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Dynamic connectedness and hedging opportunities of the commodity and stock markets in China: evidence from the TVP-VAR and cDCC-FIAPARCH

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Abstract

This study examines the dynamic connectedness and hedging opportunities between CSI300 (China Security Index 300) and copper, gold, PTA (purified terephthalic acid), and soybean in China from January 09, 2008, to June 30, 2023. A TVP-VAR and cDCC-FIAPARCH modeling framework was used for the empirical investigation. The results show that the total connectedness index can effectively capture cross-asset information transmission in China's financial markets. Copper returns are the dominant volatility transmitters, while CSI300, gold, and soybean returns are net recipients. The Russian–Ukraine war reinforced the safe-haven role of gold. Finally, investors with CSI300 long positions may benefit from prioritizing gold for hedging, while those with CSI300 short positions profit more from allocating gold to PTA. Portfolio managers and investors can use the findings to track the dynamics of systemic risk and adjust their long/short positions when investing in China's stock and commodity markets.

Keywords: TVP-VAR; connectedness, Spillover, Hedging effectiveness, Breitung–Candelon spectral Granger causality tests

Introduction

The "globalized" world has experienced several extreme disturbances (crises) over the past few decades. Many economies have experienced massive and severe financial difficulties due to these crises, and both global stock and commodity markets have responded by behaving erratically, inevitably threatening the stability of global and Chinese financial markets (Cheng et al. 2023; Tanin et al. 2022). In addition, China's financial market has become one of the most attractive investment opportunities in the world owing to its size and the way it is evolving after years of opening up to global investors.[1] Whether and how to obtain robust evidence on optimal asset allocation and information accessibility remains at the forefront of investor concerns (Ahmed and Huo 2021).

Systemic risk is associated with system failure due to global disturbance events (So et al. 2022), The 2008 global financial crisis (GFC) and the 2011 European sovereign

[1] http://en.ce.cn/main/latest/202306/23/t20230623_38601954.shtml.

debt crisis (ESDC) were extremely pervasive, primarily due to systemic risk (Anwer et al. 2022). Systemic risk propagates rapidly because investors and financial institutions participate in highly interconnected and volatile markets (So et al. 2022). Hence, connectedness ("the measurement and management of systemic risk") and contagion across global financial markets in periods of stress and normal times would be highly informative for policymakers, regulators, and investors (Amar et al. 2023). Recently, systemic risk in global financial markets has drawn renewed attention due to the COVID-19 pandemic and the Russia-Ukraine war. The global stock and commodity markets, in particular, responded immediately to the Russia-Ukraine war, significantly affecting agricultural commodities (e.g., wheat) and metals (e.g., nickel) (Izzeldin et al. 2023). Inevitably, China's industrial and supply chains are exposed to rising production costs, which in turn affect the stability of China's economy and financial markets (Wang et al. 2023b). Against this backdrop, this study attempts to help portfolio managers and policymakers develop optimal hedging practices when investing in China's financial market.

This study is designed to address the following specific questions: Do the total connectedness index and pairwise connectedness of the new asset class exhibit any changes during the pre-COVID-19 and post-COVID-19 periods, and the Russia-Ukraine war? Do COVID-19 and the Russia-Ukraine war exemplify the new state of dynamic connectedness (spillovers) and hedging opportunities for this new asset class? Do China's gold futures reinforce the "safe-haven" role resulting from the COVID-19 and the Russia-Ukraine war? How can investors and policymakers adjust their hedging strategies to reduce systemic risk based on the results of optimal portfolio weights and hedge ratios between the CSI300 (China Security Index 300) and liquid commodity futures contracts in China?

The motivations for the proposed scheme to address these questions are illustrated as follows. (i) Stock (equity)commodity portfolios are widely used to manage systematic and systemic risk, helping to balance returns and risk (Sadorsky 2014) and hedge against inflation driven by volatile commodity markets (Aepli et al. 2017). Investors can use diversified portfolios to optimize asset allocation, downside risk management, and hedge effectiveness (Kang et al. 2017; Walid Mensi et al. 2017). (ii) Qualified foreign investors can trade in open commodity futures, commodity options, and stock index options in China on November 1, 2021.[2] Thus, the demand for liquid assets and China's increasingly influential futures market have driven global investors to hedge risk from commodity futures. (iii) Motivated by Ahmed and Huo (2021), this study introduces a new asset class comprising four representative individual commodities–copper, gold, soybean, and PTA (purified terephthalic acid) –to represent metals, precious metals, agricultural commodities, and petrochemicals, respectively, to avoid biased results from the use of aggregate commodity price indices. First, these liquid commodity futures contracts have attracted massive capital inflows, thus constituting a high percentage of the total turnover in China's commodity futures market (Table 1). The monthly turnover of these commodities exceeded 4,500 billion yuan in June 2022.[3] Massive turnover (capital inflow) promotes commodity financialization, which further amplifies commodity market

[2] https://www.caixinglobal.com/2021-10-16/china-clears-foreign-investors-to-trade-more-onshore-derivatives-101787347.html.

[3] Author's calculation according to data from Choice dataset.

Table 1 Annual turnover of copper, gold, PTA, and soybean futures, 2017–2020 (percentage share)

	Copper (%)	Gold (%)	PTA (%)	Soybean (%)
2020	12.63	18.51	11.74	4.01
2019	10.75	18.48	18.84	3.12
2018	18.46	6.29	15.96	5.91
2017	18.18	7.36	13.29	3.68

The percentages for copper and gold are shares of metal futures contracts, while the PTA and soybean (Nos. 1 and 2) percentages are shares of energy and agricultural commodity futures contracts, respectively

instability and intensifies the dynamic linkages between the commodity and stock markets (Ding et al, 2021; Adams et al. 2020). Second, China is the world's leading consumer of copper, and copper futures contracts are among China's most frequently traded metal futures. Gold futures are generally regarded as valuable hedging and safe-haven instruments (Arouri et al. 2015; Junttila et al. 2018). PTA is a downstream petrochemical derivative that is significantly associated with energy prices. China is the world's largest producer and consumer of PTA, accounting for 56% and 58% of the world's PTA production capacity and consumption, respectively.[4] Moreover, PTA futures contracts were be the most traded commodity futures on the Zhengzhou Commodity Exchange in 2021. China is the world's leading soybean importer and imported approximately 96 million metric tons of soybeans in 2022.[5] Finally, the CSI300 is the underlying asset of CSI300 futures contracts and serves as a proxy for China's stock market index. The overall market capitalization of CSI300 accounts for nearly 52% of Chinese A-shares.[6]A total of 58% and 42% of the stocks were compiled from the Shanghai- and Shenzhen Stock Exchanges, respectively, and consisted of domestically listed companies from China's major industrial sectors. (iv) The motivation for introducing the econometric modeling framework stems from those proposed by Dai and Zhu (2022) and Wen et al. (2021). Antonakakis et al. (2020) empirically verified dynamic TVP-VAR connectedness to display the transmission mechanism and identify volatility transmitters and recipients across asset returns. This technique benefits from the dynamic connectedness analysis by not imposing a user-defined rolling window size, thus avoiding omitted observations and ensuring robust findings (Wen et al. 2021; Antonakakis et al. 2020).

This study contributes to existing literature in several ways. First, we propose a novel analytical framework consisting of TVP-VAR connectedness and cDCC-FIAPARCH. The cDCC-FIAPARCH can effectively capture volatility spillover effects and the transmission mechanism of asset classes and account for both asymmetric and persistent effects (Guesmi et al. 2020). Notably, the dynamic conditional correlations (DCCs) resulting from the cDCC-GARCH models can guarantee consistency, flexibility, and manageability compared to the commonly used DCC-GARCH model (Aielli 2013), which enables the FIAPARCH models to identify superior forecasting performance (Chkili et al. 2012; Karanasos et al. 2016). Second, this study examines the dynamic connectedness and hedging opportunities among CSI300 and China's commodity futures contracts for copper, gold, PTA, and soybean from January 09, 2008 (the launch date for

[4] https://www.chinairn.com/hyzx/20220718/17004486.shtml.

[5] https://www.statista.com/statistics/612422/soybeans-import-volume-worldwide-by-country/.

