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Commodity markets in flux: examining asymmetric interconnectedness across global crises

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Abstract

Commodities are key to global trade and play a crucial role in driving economic growth and ensuring market stability. This paper offers valuable insights into the asymmetric interconnectedness between major commodity markets and sheds light on the changing structure of these markets during periods of uncertainty, providing valuable information for investors and policymakers. Using a comprehensive dataset spanning from 10 January 1983 to 26 June 2024, this study analyses the spillover effects among the five key S&P GSCI commodity indices (Energy, Agriculture, Industrial Metals, Precious Metals and Livestock) employing the asymmetric time-varying parameter vector autoregression (TVP-VAR) connectedness methodology. Unlike previous studies, our study sheds light on the nearly four-decade history of key commodities, revealing how they asymmetrically transmit and absorb shocks through various global crises, including financial meltdowns, geopolitical conflicts, trade wars and pandemics. Our findings highlight that energy, industrial metals, and precious metals act as strong net transmitters of both positive and negative shocks, whereas the livestock sector predominantly absorbs these shocks. Additionally, we observe a marked increase in time-varying interconnectedness, particularly during global turmoils, indicating greater synchronization among market participants. Based on these findings, we suggest that policymakers should adopt more adaptive and inclusive strategies to maintain market stability during crises, while investors should adjust their portfolio diversification strategies to evolving market conditions. By analyzing crisis-driven market behavior, our findings provide an important roadmap for controlling risks across commodity markets in future uncertainty periods.

Keywords: Asymmetric connectedness, Dynamic connectedness, TVP-VAR, S&P commodity indices

JEL Classification: C32, C50, G10

Introduction

Commodities play a pivotal role in global trade, economic activity, and wealth accumulation, significantly influencing inflation and portfolio construction (Bhar and Hamori 2008; Mallick and Sousa 2013; Holtemöller and Mallick 2016; Zhang et al. 2019). Their positive correlation with inflation, negative correlation with traditional assets, and

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ability to offer comparable risk-adjusted returns make them attractive to portfolio managers for hedging and diversification purposes (Silvennoinen and Thorp 2013; Kang et al. 2017). The "Commodity Futures Modernization Act" enacted in the early 2000 s marked the beginning of the financialization of commodities (Tang and Xiong 2012), encouraging increased investment in commodity markets (Silvennoinen and Thorp 2013). This financialization, combined with global market integration, has led to heightened price volatility and speculation, thus amplifying the risk and return linkages among various commodity markets (Rehman et al. 2018; Kang et al. 2019; Tiwari et al. 2020).

As the share of commodities in the global financial system has increased, the correlation between commodities and other financial assets has intensified, making portfolio management strategies and decision-making difficult. Therefore, many studies examine the relationship between commodities and financial assets such as stock markets, bonds or currencies (Mensi et al. 2013; Polat 2020; Bouri et al. 2021a; Li et al. 2021, 2024; Ertugrul et al. 2024) and decentralized financial assets such as cryptocurrencies and nonfungible tokens (Ji et al. 2019; Umar et al. 2022a; Hanif et al. 2023) and show that movements between commodities and other financial assets are susceptible to each other. In addition, some studies (Angelopoulos et al. 2020; Melas and Michail 2021, 2024; Bandyopadhyay and Rajib 2023) offer a different perspective on the existing body of knowledge by linking commodity dynamics to transportation and logistics markets. However, in addition to being important financial assets, commodity markets have a critical role in global economies, and each sector contributes significantly to economic stability and development. Energy, which drives the production and transport costs of all commodities, and agriculture, which ensures food security, are crucial for economic stability (Fowowe 2016). Industrial metals support production (Gong et al. 2022), while precious metals serve as a safe haven in times of uncertainty (Baur and McDermott 2010). Livestock supports the food sector, emphasizing the reciprocal nature of the two sectors. Therefore, these sectors together reflect the complex interaction of the market and justify their role as key components in research examining the behavior of commodity markets.

During stressful periods in recent history, increased market integration has fuelled contagion among global commodity markets. One of the most important of these stressful periods, the Global Financial Crisis (GFC), which erupted in mid-September 2008, led to a rapid collapse in world trade and a sharp increase in commodity prices. With the onset of the crisis, food prices increased by 40% compared to the previous year (FAO 2009). Similarly, gold prices were approximately 40% higher than the previous year, and oil prices were approximately 30% above the record set in 1979 (IMF 2008). Then, the COVID-19 pandemic in 2020 brought unprecedented impacts on the supply and demand of various commodity groups. During this period, travel and trade restrictions imposed as part of pandemic prevention strategies resulted in a significant drop in oil prices, which fell by approximately 65% to $40 per barrel (World Bank 2020). In the same period, natural gas prices fell sharply by 38% due to disruptions in production chains and supply disruptions (IMF 2020). Food prices were also affected by the uncertainty and global recession caused by the pandemic, and the FAO Food Price Index fell to its lowest recorded level in May 2020 (FAO 2020). In contrast to the declines in energy and food prices, precious metal prices experienced an increase, especially due to

the rise in gold prices. Accordingly, the World Bank Precious Metals Index experienced a significant increase of 5.4% in the first quarter of 2020 (World Bank 2020). Finally, the Russia-Ukraine Conflict (RUC), which erupted in February 2022, has caused restrictions in the global energy supply, shortages in food supplies and disruptions in the global supply chain compared to other geopolitical conflicts in the past. In this respect, it had a far more dominant influence in shaping the world economic landscape (Liadze et al. 2022; Mbah and Wasum 2022; Astrov et al. 2022). Russia and Ukraine, which together account for approximately 30% of global wheat exports, 20% of maize, mineral fertilizer and natural gas exports, and 11% of oil exports, have caused food, mineral and energy prices to rise, leading to global inflationary pressures (OECD 2022). The uncertainties arising from this conflict have led to an increase in the risk premiums of economies and the devaluation of their currencies, thus adding further complexity to the network of global economic repercussions (Umar et al. 2022b).

Asymmetries are a fundamental characteristic of financial markets, particularly in commodity markets, where investor behavior often exhibits a greater sensitivity to negative shocks than to positive shocks. For example, in both bullish and bearish market conditions, hedgers may respond more strongly to negative news, as it can significantly affect market sentiment and investment strategies (Beber and Brandt 2010). While previous studies have documented the presence of asymmetries (Christie 1982; French et al. 1987), there remains a relatively limited body of research specifically examining the asymmetric connectedness between assets (Baruník et al. 2016; Wang and Wu 2018; Iqbal et al. 2023; Mensi et al. 2021). This gap in the literature highlights that the study of asymmetric connectedness, particularly within the context of commodities, is still an emerging field of research. Understanding these asymmetric relationships is crucial, as it allows for a more refined analysis of how commodities react to different market conditions and how shocks in one market may impact others in a nonlinear and often disproportionate manner.

