and recipients of return shocks, while the GPR is the fewest transmitter and recipient of shocks. This conclusion is similar to the findings of Gong et al. [30] and emphasizes the importance of fuel energy in the spread of return shocks to other indices across time. Accordingly, fuel energy, crude oil, and vegetable oil price indices are persistent net transmitters of return shocks, but the meat price index is a persistent net recipient of shocks. Typically, crude oil and vegetable oils serve as primary feedstocks for biodiesel production. As crude oil prices increase, the demand for vegetable oils may also increase. This raises the cost of biodiesel production and increases the price of vegetable oil. Generally, increased expenses result in higher biodiesel pricing. The linkage between crude oil, vegetable oil, and biodiesel is supported by our finding that crude oil and vegetable oil are net transmitters of their indices.

Second, in line with previous research [35,45,60], our findings for frequency-dependent connectedness networks of short-, medium- and long-term returns suggest that short-term connectedness is relatively larger than medium- and long-term interconnectedness. According to our findings for short-term connectedness topologies, the largest nodes in temporary connectedness networks are crude oil and grains. Moreover, CPI and VOPI, and COPI and FEI, COPI and FEI, and NGPI and FEI

Table 3
Average MVP, MCP, and MCP Allocations, and HE.

Minimum Variance Portfolio						
	Mean	Std. Dev.	5%	95%	HE	*p*-value
FEI	0.00	0.00	0.00	0.00	0.89	0.00
COPI	0.14	0.05	0.02	0.19	0.91	0.00
NGPI	0.07	0.03	0.01	0.10	0.95	0.00
MEPI	0.50	0.05	0.45	0.61	−0.31	0.05
DPI	0.15	0.02	0.11	0.19	0.54	0.00
CPI	0.10	0.02	0.08	0.13	0.63	0.00
VOPI	0.00	0.00	0.00	0.00	0.80	0.00
SPI	0.04	0.01	0.03	0.05	0.86	0.00
Minimum Correlation Portfolio						
	Mean	**Std. Dev.**	**5%**	**95%**	**HE**	**p-value**
FEI	0.00	0.00	0.00	0.00	0.41	0.00
COPI	0.46	0.01	0.45	0.48	0.53	0.00
NGPI	0.30	0.02	0.27	0.33	0.74	0.00
MEPI	0.06	0.01	0.04	0.08	−6.22	0.00
DPI	0.08	0.01	0.07	0.09	−1.54	0.00
CPI	0.04	0.01	0.03	0.05	−1.03	0.00
VOPI	0.01	0.00	0.00	0.02	−0.10	0.50
SPI	0.06	0.00	0.05	0.06	0.24	0.05
Minimum Connectedness Portfolio						
	Mean	**Std. Dev.**	**5%**	**95%**	**HE**	**p-value**
FEI	0.00	0.00	0.00	0.00	0.50	0.00
COPI	0.42	0.03	0.39	0.47	0.60	0.00
NGPI	0.24	0.03	0.20	0.28	0.78	0.00
MEPI	0.08	0.01	0.07	0.09	−5.09	0.00
DPI	0.09	0.01	0.08	0.11	−1.14	0.00
CPI	0.06	0.01	0.04	0.07	−0.72	0.00
VOPI	0.03	0.01	0.02	0.04	0.08	0.56
SPI	0.09	0.01	0.06	0.10	0.36	0.00

Notes: Results are estimated by the TVP-VAR. The HE is computed by the following formula: $HE = 1 - \frac{Var\left(y_p\right)}{Var\left(y_{unhedged}\right)}$ following Ederington [22].

have the strongest connectedness in the connectedness networks, respectively.

Finally, in accordance with the findings of Broadstock et al. [12], portfolio performances under 3 portfolio construction techniques follow analogous trends, especially showing a remarkable growth phase from early 2020 to early 2022 under the MCP and MCoP strategies. This upturn coincided with the emergence of the COVID pandemic, and the cumulative returns experienced a considerable surge Notably, the indexes began to decline from early 2022, which can be attributed to the RUC. Furthermore, the portfolio performances demonstrated a substantial upswing during the GFC, though they remained comparably lower in comparison to the COVID-19 period. Moreover, all portfolio performances witnessed a significant decrease between mid-2014 and early-2016, potentially linked to the substantial decline in oil prices during that period.

Considering these main results, several significant findings stand out from this study. To begin with, the TCI demonstrates noteworthy fluctuations, ranging from 29% to 59%, in response to major financial and geopolitical events, highlighting the vulnerability of commodity prices to external shocks. Additionally, the analysis identifies fuel energy and crude oil price indexes as central transmitters and recipients of return shocks, accentuating the substantial impact of fuel energy prices on other commodity indexes over time. Furthermore, the study underscores that short-term connectedness is more pronounced than medium and long-term interconnectedness, offering valuable insights into the temporal dynamics of interlinkages among the examined indexes. These findings carry significant policy implications, suggesting that policymakers should vigilantly monitor spillover effects between energy and food indexes during significant financial and geopolitical events. The study emphasizes the roles of fossil energies and agricultural foods, particularly vegetable oils, as key risk transmitters between the energy and food sectors. As a result, policymakers may consider actions to mitigate short-term interdependence between energy and food indexes, such as enhancing supply security and implementing effective risk management strategies.

While this work adds to the literature, it does have several limitations that other researchers should take into account. First, this analysis exclusively looks at the connections between food and energy commodities. In terms of future research avenues, we contemplate several promising directions. Precious and industrial metals may be examined in future investigations. Second, the food and energy commodity connectedness in terms of returns is the only topic of this study. Volatility could also be the subject of future research. Finally, this study employs all food indices without considering sub-food products. The individual sub-sectoral analysis is recommended for more detailed inferences.

CRediT authorship contribution statement

Onur Polat: Writing – original draft, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hasan Murat Ertuğrul:** Writing – original draft, Supervision, Project administration, Conceptualization. **Burçhan Sakarya:** Writing – original draft, Conceptualization. **Ali Akgül:** Writing – original draft, Conceptualization.

Declaration of Competing Interest

No potential competing interest was reported by the authors.

Data availability

Data will be made available on request.

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