[6] https://www.xyfinance.org/hot/496078.

gold futures trading) to June 30, 2023. We divide all sample periods into three phases: the pre-COVID-19 period, the post-COVID-19 period, and the Russia-Ukraine war period,[7] which shed light on how China's stock and commodity markets behave under heterogeneous trading conditions. To the best of our knowledge, this is the first study to integrate PTA futures contracts into asset classes. Finally, this study offers hedging opportunities to determine which commodity assets should take a long/short position to help hedge the risks of investing in CSI300 long/short positions by shedding light on comparative analysis. Hence, it guides participants seeking to optimize the risk-return profiles of different asset classes to facilitate investors in managing systemic risk more effectively in conformity with their risk preferences.

The remainder of this paper is organized as follows. The literature review (Chapter 2) provides a brief review of existing studies and indicates the gaps in the scientific literature that this study aims to address. The methods section (Chapter 3) introduces the econometric modeling framework, and the empirical results section (Chapter 4) provides the results using the TVP-VAR connectedness and cDCC-FIAPARCH. A comprehensive hedging opportunity analysis that provides the findings of the hedging strategies is presented in the results section (Chapter 4). Finally, a conclusions and implications section summarizes the results, as well as the limitations of this work.

Literature review

Previous studies have validated the diversification benefits of commodity futures (Robiyanto and Yunitaria 2022; Ahmed and Huo 2021; Jaiswal and Uchil 2018; Alshammari and Obeid 2023) and hedged portfolios based on stock (equity) commodities that are expected to significantly outperform unhedged portfolios (Hanif et al. 2023; Alshammari and Obeid 2023).

A review of recent literature reveals that several studies have intensified their efforts to suggest diversified portfolios of global stock indices and commodities for investors' risk management. Gold and crude oil futures have frequently been examined as hedging and safe-haven assets (Tuna and Tuna 2022; Cheng et al. 2023; Junttila et al. 2018; Mensi et al. 2022; Wang et al. 2023a). For instance, Mensi et al. (2023) investigate the time–frequency spillovers and dynamic linkage between gold, WTI crude oil futures, S&P 500, and other asset returns. Gold is identified as a safe haven in both the short- and long-term horizons, whereas crude oil fails to be a safe haven for the S&P 500 from the perspective of time–frequency spillovers and connectedness. Younis et al. (2023) use the wavelet TVP-VAR approach to investigate the static and dynamic linkages (spillovers) between the crude oil, gold, and stock markets of 11 developing and developed countries. Portfolio analysis shows that gold and oil benefit stock markets for portfolio diversification and hedging under different market conditions. It is worth noting that growing concerns over global financial market volatility have motivated attempts to examine other commodities to reduce investors'systemic risk. Azimli (2022) emphasizes the dynamic connectedness of asset classes among four commodities–copper, iron, gold, and silver, and ten major global stock indices. The evidence suggests that silver outperforms gold as a safe haven asset in the

[7] Pre-COVID: Jan.09, 2008-Dec.30,2019; post-COVID Dec. 31, 2019- Jun, 30, 2023; Russia-Ukraine war: Feb.24, 2022-Jun.30, 2023.

post-COVID-19 period, whereas both copper and iron have weak hedging effects on global stock indices. Furthermore, as emerging cryptocurrencies affect traditional financial assets (Li et al. 2023; Cui and Maghyereh 2022), investors' preferences have prompted them to pursue traditional (i.e., gold) and emerging assets (i.e., Bitcoin) to optimize their hedging strategies (Ustaoglu 2023).

Similarly, studies on connectedness (spillovers) and hedging strategies in China's financial markets have gained considerable attention and have provided valuable insights. For instance, Wen et al. (2022) reveal that China's financial market is characterized by dynamic dependence and risk contagion effects across financial markets, and commodity price volatility is more sensitive to changes in international crude oil prices than is China's stock market. Ahmed and Huo (2021) suggest incorporating individual commodity futures to avoid biased results when using aggregate commodity price indices. Specifically, the work from Ahmed and Huo (2021) contributes to the analysis of spillovers on the CSI300 and individual commodity futures, namely, global oil, gold, silver, copper, wheat, aluminum, and soybean, by adopting a tri-variate VAR-BEKK-GARCH model for the period from 2012 to 2017. The results indicate that incorporating a diversified portfolio of equity or global crude oil into commodity futures contracts in China can reduce investors' investment risk.

Table 2 summarizes previous studies on econometric modeling frameworks using the TVP-VAR and multivariate GARCH family models. Notably, the suggested econometric modeling framework is a practical methodology for investigating investors' hedging strategies and portfolio management (Wen et al. 2021; Balcilar et al. 2021; Mishra and Ghate 2022; Dai and Zhu 2022). For example, Dai and Zhu (2022) adopted the TVP-VAR connectedness and DCC-GARCH t-copula models to investigate the dynamic connectedness between commodities (oil and gold) and China's stock market and hedging effectiveness from 2014 to 2021. The results show that oil and gold prices are both net recipients of systemic shocks, while all examined sectoral stock indices appear to be net transmitters. Moreover, previous studies reported the possibility and effectiveness of adopting cDCC-GARCH models. Mensi et al. (2016) adopt GARCH family models (i.e., FIAPARCH), incorporating the cDCC specification proposed by Aielli (2013) to address many of the stylized facts typical of financial time series. This study examines the DCCs of the Dow Jones and conventional sectors and highlights the benefits of cross-market hedging, portfolio allocation, and diversification. Sarwar et al. (2019) examined the DCCs between major stock markets (Shanghai Stock Exchange, Nikkei Stock Exchange, and Bombay Stock Exchange) and crude oil by employing BEKK-GARCH, DCC-GARCH, cDCC-GARCH, and GO-GARCH. The cDCC-GARCH model is validated and outperforms other GARCH models in the hedging analysis. Guesmi et al. (2020) investigated the DCCs between Brent oil price volatility and major stock indices of OECD countries by adopting cDCC-FIAPARCH, showing the dynamic characteristics of both asymmetry and long memory and further analyzing the diversification potential.

Taking an overall review of the related literature, to the best of our knowledge, no previous studies have examined the dynamic connectedness (spillovers) and hedging opportunities between the CSI300 and a different set of commodity indices, namely, copper, gold, PTA, and soybean, for the pre-COVID, post-COVID, and Russia-Ukraine war periods. These individual commodity futures are prioritized in this

Table 2 Survey of the literature on the dynamic linkages of stock-commodities using TVP-VAR connectedness and multivariate GARCH family models

Author	Year	Frequency	Stock	Commodity	Method
Hanif et al. (2023)	2020–2022	Intraday	EUROSTOXX50 FTSE100 NIKKEI225 etc	Bitcoin; Brent crude oil;gold	TVP-VAR Frequency spillover
Wang et al. (2023a)	2008–2022	Daily	China's electricity sector	Crude oil and gold	TVP VAR DCC-GARCH
Dai and Zhu (2022)	2010–2021	Daily	China's sectoral stock indices	WTI oil, natural gas	TVP-VAR; DCC-GARCH
Wen et al. (2021)	2009–2020	Daily	Shanghai composite index	Precious metals, nonferrous metals, energy index, fuel oil chemical, grain, etc	TVP-VAR DCC-GARCH
Wen and Wang (2021)	1960–2020	Monthly	US stock index	Energy, agriculture, food, raw materials Metals and minerals Precious metals	TVP-VAR DCC-GARCH
Adekoya et al. (2022)	2013–2021	Daily	Nine Islamic sectoral stocks	Brent crude oil, gold	Asymmetric TVP-VAR
Ha et al. (2022)	2018–2021	Daily	S&P 500	Crude oil, gold, cryptocurrency	TVP-VAR
Bouri et al. (2021)	2006–2019	Intraday	S&P 500	Gold, oil	TVP-VAR
Adekoya and Oliyide (2021)	2020	Intraday	S&P 500	Eexchange rate, gold Crude oil, bitcoin	TVP-VAR; Granger causality
Zhao et al. (2022)	2014–2021	Daily	CSI300	Wind commodity index, Carbon market	TVP-VAR
Mensi et al. (2022)	2018–2020	Intraday	S&P 500	Gold, Brent oil	DCC-FIAPARCH
Dong et al. (2021)	2000–2020	Daily	Korean, Taiwan, Hongkong, Singapore	Gold, U.S. dollar	DCC-FIAPARCH
Guesmi et al. (2020)	1998–2018	Daily	17 OECD stock indices etc	Crude oil	cDCC-FIAPARCH
Mensi et al. (2021)	2007–2020	Weekly	ASEAN stock indices	Precious metals futures (gold, palladium, platinum, and silver), Brent oil	DCC-FIAPARCH
Lin et al. (2021)	2002–2019	Daily	Shanghai stock index; S&P 500; European 600	Global crude oil market (WTI, Brent, and Dubai)	cDCC-FIAPARCH

analysis to avoid the aggregation bias of commodity price indices, all of which are China's frequently traded commodity futures contracts and are eligible to be representative of industrial metals, precious metals, petrochemicals, and agriculture.