Therefore, our motivation is to investigate in depth the dynamics of the mutual spillovers of commodities, which have become an attractive instrument for hedging risk, taking into account extreme (positive and negative) market conditions, especially during turbulent periods. In this respect, our study captures the responses of return networks in various commodity sectors to unprecedented and significant catastrophic shocks, thereby making important contributions to the literature on contagion. First, while many studies have investigated average return interconnectedness across commodities using different spillover methodologies (Balli et al. 2019; Caporin et al. 2021; Dai and Wu 2024; Polat et al. 2024), there is a notable research gap in documenting the negative and positive return connectedness network in commodity markets. To fill this gap, we use the asymmetric TVP-VAR connectedness methodology. This state-of-the-art methodology takes into account the negative and positive spillovers of the series, bypassing the traditional methods that focus on average spillovers. Our approach increases the depth of analysis of the linkages between major commodity markets and sheds light on the complex dynamics between commodity markets, particularly during bearish and bullish periods. Second, in contrast to recent studies that focus on the COVID-19 pandemic and the RUC periods, we extend our dataset from January 1983 to June 2024 to cover the period before and during the GFC, which triggered extreme uncertainty in financial

markets, leading to panic trading and severe economic losses. Thus, we aim to present the return interconnectedness networks across commodity markets, taking into account the political, economic and geopolitical events that occurred before and during the GFC, the COVID-19 pandemic and the RUC. Finally, past studies have focused on individual commodities (Xiao et al. 2020; Chishti et al. 2023; Mandaci et al. 2023), ignoring the effects of sectoral spillovers. While examining individual commodities helps to understand price movements, it loses the advantage of analyzing how specific sectors react to the overall market dynamics that sectoral studies provide. However, sectoral market analyses are becoming an important tool for investors and portfolio managers to minimize their risks and develop investment strategies. Therefore, we focus on five critical sectors (Energy, Agriculture, Industrial Metals, Precious Metals and Livestock) and provide a comprehensive and innovative perspective on the spillovers of shocks across commodity markets. In this sense, the study makes an important contribution to the literature by providing a solid foundation for the development of appropriate policy and investment strategies during periods of potential resilience or vulnerability.

The hypotheses of our study are as follows:

Hypothesis 1 (H1) Recent studies provide evidence of increased interconnectedness between commodity markets during turbulent periods such as the GFC and COVID-19 (Mensi et al. 2013; Tiwari et al. 2020). Based on this evidence, we hypothesize that commodity markets exhibit significant interconnectedness, which intensifies during periods of extreme market stress such as the GFC, the COVID-19 health crisis and the RUC.

Hypothesis 2 (H2) Studies indicate that negativeshocks have stronger effects on markets due to investors' sudden and erratic reactions to negative news to avoid risk (Beber and Brandt 2010; Wang and Wu 2018). Therefore, we hypothesize that negative shocks have more pronounced effects on the interconnectedness of commodity markets than positive shocks and reflect asymmetric effects.

Hypothesis 3 (H3) Previous studies have revealed the changing nature of commodity market interconnectedness during bullish and bearish cycles (Baruník et al. 2016; Iqbal et al., 2023). Therefore, we hypothesize that the interconnectedness of commodity markets during bullish and bearish market cycles changes in both magnitude and direction (positive and negative spillovers), revealing undetected linkages.

Several important findings emerge from the main results of this study. First, the Total Connectedness Index (TCI) reacts to major financial and geopolitical events such as the GFC, COVID-19 and RUC, with the most pronounced TCI spikes exhibited for negative shocks. This highlights the sensitivity of commodity markets to negative shocks. In addition, industrial metals, precious metals and energy are the strongest transmitters of both positive and negative shocks and have significant impacts on other indices. This proves that these markets have a dual role as both shock transmitters and shock receivers. Finally, the net connectedness of positive and negative shocks indicates that energy and industrial metals and precious metals are prone to transmit shocks, while livestock is more of a receiver.

In this study, we highlight the dynamics of interconnectedness among major commodity markets and the impact of systemic shocks and market turmoil on risk transmission and market behavior under different economic, political and geopolitical conditions. We thus provide important insights for policymakers, investors and academics. These findings are valuable for policymakers in building supervisory and regulatory structures that support market resilience and financial stability. For investors, they have implications for both risk management during negative uncertainty shocks and portfolio diversification strategies during positive financial recovery shocks. Finally, academics can benefit from our empirical findings and lead future research by examining the complex dynamics between commodity markets and other financial assets. Thus, we aim to contribute to the understanding of the linkages between commodity markets in today's era of uncertainty by building a bridge that brings together both theoretical understanding and empirical application. Our study offers broad insights into how systemic shocks spread across commodity markets by examining several global crises together. These widely applicable insights will assist investors and policymakers in anticipating and managing risks during upcoming global disruptions.

The subsequent sections of the article are structured as follows: Sect. "Literature review" provides an overview of the literature. A description of the data and methodology is provided in Sect. "Data and methodology". Sect. "Empirical results" is devoted to the results of the empirical analysis, Sect. "Discussion" provides the discussion and policy implications, and Sect. "Conclusion" concludes the study.

Literature review

The complex linkages between commodity markets have been the subject of extensive analysis, reflecting their important role in the financial system. The inclusion of commodity futures in diversified investment portfolios is important for investors and fund managers seeking a comprehensive understanding of intermarket relationships and to reduce risk exposure. In this context, the pioneering work on commodity markets by Pindyck and Rotemberg (1990) opened up a new area of research in the literature by showing that commodity prices tend to move together due to similar market behavior.

Since the pioneering research, the world has experienced a series of upheavals resulting from economic turmoil, trade tensions, political instability, civil conflicts, regional war and acts of terrorism. The Black Monday in 1987, the Asian financial crisis in 1997, the Dot-com bubble in 2000, the terrorist attacks in 2001, the Global Financial Crisis (GFC) in 2008, the Arab Spring, the Syrian civil war and the associated migrant movement in 2012, the terrorist attacks in Paris in 2015, the North Korea-US crisis in 2017, and the China–US trade tensions in 2018 are just a few examples of these upheavals. Moreover, the recent Brexit, the COVID-19 pandemic, the ongoing RUC since 2022 and Israel's attempt to occupy Palestine since 2023 have further contributed to the turbulent situation, and the global economic atmosphere has been negatively affected.

A series of global turmoil spurred interest in the response of commodity markets under stress, prompting a follow-up to the pioneering research. In particular, the 2008 GFC was a period of intensified risk contagion across commodity markets and became an important focus of analysis for contagion studies. Among the earliest studies, Nazlioglu et al. (2013) highlight that the transmission of volatility between oil and agricultural

commodities intensified, particularly during the GFC, highlighting the role of energy commodities in shaping agricultural prices during periods of financial turmoil. Similarly, Ji et al. (2018) argue that the interdependence between energy and agricultural commodity markets is particularly realized in the lower tail and is stronger in bearish regimes. Kang et al. (2017) provide evidence that the positive correlation between energy and agricultural returns became stronger during the GFC, suggesting an increase in systemic risk during this period. The findings of Tiwari et al. (2020) highlight that there are significant pairwise wavelet-based correlations between fuel-agriculture and fuel-metal prices and that the agriculture sector is highly sensitive to shocks from other markets.

The COVID-19 pandemic has introduced new uncertainties about the complex linkages between commodity markets, prompting research to focus on the dual effects of the GFC and COVID-19 periods. For example, Nekhili et al. (2021) examine time- and frequency-based return and volatility spillovers between energy, agricultural, metal commodities and foreign exchange markets and show that crude oil is the largest driver of volatility. Moreover, although short-term return spillovers were more dominant, the GFC and COVID-19 were the periods when long-term volatility spillovers were more concentrated. Similarly, Shahzad et al. (2021) support these findings and highlight the systemic role of energy markets by showing that time-varying causality between energy, agricultural and precious metal commodities intensifies during periods of turmoil.

Recent research focusing on the COVID-19 pandemic and the RUC period has revealed new complexities regarding the spillover dynamics in commodity markets. For example, Fang and Shao (2022) analyze the volatility risks of commodity prices and find significant increases in volatility spreads of agricultural, metal and energy prices during the peak of the RUC. Similarly, Chishti et al. (2023) show that agricultural, metal and energy commodities, with the exception of natural gas, are negatively affected by conflicts during the RUC period. In contrast, Bouri et al. (2023) find that correlations between agricultural, metal and energy commodities exhibit heterogeneity and changes in stability over time, with no clear contagion in returns or volatility during market instability.

In Table 1, we present the findings of relevant existing studies in the literature according to crisis events (2008 GFC, COVID-19, and RUC).