Moreover, using a particular modeling framework that combines the TVP-VAR and cDCC-FIAPARCH models may be more suitable than the DCC-GARCH models for research purposes. The cDCC-FIAPARCH model is not only valuable for computing DCCs, optimal weights, and hedge ratios but also has other benefits. To ensure that the designed methods function accurately, this study provides a comparison of the outcomes of the DCC-FIAPARCH and cDCC-FIAPARCH to validate that the models perform as effectively as expected (Table 5).

Methods

TVP-VAR connectedness

The DY method (Diebold and Yılmaz 2014) has been widely used in prior studies to examine the spillover effects of directional volatility and to shed light on the transmission mechanism of volatility across different variables. This method has primarily been used to apply the rolling-window technique. Consequently, inherent drawbacks have been revealed when using rolling windows of different sizes, and some observations have dropped accordingly (Dai and Zhu 2022). Hence, Antonakakis et al. (2020) suggested the TVP-VAR method, in which the size of the rolling window can be adopted subjectively such that no observations are lost in the estimation (Mishra and Ghate 2022).

We build on the work of Antonakakis et al. (2020) by using TVP-VAR (1), a Bayesian information criterion (BIC)-based model, to capture the connectedness of asset returns in the asset class. The following equations illustrate this model mathematically:

$$\lambda_t = B_t\lambda_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, S_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + u_t, u_t \sim N(0, R_t) \tag{2}$$

where λ_t, λ_{t-1} and the error term ε_t are specified as $k \times 1$ dimensional vectors. $vec(B_t)$ represents the vectorized form of B_t, and S_t and R_t represent the variance–covariance matrices. Note that B_t and S_t are $k \times k$ dimensional matrices. u_t is a $k^2 \times 1$ dimensional vector, and R_t is specified by a $k^2 \times k^2$ dimensional matrix.

Generalized spillover analysis was performed by obtaining the scaled generalized forecast error variance decomposition (GFEVD), which integrates the H-step forecast (Diebold and Yılmaz 2014). This model permits the estimation of the directional and net connectedness of asset returns. The n-variable procedure $\lambda_t = (\lambda_{t,1}, \ldots, \lambda_{t,n})$ is given by a multidimensional covariance stationary VAR (p) process:

$$\lambda_t = \sum_{s=1}^{p} \vartheta_h \lambda_{t-s} + \varepsilon_t \tag{3}$$

where ϑ_h is an $n \times n$ p-order lag polynomial, and ε_t represents white noise with a nondiagonal error term matrix. The VAR (p) procedure adheres to the moving average specification. Additionally, the TVP-VAR procedure must be transformed into time-varying coefficients of the vector moving average (VMA) defined in Eq. (4):

$$z_t = B_t z_{t-1} + \varepsilon_t = \sum_{z=0}^{\infty} A_{jt}\varepsilon_{t-j}\# \tag{4}$$

where A_{jt} denotes the square matrix of the coefficients. The GFEVD of the H-step forecast of the j-th asset return in response to shocks from the i-th asset return can be obtained using Eq. (5):

$$\Phi_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_t \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_t \Sigma e_j\right)}\# \tag{5}$$

When $\Theta_{ij}^{g}(H)$ is normalized, the spillover index can be represented as follows:

$$\widetilde{\Theta}_{ij,t}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1,i=1}^{N}\Theta_{ij}^{g}(H)}\# \tag{6}$$

where e_j refers to a vector with one on the position of *the j-th* asset return, and $\sum_{j=1}^{N}\Theta_{ij}^{g}(H) = 1$ and $\sum_{ij=1}^{N}\Theta_{ij}^{g}(H) = N$. σ_{jj}^{-1} denotes the standard deviation of the error term. The total connectedness index (TCI), FROM, TO connectedness, net directional connectedness, and net pairwise directional connectedness indices were obtained from Eqs. (7) and (11), respectively:

Total connectedness index (TCI):

$$TCI_t^g(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\Theta}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\Theta}_{ij,t}^{g}(H)} = \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\Theta}_{ij,t}^{g}(H)}{N} \times 100\# \tag{7}$$

FROM and TO connectedness index:

$$TD_{i-j}(H) = \frac{\sum_{i=1,i\neq j}^{N}\widetilde{\Theta}_{ji,t}^{g}(H)}{\sum_{j=1,i\neq j}^{N}\widetilde{\Theta}_{ji,t}^{g}(H)} \times 100\# \tag{8}$$

$$TD_{j-i}(H) = \frac{\sum_{i=1,i\neq j}^{N}\widetilde{\Theta}_{ij,t}^{g}(H)}{\sum_{i=1,i\neq j}^{N}\widetilde{\Theta}_{ij,t}^{g}(H)} \times 100\# \tag{9}$$

Net directional connectedness index (NDC):

$$CI_{i,t}^{g}(H) = TD_{i-j}(H) - TD_{i-j}(H)\# \tag{10}$$

Net pairwise directional connectedness index (NPDC):

$$NPDC_{ij}(H) = \left(\widetilde{\Theta}_{\mathrm{ji},t}^{g}(H) - \widetilde{\Theta}_{ij,t}^{g}(H)\right) \times 100\# \tag{11}$$

DCC- and cDCC-FIAPARCH

The asset return generating process (r_t) can be specified by an autoregression AR (1) process as follows:

$$r_t = \alpha + \vartheta r_{t-1} + \varepsilon_t, t \in N, with\varepsilon_t = z_t\sqrt{H_t}\# \tag{12}$$

where α and ϑ are vectors of constant and residual terms, respectively, with $\alpha \in [0, \infty)$,$|\vartheta| < 1$, whereas z_t denotes an $n \times 1$ vector of error of r_t.

The FIAPARCH enhances the flexibility of the conditional variance h_t of GARCH models by capturing the leverage effect and long memory of dependence and power terms (Baillie et al. 1996). These beneficial properties of volatility are crucial for portfolio diversification. The FIAPARCH includes two ARCH equations: APARCH and FIGARCH. FIGARCH was formulated by Baillie et al. (1996), as shown in Eq. (13):

$$\sigma_t = \omega[1-\beta(p)]^{-1} + \left[1 - [1-\beta(p)]^{-1}\varphi(p)(1-p)^d\right]\# \tag{13}$$

where ω is the mean value of the FIGARCH process, is the GARCH parameter, and φ is given by a finite-order lag polynomial. Moreover, p is the lag operator, and d denotes the fractional differencing parameter, with $0 \leq d \leq 1$. FIGARCH provides greater flexibility in terms of conditional variance to accommodate different ranges of persistence (Laurent and Peters 2002).

The FIAPARCH-Chung method employs the truncation $\beta(p)$ at period t-1 and extends the FIGARCH model by introducing the function $(|\varepsilon_t| - \lambda\varepsilon_t)^\delta$ of the APARCH model. δ refers to the power term of the asset return and captures the persistence of volatility. FIAPARCH-Chung was proposed to overcome the structural issue of the previous BBM procedure (Laurent and Peters 2002) and is given by Eq. (14)

$$\sigma_t{}^\delta = \omega + \left[1 - [1 - \beta(p)]^{-1}\varphi(p)(1-p)^d\right](|\varepsilon_t| - \lambda\varepsilon_t)^\delta \# \tag{14}$$

Engle (2002) proposed a dynamic conditional correlation approach designed as a two-step procedure consisting of estimating GARCH and dynamic conditional correlations. It is determined by Eq. (15), the variance–covariance matrix of the residuals (S_t) at time t. D_t denotes the $(N \times N)$ diagonal matrix of the conditional standard deviations of the residuals and is calculated using the square root of the conditional variance from the AR(1)-FIAPARCH-Chung procedure (Eq. (16), and then a matrix of time-varying conditional correlations γ_t can be obtained by Eq. (17).

$$S_t = D_t R_t D_t \# \tag{15}$$

$$D_t = diag\left(\sigma_{11,t}^{1/2} \cdot \cdots \cdot \sigma_{nn,t}^{1/2}\right)\# \tag{16}$$

$$\gamma_t = \left(\mathrm{diag}(\xi_t{}^*)\right)^{-1/2}\xi_t\left(\mathrm{diag}(\xi_t{}^*)\right)^{-1/2}, with \xi_t{}^* = diag[\xi_t]\# \tag{17}$$

The symmetric positive-definite matrix ξ_t is obtained from the squared standardized residuals $\left(\mathrm{u}_{i,t} = \varepsilon_t^i / \sqrt{\sigma_t^{ii}}\right)$ and is computed by Eq. (18). $\overline{\xi}$ and ξ_{t-1} denote the unconditional variance–covariance matrix and its lagged form, respectively.

$$\xi_{t,DCC} = (1 - \alpha - \beta)\overline{\xi} + a\varepsilon_{t-1}\varepsilon_{t-1'} + b\xi_{t-1}a, b > 0, a + b < 1\# \tag{18}$$

Aielli (2013) proposed a corrected dynamic conditional correlation model and reformulated the correlation process to improve the DCC-GARCH model, as shown in Eq. (19):

$$\xi_{t,cDCC} = (1 - \alpha - \beta)S + \alpha\left(\xi_{t-1}^{*\frac{1}{2}}\varepsilon_{t-1}\varepsilon'_{t-1}\xi_{t-1}^{*\frac{1}{2}}\right) + \beta Q_{t-1}\,\kappa_1, \kappa_2 > 0,\ \kappa_1 + \kappa_2 < 1 \tag{19}$$

Breitung–Candelon spectral Granger causality test (BC-SGc)

Breitung and Candelon (2006) first proposed the BC-SGc, which has been confirmed as superior for analyzing robustness checks (Tuna and Tuna 2022). BC-SGc can reduce seasonality errors in time-series data models by capturing nonlinear causality relationships. This method categorizes long-, medium-, and short-run Granger causality across variables at specific frequencies (Abakah et al. 2023).

Table 3 Preliminary statistics for the logarithm variables

	LNCSI	LNCU	LNGOLD	LNPTA	LNSOY
Mean	− 0.0101	0.0022	0.0186	− 0.0080	0.0023
Median	0.0335	0.0243	0.0266	0.0000	0.0000
Maximum	8.9310	6.1602	5.6755	6.8431	11.6699
Minimum	− 9.1542	− 6.5687	− 7.8433	− 18.2903	− 7.8537
Std. Dev	1.6233	1.4097	1.0692	1.5762	1.2098
Skewness	− 0.4913	− 0.2134	− 0.3518	− 0.5084	0.0082
Kurtosis	7.3457	6.2708	7.9886	9.9867	9.5925
Jarque–Bera	3110.7339	1705.0160	3977.4394	7811.5618	6810.6642
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH-LM(2)	115.91	244.49***	132.21***	29.592***	28.103***
ARCH-LM(10)	52.867 ***	82.619***	55.152***	10.819***	18.479***
ARCH-LM(20)	31.830***	45.645***	30.869***	9.5340***	10.216***
ADF	− 15.2728***	− 10.4168***	− 16.6303***	− 21.29***	− 62.7463***
Observations	3761	3761	3761	3761	3761

*** Denotes significance at the 1% level

A bivariate time-series vector $\left|x_t, y_t\right|$ with R_t can be derived from the VAR analytical scheme in Eq. (20)-(21):

$$\chi(L)R_t = \epsilon_t \tag{20}$$

$$\varphi(L) = 1 - \varphi_1 L - \cdots - \varphi_p L^p \tag{21}$$

This method was described in detail by Li et al. (2022). In this section, the BC-SGc at a frequency (ω) between assets of x_t and y_t is simply formulated as Eq. (22).

$$x_t = \rho_1 x_{t-1} + \cdots + \rho_p x_{t-p} + \beta_1 y_{t-1} \ldots + \beta_q y_{t-p} + \upsilon_{1t} \tag{22}$$

Data and preliminary statistics

This study uses daily closing prices from the Choice data service[8] for the period from January 09, 2008, to June 30, 2023. Asset returns, namely, LNCSI, LNCU, LNGOLD, LNPTA, and LNSOY, were calculated as $100 \times (lnprice_t / lnprice_{t-1})$.

Table 3 shows preliminary statistics for each asset return. The CSI300 returns have the most significant standard deviations, indicating higher volatility clustering of stocks than commodities. For commodity futures returns, PTA and copper returns outperform soybean and gold returns, indicating higher risk-adjusted yields. The shape of the probability distributions of the asset returns is supported by kurtosis and skewness. Positive kurtosis statistically implies that the probability distributions of all asset returns are fat-tailed, while skewness suggests that the probability distributions are negatively skewed. The Jarque–Bera (J-B) test statistics are shown to reject the null hypothesis that each asset return is not normally distributed at the 1% significance level. The augmented

[8] https://choice.eastmoney.com/

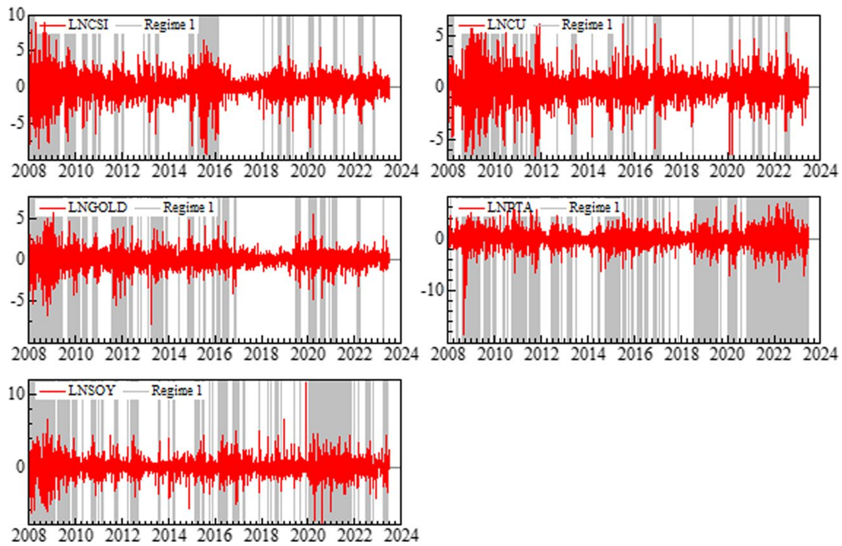

Fig. 1 Graphs of CSI300, copper, gold, soybean, and PTA returns. Note: the shaded areas are drawn to highlight the periods of excessive volatility by using Markov-switching dynamic regression (MS-DR) (Kumar et al. 2019)

Dickey-Fuller (ADF) results for each asset return indicate stationarity at the 1% significance level. In addition, the ARCH-LM (2), (10), and (20) tests confirm the strong significance of ARCH for all asset returns.

Figure 1 plots the time-varying evolution of all asset returns over the sample period. As expected, all return graphs show remarkably more volatile clustering during financial disturbance because of uncertainty related to dramatic changes in the economic and financial conditions. All asset returns show volatility clustering, revealing the presence of heteroscedasticity. These characteristics support applying GARCH models to analyze asset return dynamics (Dimitriou et al. 2013). The shaded areas highlight regimes of excess volatility according to the Markov-switching dynamic regression (MS-DR). In particular, the outbreak of COVID-19 significantly increased the volatility of PTA and soybean returns.

Figure 2 shows a scatter matrix graph visualizing the unconditional correlation between the asset returns. Positive pairwise Pearson correlations are confirmed, with the highest value between the CSI300 and copper returns.