Based on the existing body of related studies and the assessments given above, we highlight several notable gaps. First, a review of previous studies reveals causality analysis (Nazlioglu et al. 2013; Shahzad et al. 2021), cointegration analysis (Rehman et al. 2019), Diebold and Yilmaz spillover methods (Balli et al. 2019; Xiao et al. 2020; Zhang and Broadstock 2020; Ameur et al. 2021; Umar et al. 2021; Fang and Shao 2022), GARCH family models and spillover methods (Chen and Wu 2016; de Nicola et al. 2016), copula-based analysis (Ji et al. 2018), cross-quantilogram approach (Hernandez et al. 2019; Chishti et al. 2023), wavelet and spillover methods (Tiwari et al. 2020; Bouri et al. 2023; Shahzad et al. 2023), time- and frequency-based connectedness approaches (Caporin et al. 2021; Nekhili et al. 2021), TVP-VAR method (Bouri et al. 2021b; Wang et al. 2022; Polat et al. 2023, 2024; Dai and Wu 2024; Li et al. 2024) and quantile (Sifat et al. 2021; Farid et al. 2022; Iqbal et al. 2023; Mandaci et al. 2023) based models. However, in this study, we use the asymmetric TVP-VAR connectedness method, which was introduced as a new approach by extending the TVP-VAR connectedness approach by

Table 1 Summary of existing relevant studies examining the connectedness between commodities

Crisis Period	Study	Commodity Type	Key Findings
GFC (2008)	de Nicola et al. (2016)	Energy and agriculture	High correlation between agriculture and energy returns; Agricultural commodities exhibiting a marked sensitivity to fluctuations in energy prices during the GFC
	Chen and Wu (2016)	Energy, agriculture, livestocks and metals (precious and industrial)	Interconnectedness between commodity markets increased during the GFC and returned to precrisis levels after the GFC
	Balli et al. (2019)	Energy, agriculture, metals (precious and industrial)	Commodity markets reached peak linkages during the GFC and the oil price collapse of 2014–2016; Precious metals act as a safe haven during times of crisis
	Hernandez et al. (2019)	Energy, agriculture and precious metals	Positive spillovers from oil to agriculture and precious metals
	Rehman et al. (2019)	Energy and nonenergy	Oil prices negatively affect gold and silver prices in the long run
	Xiao et al. (2020)	Energy, agriculture and precious metals	The dynamic interconnectedness between commodities increases during the GFC; Precious metals (Agriculture) act as net risk transmitters (takers) of shocks
	Zhang and Broadstock (2020)	Energy, agriculture and metals (precious and industrial)	Spillovers between commodities are much higher during a GFC than before the crisis
	Bouri et al. (2021b)	Energy, agriculture and metals (precious and industrial)	Varying degrees of volatility linkages among commodities, which are driven by macroeconomic factors
	Ameur et al. (2021)	Energy, agriculture, livestocks and metals (precious and industrial)	Spillover transmission from energy to the other commodity markets
	Caporin et al. (2021)	Energy, agriculture and precious metals	The connectedness between commodities is more pronounced in negative volatilities than in positive ones
	Sifat et al. (2021)	Energy, agriculture and precious metals	Speculative activity in energy and precious metals markets during the GFC; The appeal of precious metals in times of turmoil

Table 1 (continued)

Crisis Period	Study	Commodity Type	Key Findings
GFC and COVID-19	Umar et al. (2021)	Energy, agriculture, livestock and precious metals	Agriculture and precious metals markets act as net spillover transmitters
	Farid et al. (2022)	Energy, agriculture and metals (precious and industrial)	The degree of dependence between energy, metals and agricultural commodities changes over time; Commodity market returns have become significantly more interlinked due to COVID-19
	Wang et al. (2022)	Energy, agriculture and metals (precious and industrial)	The return and volatility spreads of energy, agriculture, and metals are associated with high levels of geopolitical risk
	Iqbal et al. (2023)	Energy, agriculture and metals (precious and industrial)	Extreme risk spreads, especially during COVID-19, are very pronounced at the lower and upper quantiles
RUC	Mandaci et al. (2023)	Energy and metals (precious and industrial)	Potential spillover effect from metals to energy
	Shahzad et al. (2023)	Nonrenewable energy and precious metals	Commodities play a central role in risk transfer during RUC; GPR and oil are major risk transmitters, while gold and silver are generally safe havens that absorb shocks
	Polat et al. (2023)	Agriculture	Time-varying linkages between GPR and agricultural commodities generally increase during periods of geopolitical stress, and persistent linkages increase particularly strongly around the RUC
	Dai and Wu (2024)	Energy, agriculture, livestock and metals (precious and industrial)	Energy and livestock markets are risk transmitters; Metals, agriculture, and light energy markets are risk recipients
	Polat et al. (2024)	Energy and agriculture	The time and frequency connectedness are related to major economic and geopolitical stress periods; Energy markets are the largest transmitters of spillovers
	Li et al. (2024)	Agriculture, and metals (precious and industrial)	Strong connectedness between the RUC and Chinese commodity markets; Gold has a safe-haven status

Adekoya et al. (2022). Therefore, the most important empirical contribution of this study is to investigate directly and inversely related spillovers across commodity markets. Second, it is worth noting that existing studies tend to investigate the simultaneous dynamics between individual commodities rather than focusing on market dynamics from an aggregate perspective. Finally, we expand our observation space by using a dataset dating back to Black Monday in 1987, allowing for a wider range of analysis of this dynamic and complex structure. In conclusion, this study aims to fill the gaps identified in the

literature by adopting the asymmetric TVP-VAR connectedness methodology to study the spillovers between key commodities in the face of major economic, political and geopolitical events.

Data and methodology

Data

We employed five S&P GSCI commodity indices, namely, five S&P GSCI commodity indices—S&P GSCI Energy, S&P GSCI Agriculture, S&P GSCI Industrial Metals, S&P GSCI Precious Metals, and S&P GSCI Livestock. We collected the data from the Refinitiv database, and the sample period ranges between 10 January 1983 and 26 June 2024.[1]

Following Adekoya et al. (2022), we decompose the returns into their positive and negative components:

$$R_t = \{0, if x_t < 01, if x_t \geq 0 \tag{1}$$

$$y_t^+ = r_t.y_t \tag{2}$$

$$y_t^- = (1 - r_t).y_t \tag{3}$$

where y_t^+ and y_t^- correspond to the positive and negative returns, respectively.

We utilized the log daily returns S&P GSCI commodity indices. Table 2 and Fig. 1 report the summary statistics for the return series and their trends, respectively. We also employed the BDS nonlinearity test to identify nonlinear behavior among commodities, with the results provided in the Appendix A, Table A.1.

All series exhibit positive average returns, with energy leading the group, followed by industrial metals and precious metals, while livestock and agriculture show the lowest average returns. Energy also demonstrates the highest volatility, aligning with the risk-return trade-off principle. Except for agriculture, all return series display leptokurtic distributions and left-skewed tails. Moreover, the Jarque–Bera (JB) test confirms that these distributions deviate significantly from normality. The series also exhibit notable autocorrelation and display pronounced ARCH/GARCH effects. Furthermore, the returns are positively correlated and carry economic significance.

Upon examining return trends, we observe that the returns exhibited substantial fluctuations corresponding to financial/geopolitical turmoils such as the Black Monday in October 1987, the 1997 Asian financial crisis, the 1998 Russian financial crisis, the Dotcom bubble in March 2000, the terrorist attacks in 2001 September, the stock market downturn in October 2002, the 2007–2008 global financial crisis, the 2010 flash crash in May 2010, the August 2011 stock market crash, the 2015–2016 stock market sell-off in August 2015, the 2020 stock market crash in February 2020, and the 2022 Russian-Ukrainian conflict. Moreover, energy and industrial metals exhibit the most pronounced

[1] The selected sample period was chosen to encompass a broad range of economic conditions, allowing for an in-depth analysis of market dynamics during periods of significant events such as the GFC, the COVID-19, and the RUC. This period also provides sufficient data to capture long-term trends in commodity markets. S&P GSCI commodity indices—Energy, Agriculture, Industrial Metals, Precious Metals, and Livestock—represent key commodity sectors that reflect diverse market dynamics and economic roles. Each sector captures different aspects of global economic activity, providing a comprehensive overview of the relationship between commodities and economic variables.