Empirical results

Dynamic total connectedness

Figure 3 shows the trajectory of the total connectedness index (TCI) from 2008 to 2023, with values ranging from approximately 10–52% and an average TCI of 23.7%.

During the pre-COVID-19 period, three significant spikes in TCI were detected. Figure 3 shows the first TCI peak, the TCI reaching approximately 46% in 2008. Between 2011 and 2014, a second cycle of high connectedness ranging from 30 to 50% was observed. Importantly, higher connectedness does not diminish instantly but persists

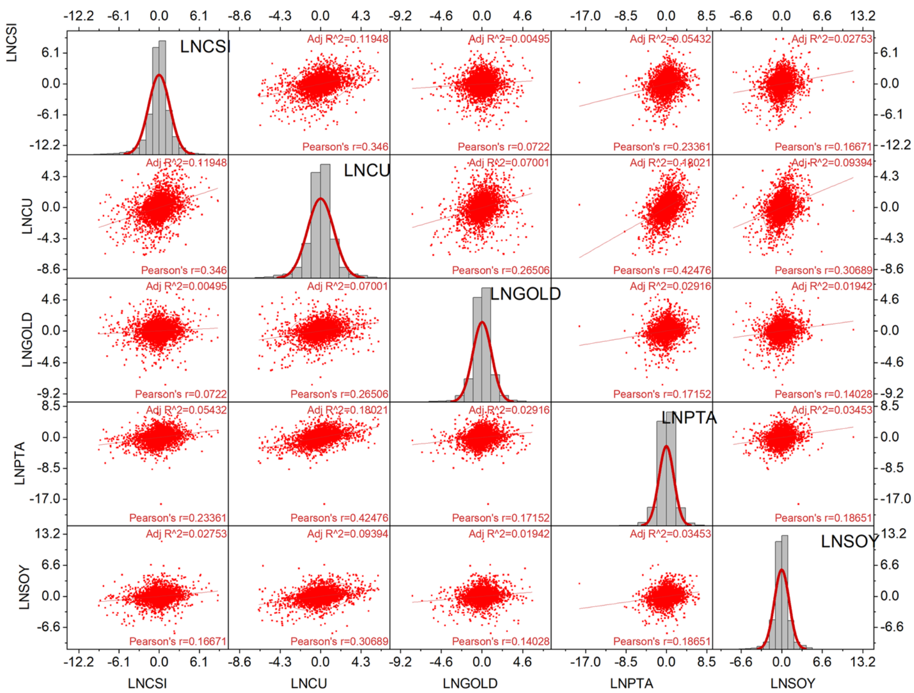

Fig. 2 Graph of the scatter matrix between the asset returns

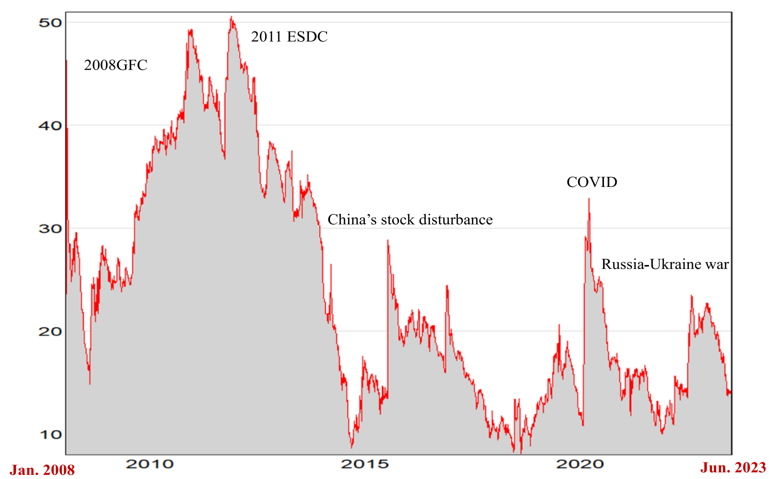

Fig. 3 Total connectedness index (TCI)

over a relatively higher TCI period. A possible cause may be interpreted as follows. The US Federal Reserve (Fed) launched three rounds of Quantitative Easing (QE) in November 2008 to address the global financial systemic risks stemming from the 2008 GFC and revive economic growth. Consequently, between 2011 and 2014, almost all commodity prices surged across the three rounds of QE (Yip et al, 2017). A third spike in TCI was detected in mid-2015, which reached a peak of approximately 29% due to the impact of China's 2015 stock disturbance. At the beginning of June 2015, the CSI300 was as high as 5353 and then plunged to 3342 by the end of August, crashing to 2000 points in three months. Systematic risk in China's financial markets hit a new peak during this

Table 4 Averaged connectedness index

	LNCSI	LNCU	LNGOLD	LNPTA	LNSOY	FROM
LNCSI	78.20	10.80	1.80	5.70	3.40	21.80
LNCU	9.20	65.90	5.30	13.20	6.30	34.10
LNGOLD	2.20	6.90	83.90	4.30	2.70	16.10
LNPTA	5.30	14.10	3.70	72.20	4.60	27.80
LNSOY	3.20	7.50	2.40	5.40	81.40	18.60
Contribution TO others	19.90	39.40	13.30	28.60	17.10	118.30
NET directional connectedness	− 1.90	5.30	− 2.80	0.90	− 1.50	TCI
NPDC transmitter	3.00	0.00	4.00	1.00	2.00	23.70%

disturbance (Chen and Gong 2019). Consequently, the TCI increased substantially from June 2015 to June 2017. Moreover, the TCI effectively captured the extreme shock generated by the outbreak of the COVID-19, reaching an intense peak of approximately 33% in 2020. It is worth noting that while the impact of the pandemic is dramatic, its duration appears to be very short, and the TCI of this asset class subsequently falls to 10%-18%. As far as the impact of the Russian-Ukraine war is concerned, the TCI shows an instantaneous increase that peaks at approximately 23% and clearly signifies weaker connectedness if compared with the period of the COVID-19 outbreak. Overall, the findings reinforce the argument that when severe economic (or financial) crises and geopolitical events occur, total volatility spillovers are expected to be magnified (Wen et al. 2021).

According to Table 4 and Fig. 3, copper returns (5.30) are identified as the most dominant volatility transmitter for the asset class, explaining 39.4% of the change in the variance of other assets, whereas the remaining assets explain 34.1% of the change in the variance of copper. The PTA returns also act as significant volatility transmitters, explaining 28.6% of the change in the variance of the other included asset returns. By contrast, CSI300 (− 1.90), gold (− 2.80), and soybean (− 1.50) returns are reported to be net recipients of this asset class.

Net connectedness and pairwise connectedness

Figure 4 depicts each asset return's net directional dynamic connectedness (NDDC). This is evidence of the time-varying pattern of the net recipient or transmitter of the asset class across the sampled periods. The CSI300, gold, and soybean returns are revealed to be net recipients of spillovers from other asset returns for most periods in this study, whereas PTA returns switch between negative (net recipient) and positive (net transmitter) from 2008 to 2023 (Fig. 4). A persistent net transmitter is evident for copper returns. Consistent with the results of Wen et al. (2021), the CSI300 return is expected to be a transmitter and switch to a recipient before mid-2020. On the other hand, the Russia-Ukraine war reinforced the spillover effects of PTA returns as a net transmitter. This finding is likely related to the prevailing uncertainty in global financial markets (Adekoya and Oliyide 2021) and investors' heterogeneous responses to relevant financial market news (Naeem et al. 2022) during the period of COVID-19 and the Ukraine war period.