Table 2 Summary statistics

	Energy	AgrCult	IndMetals	PrecMetals	Livestock
Mean	0.029	0.011	0.021*	0.020*	0.012
Variance	3.952	1.183	1.755	1.128	0.853
Skewness	−0.175***	0.004	−0.159***	−0.181***	−0.125***
Ex. Kurtosis	9.414***	3.069***	4.288***	6.353***	1.664***
JB	40,001.887***	4246.282***	8331.736***	18,251.960***	1275.612***
ERS	−30.621	−38.094	−16.101	−44.945	−21.685
Q(20)	45.059***	32.831***	16.950*	21.792***	85.834***
Q2(20)	3143.370***	2744.946***	3337.942***	930.096***	3871.930***
Kendall Correlations	*Energy*	*AgrCult*	*IndMetals*	*PrecMetals*	*Livestock*
Energy	1.000***	0.118***	0.132***	0.113***	0.051***
AgrCult	0.118***	1.000***	0.120***	0.117***	0.068***
IndMetals	0.132***	0.120***	1.000***	0.180***	0.056***
PrecMetals	0.113***	0.117***	0.180***	1.000***	0.025***
Livestock	0.051***	0.068***	0.056***	0.025***	1.000***

*****, **, *** denote 1%, 5%, and 10% statistical significance levels, respectively. ERS: Stock et al. (1996) unit root test; JB: Jarque–Bera Test. Q (20) and $Q^2(20)$ represent the Ljung–Box statistics for serial correlation in raw series and squared residuals. S&P GSCI Energy–Energy, S&P GSCI Agriculture-AgrCult, S&P GSCI Industrial Metals-IndMetals, S&P GSCI Precious Metals-PrecMetals, and S&P GSCI Livestock-Livestock

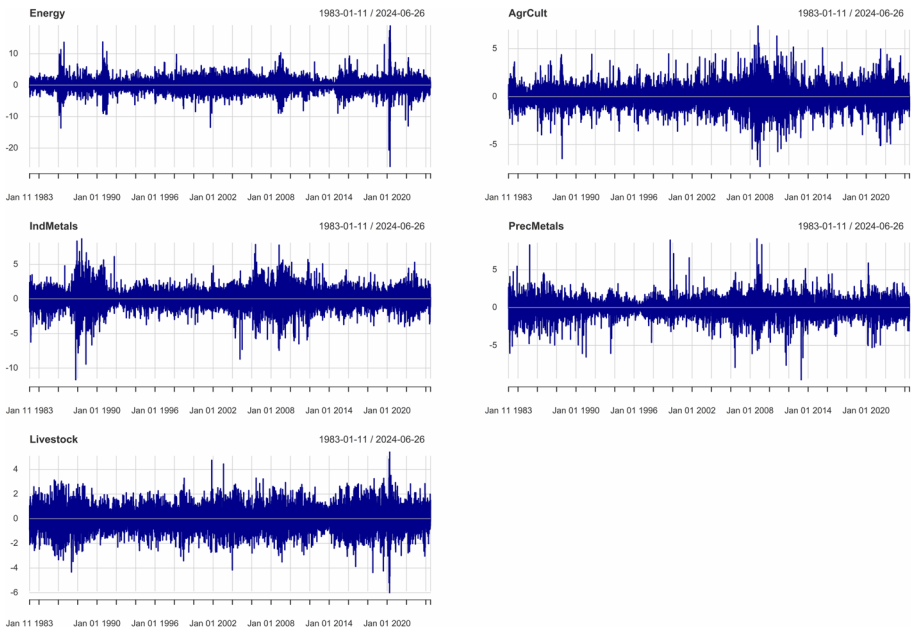

Fig. 1 Returns

price swings, suggesting higher volatility compared to the other commodities. Agriculture displays a relatively stable trend with moderate fluctuations. Precious metals demonstrate a more subdued pattern with less dramatic price movements. Livestock, while

displaying some volatility, generally follows a less extreme path than energy and industrial metals.

Methodology

Adekoya et al. (2022) introduced the TVP-VAR asymmetric connectedness approach as follows:

The $TVP-VAR(1)$ model is defined as follows:

$$y_t = A_t y_{t-1} + \nu_t \nu_t | \Omega_{t-1} \sim N(0, \Sigma_t) \tag{4}$$

$$vec(A_t) = vec(A_{t-1}) + \gamma_t \gamma_{t|\Omega_{t-1}} \sim N(0, \Gamma_t) \tag{5}$$

where Ω_{t-1} represents all information available until $t-1$, and y_t and y_{t-1} correspond to $n \times 1$ vectors. A_t, and Σ_t are $n \times n$ dimensional matrices, ε_t and γ_t are $n \times 1$ and $n^2 p \times 1$ dimensional vectors, and $vec(A_t)$ and γ_t are $n^2 \times 1$ and Γ_t is $n^2 \times n^2$ matrices.

The VMA transformation of the TVP-VAR model is given by the Wold theorem as follows:

$y_t = \sum_{i=1}^{p} A_{it} y_{t-i} + \nu_t = \sum_{j=0}^{\infty} B_{jt} \nu_{t-j}$, where B_{jt} is an $n \times n$-dimensional matrix.

$GIRF\left(\Psi_{ij,t}(H)\right)$ is defined as follows:

$$GIRF\left(H, \rho_{j,t}, \Omega_{t-1}\right) = E\left(y_t + H | e_j = \rho_{j,t}, \Omega_{t-1}\right) - E\left(y_{t+j} | \Omega_{t-1}\right) \tag{6}$$

$$\Psi_{j,t}(H) = \frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\rho_{j,t}}{\sqrt{\Sigma_{jj,t}}} j,t = \sqrt{\Sigma_{jj,t}} \tag{7}$$

$$\Psi_{j,t}(H) = {\Sigma_{jj,t}}^{-1/2} B_{H,t} \Sigma_t e_j \tag{8}$$

where e_j is an $n \times 1$ selection vector. $GFEVD\left(\widetilde{\Phi}_{ij,t}(H)\right)$ is computed based on $\widetilde{\Phi}_{ij,t}(H)$ as follows:

$$\widetilde{\Phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{9}$$

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

Total connectedness index (TCI):

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

Overall directional connectedness to others

$$C_{i \rightarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ji,t}(H)} * 100 \tag{11}$$

Overall directional connectedness from others

$$C_{i \leftarrow j,t}(H) = \frac{\sum_{j=1, i \neq j}^{n} \widetilde{\Phi}_{ij,t}(H)}{\sum_{j=1}^{n} \widetilde{\Phi}_{ij,t}(H)} * 100 \tag{12}$$

Net total directional connectedness

$$C_{i,t}(H) = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{13}$$

$$C_t(H) = \left(\frac{n}{n-1}\right)\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n} = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n-1} \tag{14}$$

Based on the above formulation, Chatziantoniou and Gabauer (2021) adjusted the TCI:

$$C_t(H) = \left(\frac{n}{n-1}\right)\frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n} = \frac{\sum_{i,j=1,i\neq j}^{n}\widetilde{\Phi}_{ij,t}(H)}{n-1} \tag{15}$$

Empirical results

Average connectedness results

We report the average symmetric, positive, and negative interlinkage findings in Table 3.