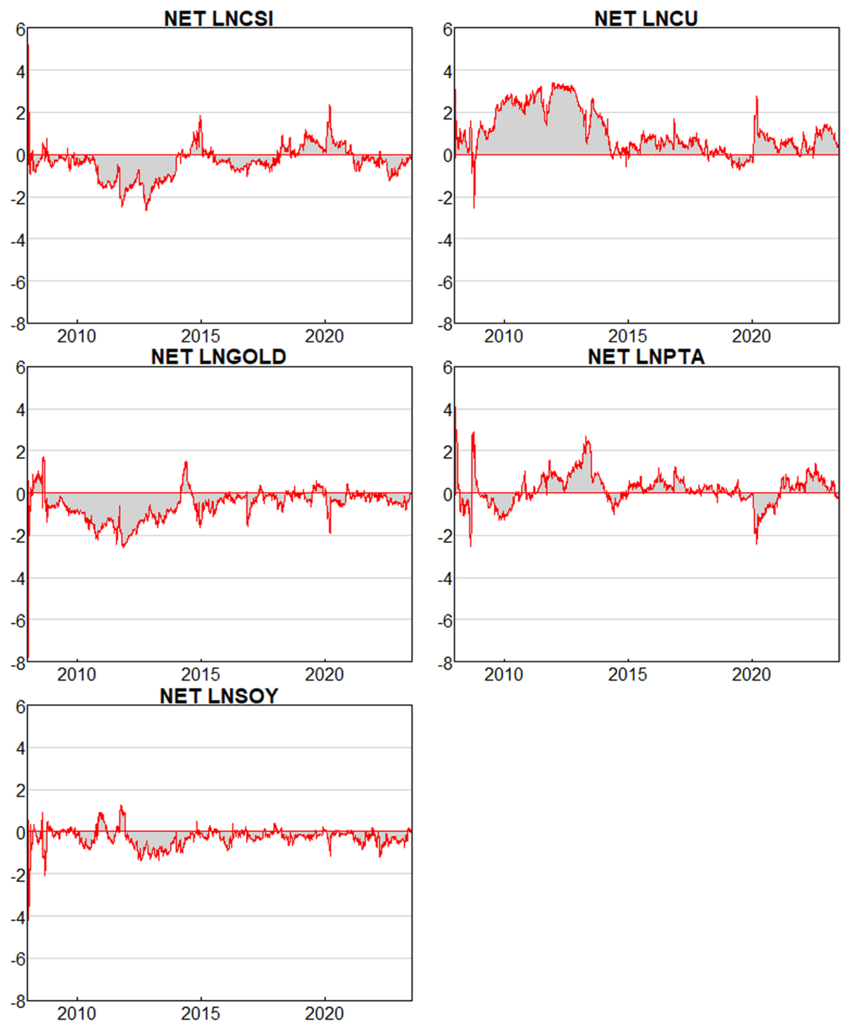

Fig. 4 Graphs of net pairwise directional connectedness (NPDC)

Figure 5a–d display the net pairwise dynamic connectedness (NPDC) of the full sample, pre-COVID-19, post-COVID-19, and Russia-Ukraine war separately, and the notable findings are as follows. First, the CSI300 return is a consistent recipient of spillovers for copper and PTA returns over the full sample period. This finding indicates that financial risk shifts from price fluctuations in China's metal and petrochemical commodities markets, which are easily transmitted to China's stock market. However, the pairwise connectedness of soybean-CSI300 is weaker than that of the other asset pairs examined, suggesting that the volatility of soybean prices may not be easily transmitted to China's stock market in the long term. Second, the CSI300 return becomes the net recipient of gold and soybean returns in the post-COVID-19 period, highlighting potential hedging opportunities for the CSI300 long position. Third, the spillover effect of the PTA dramatically intensified after the Russia-Ukraine war. One notable insight is that as a downstream petrochemical industry product, PTA prices correlate with the volatility of energy prices. Consequently, the pairwise connectedness of PTA-CSI300 increases, which was mainly attributed to the notable surge in energy prices due to the geopolitical

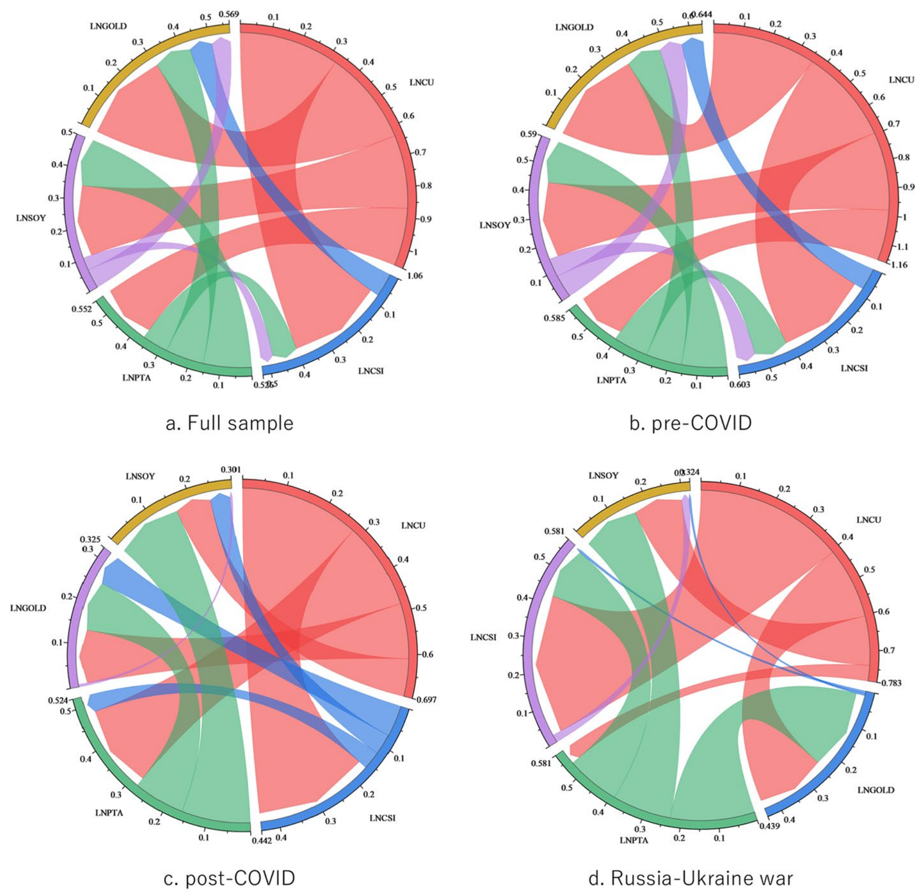

Fig. 5 Chord graphs of directional net pairwise connectedness

crisis.[9] Finally, during the Russia-Ukraine war (Fig. 5d), the pairwise connectedness of gold-CSI300 and gold-copper shows that the spillover direction and magnitude were positively skewed, thus offering possible gold-related portfolio diversification opportunities in China's financial markets.

cDCC-FIAPARCH results

Table 5 summarizes the estimated results of both the DCC- and cDCC-FIAPARCH, and Panel A reports the univariate AR (1)-FIAPARCH estimates for each asset's returns. The AR (1) process is incorporated into the mean equation: This term is not statistically significant for asset returns except for copper, which has a negative significance level of 1%. This result suggests that information regarding the asset class is instant and embodied in the copper market, which can be explained by the lack of a mean revision (Mensi et al. 2015). d-Fiagarch is statistically significant at the 1% level for all asset returns, implying that the FIAPARCH process captures long-memory behavior and that there is a higher degree of CSI300 returns.

Moreover, the sum of the short-term coefficient (ARCH) and long-term persistence coefficient (GARCH) is lower than one, indicating the presence of volatility clustering.

[9] https://www.eia.gov/todayinenergy/detail.php?id=50738.