In Table 3, off-diagonal values show the shocks from the i th component to the j th component in the network. Overall connectedness results indicate that industrial metals are the most active transmitter of return shocks, passing on 18.31% of its shocks to

Table 3 Average Connectedness Results

Overall						
	Energy	**AgrCult**	**IndMetals**	**PrecMetals**	**Livestock**	**TO**
Energy	84.99	3.99	5.51	3.99	1.52	15.01
AgrCult	4.31	86.22	3.84	3.54	2.09	13.78
IndMetals	5.49	3.57	81.69	7.8	1.45	18.31
PrecMetals	4.02	3.39	7.83	83.79	0.97	16.21
Livestock	1.84	2.44	1.85	1.16	92.72	7.28
FROM	15.65	13.38	19.03	16.49	6.03	70.59
NET	0.65	−0.4	0.72	0.29	−1.25	cTCI/TCI=17.65/14.12
Positive						
	Energy	*AgrCult*	*IndMetals*	*PrecMetals*	*Livestock*	*TO*
Energy	86.78	3.42	4.54	3.78	1.48	13.22
AgrCult	3.72	88.29	3.01	3.09	1.9	11.71
IndMetals	4.8	2.95	83.9	6.88	1.47	16.1
PrecMetals	3.8	2.96	6.85	85.43	0.96	14.57
Livestock	1.66	2.08	1.78	1.1	93.38	6.62
FROM	13.98	11.41	16.18	14.84	5.81	62.23
NET	0.76	−0.3	0.08	0.27	−0.81	cTCI/TCI=15.56/12.45
Negative						
	Energy	*AgrCult*	*IndMetals*	*PrecMetals*	*Livestock*	*TO*
Energy	85.24	3.82	5.11	3.96	1.87	14.76
AgrCult	4.08	85.98	4.19	3.48	2.26	14.02
IndMetals	5.11	4	81.04	8.04	1.82	18.96
PrecMetals	4.14	3.5	7.94	83.17	1.25	16.83
Livestock	2.38	2.78	2.23	1.42	91.19	8.81
FROM	15.71	14.1	19.47	16.89	7.2	73.37
NET	0.96	0.09	0.5	0.06	−1.61	cTCI/TCI=18.34/14.67

Results are based on the TVP-VAR model with lag 1 (BIC) and a 20-step ahead forecast error variance decomposition (FEVD)

other indices. Energy and precious metals also play significant transmitting roles, with 15.01% and 16.21% of their shocks affecting other indices, respectively. Livestock is the least active transmitter, with only 7.28% of shocks transmitted. Conversely, livestock is the most insulated from shocks, receiving 92.72% of return shocks, while energy and precious metals are major recipients, receiving approximately 85–87% of return shocks. The net connectedness values indicate that energy and industrial metals are slightly more prone to transmitting shocks than receiving them, whereas livestock is more of a recipient.

Focusing on positive return shocks, industrial metals remain the leading transmitter, passing on 16.10% of positive shocks. Agriculture and precious metals also have notable transmitting roles, contributing 11.71% and 14.57%, respectively. Livestock, with only 6.62% of positive shocks transmitted, shows the least activity in this area. Livestock receives the highest proportion of positive shocks at 93.38%, highlighting its significant exposure to positive market movements. Net connectedness for positive shocks shows that energy and industrial metals are net transmitters, while livestock is a net recipient.

For negative return shocks, industrial metals is again the highest transmitter, with 18.96% of negative shocks affecting other indices. Precious metals and energy follow closely, transmitting 16.83% and 14.76% of negative shocks, respectively. Livestock contributes the least to negative shock transmission at 8.81%. Livestock is also the most affected by negative shocks, receiving 91.19% of them. The net connectedness values indicate that energy and livestock are net transmitters of negative shocks, while agriculture, industrial metals, and precious metals show net positive connectedness.

Overall, the table illustrates the varying degrees of influence and susceptibility among the commodity indices. Industrial metals are highly active in transmitting both positive and negative shocks, while livestock is more of a recipient and particularly vulnerable to negative shocks. Energy and precious metals also play significant roles in shock transmission and receipt, with energy showing a relatively balanced net connectedness.

Time-varying asymmetric connectedness

We plot the total time-varying symmetric, positive, and negative connectedness indices (TCIs) in Fig. 2.[2]

Throughout the period, the overall connectedness (black line) exhibits significant fluctuations, with notable peaks aligning with major global economic events. For example, sharp increases in TCI are evident around the 2008 financial crisis and during the COVID-19 pandemic in 2020, reflecting heightened interconnectedness among commodity markets during periods of widespread economic turmoil. These spikes suggest that during times of global stress, the commodity sectors become more interlinked, potentially due to synchronized market reactions and shared vulnerabilities.

The positive connectedness (green line) and negative connectedness (red line) reveal further nuances. Positive connectedness often rises during periods of economic recovery, indicating that positive shocks in one sector tend to generate beneficial spillovers across others. Conversely, negative connectedness spikes during economic downturns,

[2] The black-shaded area indicates the symmetric total connectedness, and the green/red lines display the trends of TCIs for positive, and negative returns, respectively.

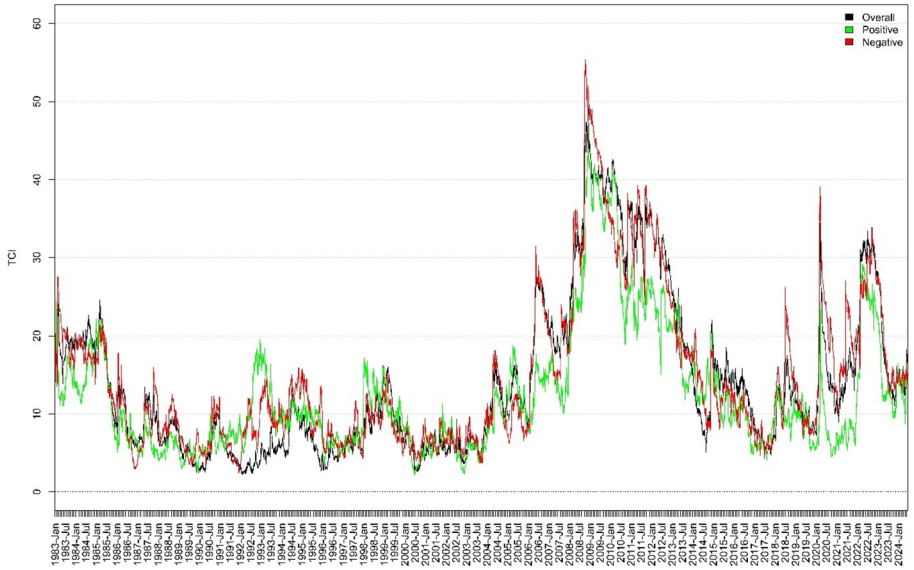

Fig. 2 Dynamics of TCIs. *Notes* The results are derived using the TVP-VAR(1) model with a lag order of 1 (selected based on BIC) and a 20-step-ahead forecast error variance decomposition (FEVD)

signaling that adverse shocks in one commodity market can propagate negative effects across other sectors. The divergence between these indices underscores the dynamic and complex nature of market relationships, shaped by both global economic conditions and sector-specific influences.

Time-varying net directional connectedness

We proceed with our analysis by examining the net directional interdependencies of returns to determine their roles as either transmitters or receivers over the study period. Figure 3 provides a visual representation of this net directional connectedness.[3]

The energy sector often emerges as a significant transmitter, particularly during periods of economic turbulence, such as the 2008 financial crisis and the early 2020s. This reflects the critical role of energy, particularly oil, in driving global economic conditions and impacting other commodity sectors. The precious metals sector, often seen as a safe haven, shows a mixed pattern, sometimes transmitting shocks but also frequently acting as a receiver, especially during financial crises when it absorbs shocks from other markets. The Agriculture and Livestock sectors generally exhibit more balanced roles, with periods of both transmitting and receiving, influenced by factors such as weather conditions, geopolitical events, and changes in global demand. Industrial metals, closely tied to industrial production, similarly demonstrate a dual role, with significant transmission of shocks during periods of global industrial expansion or contraction. Overall, the figure highlights the complex and dynamic interconnections within the commodity markets, where the influence of one sector can reverberate across others, particularly in times of economic stress.