Table 5 Estimation results of DCC- and CDCC-FIAPARCH models

	CSI300	coppEr	Gold	PTA	Soybean
Panel a: Estimates of the AR (1)-FIAPARCH process					
Cst(M)	0.0168	−0.0038	0.0188	−0.0135	−0.0033
	0.0203	0.0163***	0.0128	0.0225	0.0182
AR(1)	0.0268	−0.0449***	−0.0212	0.0059	−0.0206
	0.0176	0.0169	0.0181	0.0192	0.0198
Cst(V)	19.1523	3.1218***	3.5413**	4.3194	2.1998***
	13.0280	1.0456	1.3768	2.0432	0.6174
d-Figarch	0.6609 ***	0.3812***	0.4720***	0.3331 ***	0.2435***
	0.1269	0.0475	0.0481	0.0721	0.1056
ARCH	0.1893 ***	0.1624 *	0.2855 ***	0.1579	0.4001***
	0.0659 ***	0.0945	0.0682	0.4109	0.1317
GARCH	0.7716	0.4394 ***	0.6506***	0.4143	0.5888 ***
	0.0905	0.1193	0.0746	0.4585	0.1915
APARCH (Gamma)	0.0883	0.1189**	−0.0216	−0.0324	0.0796
	0.0800	0.0533	0.0648	0.0667	0.1890
APARCH (Delta)	1.7475 ***	1.7930 ***	1.7069 ***	1.7162***	1.5128 ***
	0.1967	0.1254	0.1589	0.3248	0.2164
Panel b. Estimates of the DCC process					
cDCC-FIAPARCH	DCC − FIAPARCH				
α	0.0135 ***		0.0117 ***		
std.Error	0.0032		0.0021		
β	0.9794***		0.9832***		
std.Error	0.0070		0.0038		
df	6.0606***		6.0282***		
std.Error	0.2070		0.2009		
Panel c. Diagnostics					
AIC	15.0562		15.0642		
SC	15.1440		15.1520		
log likelihood	−28,260.1		−28,275.262		
Hosking (20)	582.373		582.112		
Hosking2 (20)	534.001		523.562		
McLeod-Li (20)	582.132		581.871		
McLeod-Li2 (20)	534.154		523.758		

***, **, *Represent significance at the 1% level, 5% level, and 10%, respectively

The parameter of the leverage effect, APARCH (gamma), is positive and significant at the 5% significance level for copper returns, indicating that the degree of the negative impact on copper returns is greater than that of the positive impact and that the volatility of copper is asymmetric. APARCH (gamma) is insignificant for the other asset returns, thus rejecting the leverage hypothesis. The power term parameter APARCH (delta) for all asset returns is positive and significant at the 1% level.

Table 5, panel b reports the estimates of the DCC procedures using the DCC- and cDCC-FIAPARCH models that effectively correct standard errors of the DCC-GARCH misspecification (King and Roberts 2015). Parameters (α) and (β) are statistically significant at the 1% level. Short-run persistence (α) is more remarkable in the case of cDCC-FIAPARCH. In contrast, the long-run persistence (β) level is higher for DCC-FIAPARCH. Additionally, each degree of freedom (df) is significant at the 1% level, revealing a fat tail in the degree distribution and a higher estimated shape parameter for cDCC-FIAPARCH than DCC-FIAPARCH.

Table 5, panel c, shows the diagnostic test results. cDCC-FIAPARCH presents higher log-likelihood and lower AIC and SIC values than DCC-FIAPARCH. According to Hosking (20) and Hosking2 (20), FIAPARCH models capture all heteroskedasticity effects efficiently. McLeod-Li (20) and McLeod-Li2 (20) statistics indicate no statistical error for DCC and cDCC-FIAPARCH.

These findings confirm that the cDCC-FIAPARCH results are more robust and reliable than the DCC-FIAPARCH results in this asset class. Thus, the analysis of hedging opportunities can benefit from the results of the cDCC-FIAPARCH.

Dynamic conditional correlations (DCCs)

cDCC-FIAPARCH captures the conditional volatility of the included asset returns (Fig. 6). The CSI300 and copper returns exhibit relatively higher volatility than the other asset returns. In response to the disturbances, all asset returns showed significant volatility due to the COVID-19 pandemic. Most strikingly, extreme conditional volatility occurs in copper returns but lasts for a short time in response to the pandemic. However, the conditional volatility of PTA returns is more responsive to the Russia-Ukraine war than it is to the pandemic.

Figure 7 illustrates the evolving patterns and dynamics of the DCCs of each asset pair. When further reviewing the results of DCCs of the Shanghai Composite Index and Chinese Commodity Index obtained by Wen et al. (2021), the evolution of DCCs resulting from cDCC-FIAPARCH was quite similar but fluctuated more than their results. Several useful findings were obtained in this study. (i) Specifically, the DCCs of CSI300-copper were considerably higher than those of the other pairs, whereas the peak value of the DCCs reached its highest level (approximately 0.63) immediately after the pandemic. Figure 7 shows that the volatility of copper returns is more closely linked to the volatility of CSI300 returns than that of the other commodities included in this analysis. However, this dynamic linkage has decreased dramatically since the Russian-Ukraine war. (ii) As Baur and Lucey (2010) state, safe haven assets correlate nonpositively with other assets in extreme volatility. Furthermore, Liu and Lee (2022) argue that gold's safe haven role is confirmed if DCCs decrease under an externally induced shock. Therefore, during the pre-COVID-19 period, gold is not a long-term hedging instrument against the volatility of China's stock market, which is consistent with the results of Liu and Lee (2022), and the average DCCs are greater than 0. However, during the Russia-Ukraine war, this DCC dropped to an average of − 0.009 (Table 6), indicating that the safe-haven role was strengthened. (iii) Concerning the CSI300-PTA pair, the highest DCCs were observed at the beginning of COVID-19 from the cDCC-FIAPARCH estimates, which is similar to the findings from the DCCs of stock chemicals reported by Wen et al. (2021), reinforcing the evidence of significant spillover effects between stock and petrochemical markets in China due to the pandemic. Moreover, as shown in Fig. 7, it is worth noting that the Russia-Ukraine war resulted in a dramatic increase in DCCs in the copper-PTA

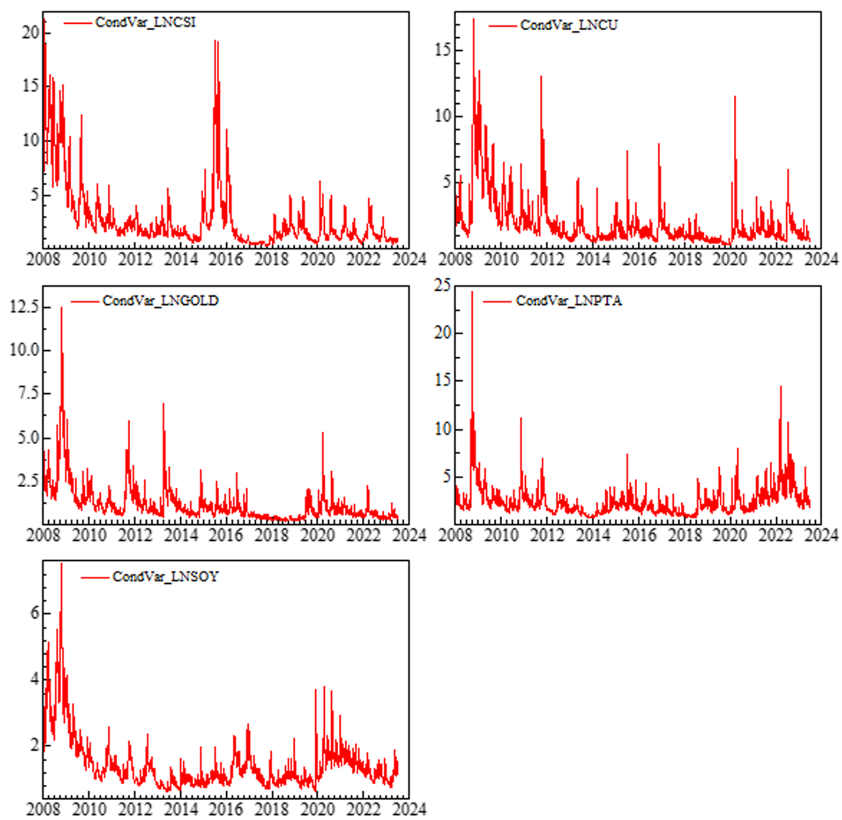

Fig. 6 Conditional variance of asset returns captured by cDCC-FIAPARCH

and gold-PTA pairs (Table 6). (iv) Fig. 7 shows that the DCCs of the CSI300-soybean pair were less favorable than those of the CSI-copper and CSI-PTA pairs and declined to nearly zero after March 2020. The average DCCs of CSI300-soybean were nearly zero (0.091) during the Russian-Ukrainian war period investigated here (Table 6), revealing the potential hedging opportunities for CSI300.

The DCCs for the asset pairs differed significantly, implying varying degrees of financial integration between asset returns, and it is worth analyzing them separately to draw sound implications for constructing portfolios.