[3] Positive/negative values denote the transmitters/recipients in the system.

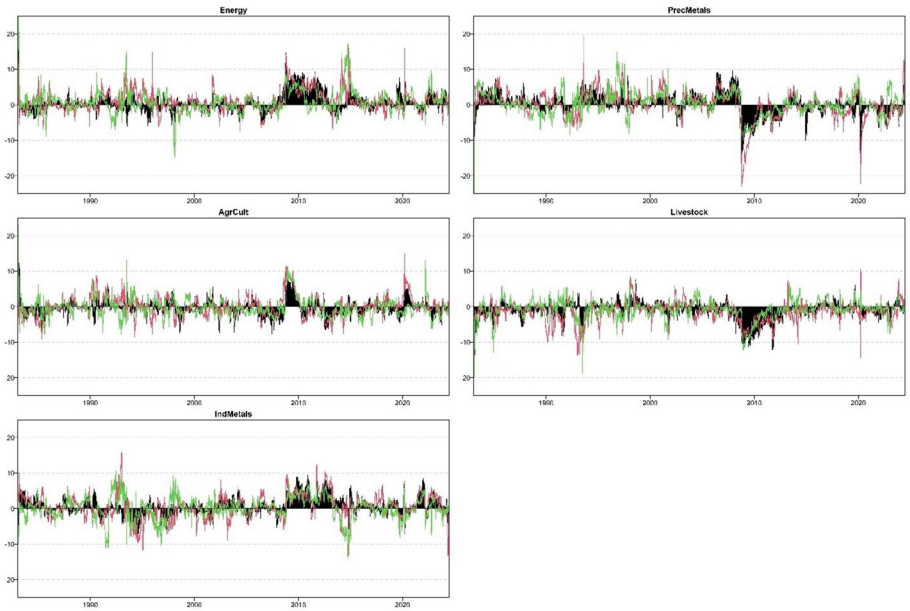

Fig. 3 Time-varying Net Total Directional Connectedness. *Notes* The results are based on the TVP-VAR(1) model with a lag order of 1 (selected based on BIC) and a 20-step-ahead FEVD. The black, green, and red lines represent overall, positive, and negative spillovers, respectively

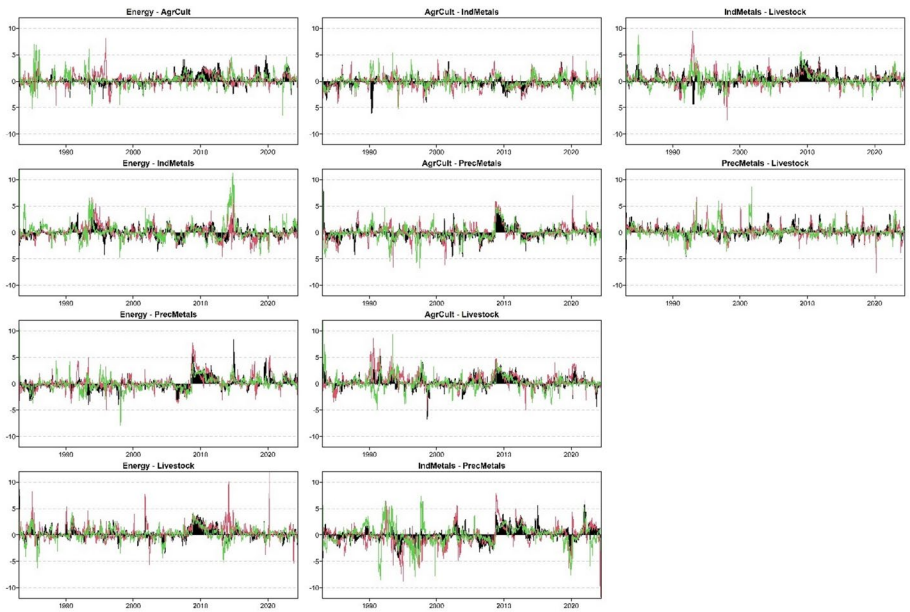

Fig. 4 Net pairwise spillovers. *Notes* The results are based on the TVP-VAR(1) model with a lag order of 1 (selected based on BIC) and a 20-step-ahead FEVD. The black, green, and red lines show overall, positive, and negative spillovers, respectively

Time-varying net pairwise connectedness

We compute net pairwise spillovers and plot them in Fig. 4.

The net pairwise spillover measures further support our earlier findings, highlighting significant spikes during periods of financial or geopolitical stress as well as market

downturns. Notably, the negative return spillovers tend to be larger than the positive return spillovers, especially during financial crises or market bursts. This finding reinforces the notion that negative shocks tend to have a more pronounced and persistent impact on market dynamics compared to positive shocks, particularly during times of heightened uncertainty.[4]

Discussion

Commodity markets are both a measure of economic health and a key driver of financial markets. Due to the interconnectedness of these markets, which in particular include energy, industrial and precious metals, agriculture and livestock, shocks from one sector to another have the power to shape overall market behavior. It is therefore crucial for investors, policymakers and economists to understand the complex dynamics of these linkages, which are influenced by numerous factors such as geopolitical tensions and financial crises.

Our findings provide new insights into the interconnectedness between commodity markets, and we observe significant asymmetry in general and directional terms. Consistent with previous research (Luo and Ji 2018; Shahzad et al. 2018), our findings prove that positive shocks are more effective and persistent during periods of economic growth, while negative shocks are more effective and persistent during periods of economic downturn. The results of the TCI, which are consistent with the findings of Shahzad et al. (2021), Umar et al. (2021) and Farid et al. (2022), indicate that the spikes experienced, especially during the 2008 GFC and the COVID-19 pandemic, strengthened the asymmetry. Significant spikes underline the sensitivity of commodity linkages to market synchronization and global disruptions.

Energy, industrial metals and precious metals are notably strong transmitters of average shocks. Our findings are consistent with other studies (Xiao et al. 2020; Fang and Shao 2022; Farid et al. 2022), which support the leading position of these commodities in terms of their power to influence markets. Moreover, these commodities are strong transmitters of positive and negative shocks as well as averages and have significant effects on other indices. Thus, in addition to other studies highlighting the important role of the three key commodities in the market, we make important contributions to the existing body of knowledge by capturing asymmetric interconnectedness among these commodities. Considering the direct or indirect dependence of sectors such as agriculture, industry and livestock on energy and industrial metals, it may support energy and industrial metals as an important component in the propagation of positive or negative shocks to other economic sectors. On the other hand, the fact that precious metals exhibit safe haven characteristics and experience price fluctuations, especially during periods of uncertainty, may be due to their shock-receiving role, and the fact that these price fluctuations lead to volatility in other financial assets through expectations may be due to the shock transmitter aspect.

Agriculture is predominantly a net receiver of average shocks, in line with the findings of Iqbal et al. (2023) and Dai and Wu (2024) but differs from other studies by showing a

[4] As complementary analysis for our results, we employed the quantile VAR (QVAR) connectedness approach of Chatziantoniou et al. (2021) and provided its results in the Appendix B.

notable asymmetry. The fact that agriculture is a net transmitter of positive shocks and a net risk absorber of negative shocks can be explained by its sensitivity to climate change and global market dynamics as a provider of basic consumer goods. Accordingly, cost-driven spillovers in energy, industrial and livestock markets are triggered by positive shocks such as increased demand for agricultural inputs in the food and industrial sectors. On the other hand, the inelastic demand structure of food products and the significant exposure of agriculture to climate change may be the reason for the net risk-taking role of agriculture during periods of negative shocks.

The livestock sector is distinguished from other sectors by its strong absorptive capacity to shocks and minimal spillover effect. The livestock sector, which appears to have the most isolated market structure with this characteristic, has important links with the agriculture and energy sectors, but the links are both unidirectional, and the shock transmission capacity is limited. The isolated, localized and production-oriented structure of the livestock sector makes it resilient to intermarket fluctuations.

Finally, our findings provide valuable implications for policymakers, investors and market participants with evidence on asymmetries and the transmission or absorption of shocks. They also provide an important contribution to the literature with a comprehensive and time-varying perspective on interconnectedness across commodity markets. Policymakers focused on designing welfare policies should take into account sectoral asymmetries and their changing roles in different economic cycles. Moreover, understanding the contagion or spillover effect from one good to another is essential to avoid systemic risk. This directly or indirectly affects the most vulnerable segments of society, especially in terms of basic needs such as agriculture. Our findings can therefore be useful in designing subsidies for less advantaged groups. It is important for investors to distinguish between net receivers and net transmitters of commodities. Information on net receivers and net transmitters can be useful for portfolio diversification, risk management and investment strategy development. On the other hand, the isolated nature of the livestock sector and the duality of agriculture should be clearly understood by market participants to manage both periods of economic stability and volatility.

Conclusion

This paper analyzes the asymmetric nature of the interconnectedness dynamics of commodities, which have recently become attractive investment instruments for hedging risk. Specifically, we consider spillovers across five major commodity markets—energy, agriculture, industrial metals, precious metals, and livestock—and extend our dataset back to Black Monday in 1987, allowing for a broad view of this asymmetric structure. We use the asymmetric TVP-VAR framework to identify hidden linkages and investigate how positive and negative shocks propagate across commodity markets. In this way, our study fills the gap in dynamic and crisis-sensitive behavior between symmetric analyses and real markets, providing important insights into asymmetric spillovers across commodity markets and implications for effective portfolio management, especially for investors and fund managers.

The results of our time-varying analysis provide significant evidence that spillovers across the sample are heterogeneous and that the linkages between commodities vary over time. Accordingly, we find that during periods of turbulence such as the 2008 global

financial crisis and the 2020 COVID-19 pandemic, dynamic interconnectedness shows sharp peaks with TCI values above 50% and 35%, respectively.

Regarding average connectedness, industrial metals emerge as the strongest transmitter of return shocks, transferring 18.31% of their shocks to others. Energy and precious metals also have significant impacts, transferring 15.01% and 16.21% of shocks, respectively. Conversely, livestock is the least active transmitter, contributing only 7.28% of shocks. However, livestock is the most isolated sector, having the highest absorption rate, with 92.72% of the returns of shocks.

The distinction between positive and negative linkages is particularly important in this context. When analyzing positive return shocks, industrial metals still remain in first place, transmitting 16.10% of positive return shocks. This is followed by 11.71% and 14.57% for agriculture and precious metals, respectively. Livestock is once again the least important sector, delivering only 6.62% of transitory shocks, while absorbing a remarkable 93.38%, indicating a high exposure to market booms.

In the case of negative return shocks, industrial metals are once again the dominant transmitters, contributing 18.96% of shocks. Precious metals and energy followed, with 16.83% and 14.76%, respectively. Livestock is the least affected sector, with only 8.81%, absorbing 91.19% of negative shocks, making it highly vulnerable to a market downturn. These differences across commodities highlight the dynamic nature of the asymmetric structure shaped by global conditions and sector-specific factors.

While our research makes important contributions to the existing body of knowledge, it has several limitations on which future research can build. First, the study focuses on five main commodity sectors and does not consider subcommodities. While focusing on major commodities may provide the advantage of capturing broader dynamics in commodity markets, focusing on subcommodities may provide the advantage of capturing different market behaviors. Moreover, it is important to recognize that the linkages between commodity markets are not only shaped by sector-specific dynamics but are also influenced by broader economic and geopolitical variables. Therefore, future work could incorporate different measures of economic and geopolitical uncertainty into the model. By incorporating these external factors into the modeling process, future research efforts can delve deeper into the intricacies of market interconnectedness and allow for a more comprehensive examination of both negative and positive aspects. Finally, while existing methods for analyzing interconnectedness are useful for understanding market relationships, the application of more sophisticated and cutting-edge modeling techniques, such as machine learning and deep learning algorithms, can provide broader insights. These approaches will enable academics to gain a more nuanced understanding of how global economic recessions and geopolitical events affect various markets, thereby shedding light on this complex interaction.

Appendix A

Nonlinearity analysis

The BDS test is utilized to detect nonlinearity, with the null hypothesis representing linearity and the alternative hypothesis indicating nonlinearity. Based on the test results,

Table A.1. BDS Results

	Dimension					Decision
Variable	**2**	**3**	**4**	**5**	**6**	
AgrCult	0.012***	0.027***	0.038***	0.045***	0.049***	Nonlinear
Energy	0.015***	0.032***	0.044***	0.051***	0.055***	Nonlinear
IndMetals	0.016***	0.034***	0.047***	0.055***	0.059***	Nonlinear
Livestock	0.008***	0.017***	0.024***	0.027***	0.028***	Nonlinear
PrecMetals	0.009***	0.019***	0.028***	0.034***	0.037***	Nonlinear

***, **, * denote 1%, 5%, and 10% statistical significance levels, respectively

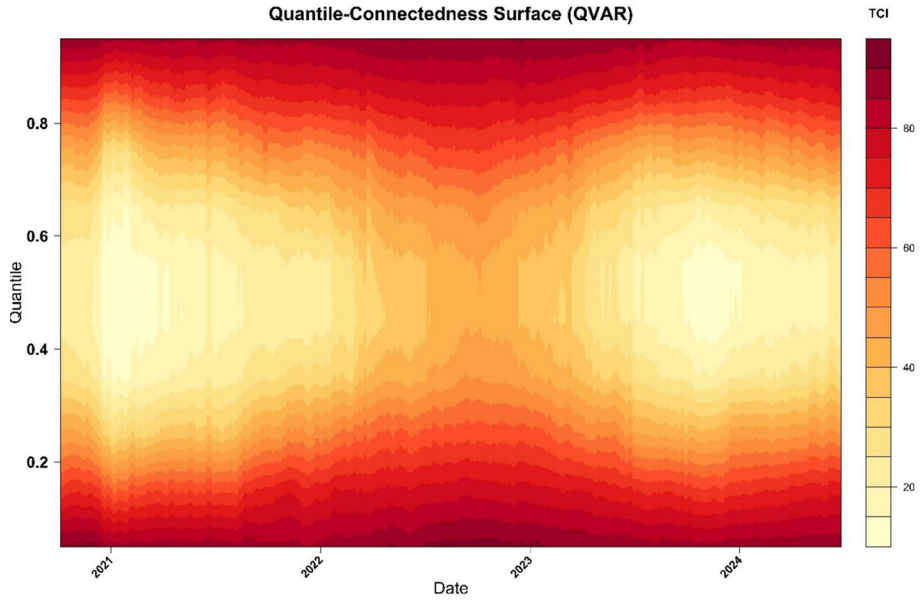

Fig. B.1 QVAR Dynamic Connectedness. *Notes* The analysis uses a QVAR model with a 200-day rolling window, a lag of 1 (chosen by BIC), and a 20-step-ahead forecast

the null hypothesis of linearity is rejected for all variables analyzed, confirming that the series exhibits nonlinearity (Table A.1).

Appendix B

QVAR connectedness approach

In the framework of quantile connectedness introduced by Ando et al. (2018), quantile vector autoregression, QVAR(p), which mainly aims to measure various connectedness metrics, is estimated as summarized below (Fig. B.1).

$$\boldsymbol{y}_t = \boldsymbol{\mu}_t + \sum_{j=1}^{p} \boldsymbol{\phi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) \tag{B.1}$$

In Eq. (B.1), the $k \times 1$ dimensional endogenous variable vectors y_t and y_{t-j}, consisting of the 1-year IRSs with first difference, are represented by τ with a quantile of interest between [0,1] and the lag length p of the QVAR model. The $k \times k$-dimensional QVAR coefficient matrix is denoted by$\Phi j(\tau)$, the $k \times 1$-dimensional conditional mean vector

$\mu(\tau)$, the $k \times k$-dimensional variance–covariance matrix $u_t(\tau)$ and the $k \times 1$-dimensional error vector $\Sigma(\tau)$. QVAR (p) is transformed by Wold's theorem into the representation QVMA (∞) as in Eq. (B.2):

$$\boldsymbol{y}_t = \boldsymbol{\mu}_t + \sum_{j=1}^{p} \boldsymbol{\phi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}_t + \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i(\tau)\boldsymbol{u}_{t-i} \tag{B.2}$$

Then, to represent the effect of the shock in variable j on variable i, the H-step ahead generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) is calculated as in Eq. (B.3):

$$\begin{aligned} \Psi_{ij}^{g}(H) &= \frac{\sum(\tau)_{ii}^{-1}\sum_{h=0}^{H-1}(\boldsymbol{e_i'}\boldsymbol{\Psi}_h(\tau)\sum(\tau)\boldsymbol{e_j})^2}{\sum_{h=0}^{H-1}(\boldsymbol{e_i'}\boldsymbol{\Psi}_h(\tau)\sum(\tau)\boldsymbol{\Psi}_h(\tau)'\boldsymbol{e_i})} \\ \widetilde{\Psi}_{ij}^{g}(H) &= \frac{\Psi_{ij}^{g}(H)}{\sum_{j=1}^{k}\phi_{ij}^{g}(H)} \end{aligned} \tag{B.3}$$

In Eq. (B.3), i^{th} is represented by a zero vector with unity at e_i. The following two equations show the normalization:

$$\sum_{j=1}^{k} \widetilde{\Psi}_{ij}^{g}(H) = 1 \; and \; \sum_{i,j=1}^{k} \widetilde{\Psi}_{ij}^{g}(H) = k \tag{B.4}$$

For the overall effect of variable i on all other j variables, the total directional connectedness to others is calculated as in Eq. (B.5):

$$C_{i\rightarrow j}^{g} = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H) \tag{B.5}$$

Then, shocks of all other j variables on variable i are evaluated with total directional connectedness from all others as in Eq. (B.6):

$$C_{i\leftarrow j}^{g} = \sum_{j=1,i\neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H) \tag{B.6}$$

The net effect of variable i on the analyzed network shows net total directional connectedness as the difference between total directional connectedness to others and total directional connectedness from others.

$$C_{i}^{g}(H) = C_{i\rightarrow j}^{g}(H) - C_{i\leftarrow j}^{g}(H) \tag{B.7}$$

The final measure of connectedness in Chatziantoniou and Gabauer (2021) with Gabauer (2021) is the adjusted TCI ranging from [0,1]:

$$TCI(H) = \frac{\sum_{i,j=1,i\neq j}^{k} \widetilde{\Psi}_{ij}^{g}(H)}{k-1} \tag{B.8}$$

This value is used as a market risk indicator. A high TCI value means that interconnectedness is also high.

The total connectedness index (TCI) presented in the figure illustrates the dynamic quantile-based interconnectedness among the five S&P GSCI commodity indices: energy, agriculture, industrial metals, precious metals, and livestock. The warmer shades (yellow, orange, red) indicate periods of heightened connectedness, where shocks in one index propagate strongly across others, often associated with significant market events or stress, such as periods of extreme price changes. Cooler shades reflect lower

levels of connectedness, suggesting reduced spillover effects and more isolated behavior among the indices. The cyclical nature of the TCI implies that connectedness fluctuates over time and is influenced by market-specific events or global economic disruptions (Fig. B.2).

Each panel represents one commodity index, with the vertical axis showing quantile levels (from 0 to 1) and the horizontal axis showing time. The color gradients (red to blue) indicate the nature and intensity of spillovers, with red shades representing positive spillovers (where shocks in one index transmit positively to others) and blue shades representing negative spillovers (where shocks have inverse effects on others).

The panels reveal distinct patterns of interconnectedness for each commodity index. Energy, for instance, exhibits strong spillover effects during specific periods, likely reflecting the critical role of oil and gas in global markets, especially during geopolitical tensions or oil price shocks. Agriculture shows variability in connectedness, which could be linked to factors such as weather shocks, trade policies, or global supply chain disruptions. Industrial metals display heightened connectedness during periods of industrial demand surges or global growth contractions, such as during financial crises. Precious metals, often viewed as safe-haven assets, show varying spillover dynamics, particularly during periods of economic uncertainty or monetary policy shifts. Livestock exhibits less intense but still notable connectedness, likely driven by supply chain and demand fluctuations in agricultural markets.

The vertical axis highlights how the intensity of connectedness varies across quantiles, with stronger spillovers (both positive and negative) observed at higher quantiles, indicating extreme market conditions such as booms or crashes. Periods with widespread red or blue shading across multiple panels suggest synchronized movements among the indices, likely driven by systemic events such as the 2008 Global Financial Crisis or the COVID-19 pandemic.

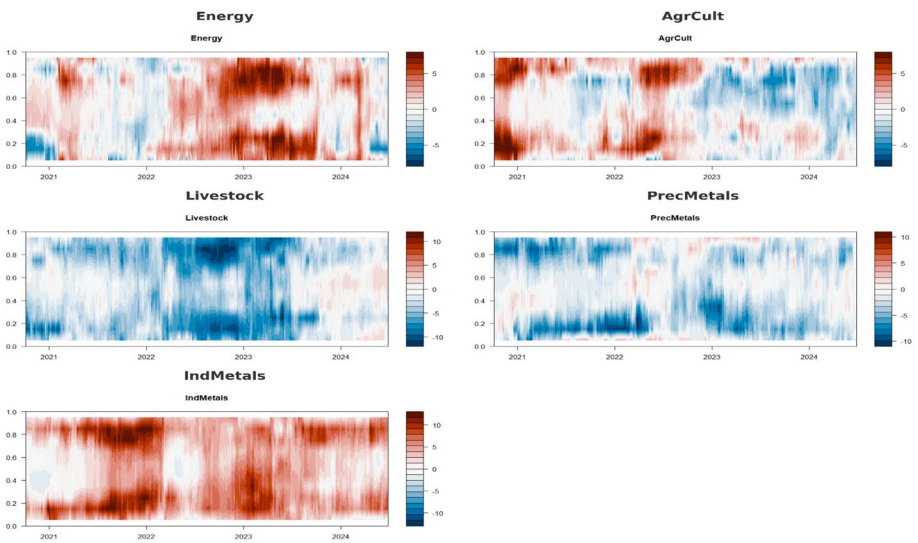

Fig. B.2 Total Net Connectedness of Commodities. *Notes* The analysis uses a QVAR model with a 200-day rolling window, a lag of 1 (chosen by BIC), and a 20-step-ahead forecast

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Author contributions
HME: Writing—original draft, Supervision, Project administration, Conceptualization. OP: Writing—original draft, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. BY: Writing—original draft, Conceptualization. AA: Writing—original draft, Conceptualization. Each author has reviewed and approved the final manuscript.

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Data availability
The data will be accessible upon request.

Declarations

Competing interests
The authors declare no conflict of interest.

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