Hedging opportunities analysis

The results of dynamic connectedness and DCCs collectively draw strong conclusions to further explore portfolio asset allocation, risk management, and portfolio diversification in a practical manner for CSI300 portfolios. Following Dai and Zhu (2022) and Wen et al. (2021), the analysis of hedging opportunities employs the outputs of the cDCC-FIAPARCH to calculate the optimal hedge ratios (OHRs), portfolio weights (OPWs), and hedging effectiveness (HE) between CSI300 and commodity returns.

Hedge ratios are defined as the costs of hedging a 1-unit long position of the CSI300 return (or commodity return) with a $\rho_{ji,t}$ unit short position of the commodity asset return (or CSI300 return), where ρ_{ji} (OHRs) at time t is given by:

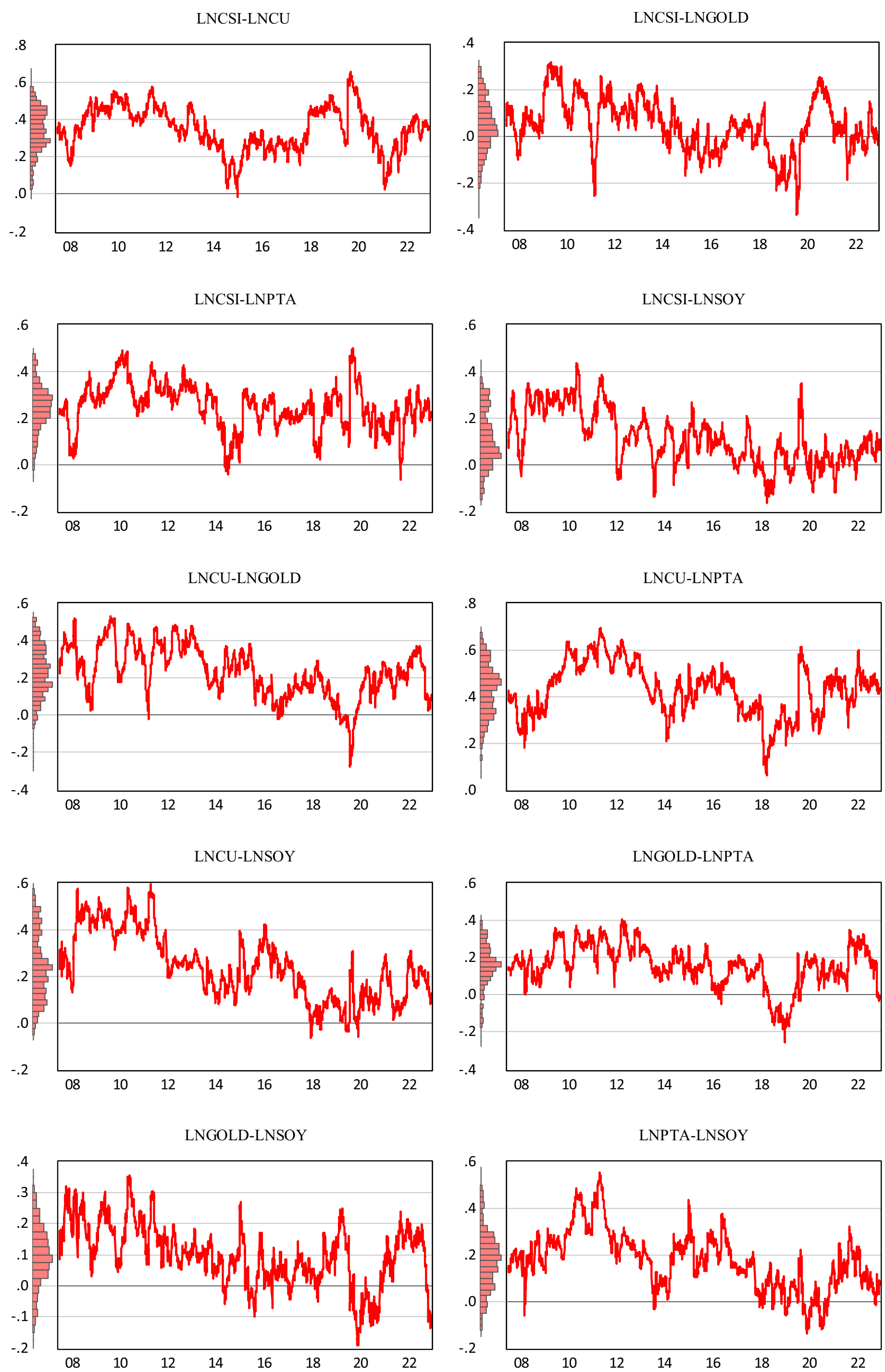

Fig. 7 The DCCs between asset pairs captured by cDCC-FIAPARCH

$$\rho_{ji,t} = \frac{h_{ij,t}}{h_{ii,t}} \tag{23}$$

where $h_{ij,t}$ denotes the conditional covariance between CSI300 and commodity returns and $h_{ii,t}$ is the conditional variance of the commodity or CSI300 return.

Table 6 The mean value of the DCCs

	Pre-COVID	Post-Covid	Russia-Ukraine war	Full-sample
LNCSI-LNCU	0.351	0.335	0.334	0.347
LNCSI-LNGOLD	0.047	0.038	− 0.009	0.045
LNCSI-LNPTA	0.252	0.223	0.211	0.245
LNCSI-LNSOY	0.13	0.043	0.058	0.111
LNCU-LNGOLD	0.249	0.167	0.231	0.231
LNCU-LNPTA	0.426	0.434	0.446	0.428
LNCU-LNSOY	0.269	0.135	0.17	0.239
LNGOLD-LNPTA	0.156	0.156	0.209	0.156
LNGOLD-LNSOY	0.117	0.038	0.116	0.099
LNPTA-LNSOY	0.203	0.073	0.128	0.174

The OPWs of CSI300 and commodity returns are constructed in a specific portfolio ($\omega_{ji,t}$), as given by Eq. (24).

$$\omega_{ji,t} = \frac{h_{ii,t} - h_{ij,t}}{h_{jj,t} - 2h_{ij,t} + h_{ii,t}} \tag{24}$$

$$\text{with } \omega_{ji,t} = \begin{cases} 0 & \text{if } \omega_{ji,t} < 0 \\ \omega_{ji,t} & \text{if } 0 \le \omega_{ji,t} \le 1 \\ 1 & \text{if } \omega_{ji,t} > 1 \end{cases}$$

$\omega_{ji,t}$ represents the weight of asset j in a 1-unit portfolio, and the weight of asset i can be written as $1 - \omega_{ji,t}$. Hedging effectiveness (HE) measures the risk reduction effectiveness of a portfolio of instruments by calculating the percentage reduction in variance across different portfolios, as given by Eqs. (25)–(27):

$$\gamma_\rho = \varphi_{jt} - \rho_{jit}\varphi_{it} \tag{25}$$

$$\gamma_\omega = \omega_{jit}\varphi_{jt} + \left(1 - \omega_{jit}\right)\varphi_{it} \tag{26}$$

$$\mathrm{HE}_{ij} = 1 - \frac{var_{Pj}}{var_{Pi}} \tag{27}$$

where γ_ρ and γ_ω represent the portfolio returns of the OHRs and OPWs, respectively. φ_{jt} and φ_{it} are the returns on i and j, respectively. Here,var_{Pj} and var_{Pi} denote the variance of the CSI300 and commodity futures portfolios and the variance of the unhedged positions, respectively. A higher HE generally implies better risk reduction performance (Dai and Zhu 2022).

Figure 8 and 9 show the OHRs and OPWs and show a highly fluctuating time-varying pattern and considerable variability for different asset pairs. These figures also show abrupt increases or decreases during disturbance events. Table 5 displays the mean values of OHRs, OPWs, and the corresponding HE between the CSI300 and the investigated commodity returns during the pre-COVID-19, COVID-19, and Russia-Ukraine war periods. Moreover, Figs. 9 and 10 and Table 7 are presented in several ways.

First, the OHRs of CSI300-copper outperform the others in most cases, indicating that copper futures are costlier than other commodity futures when hedging CSI300 long or

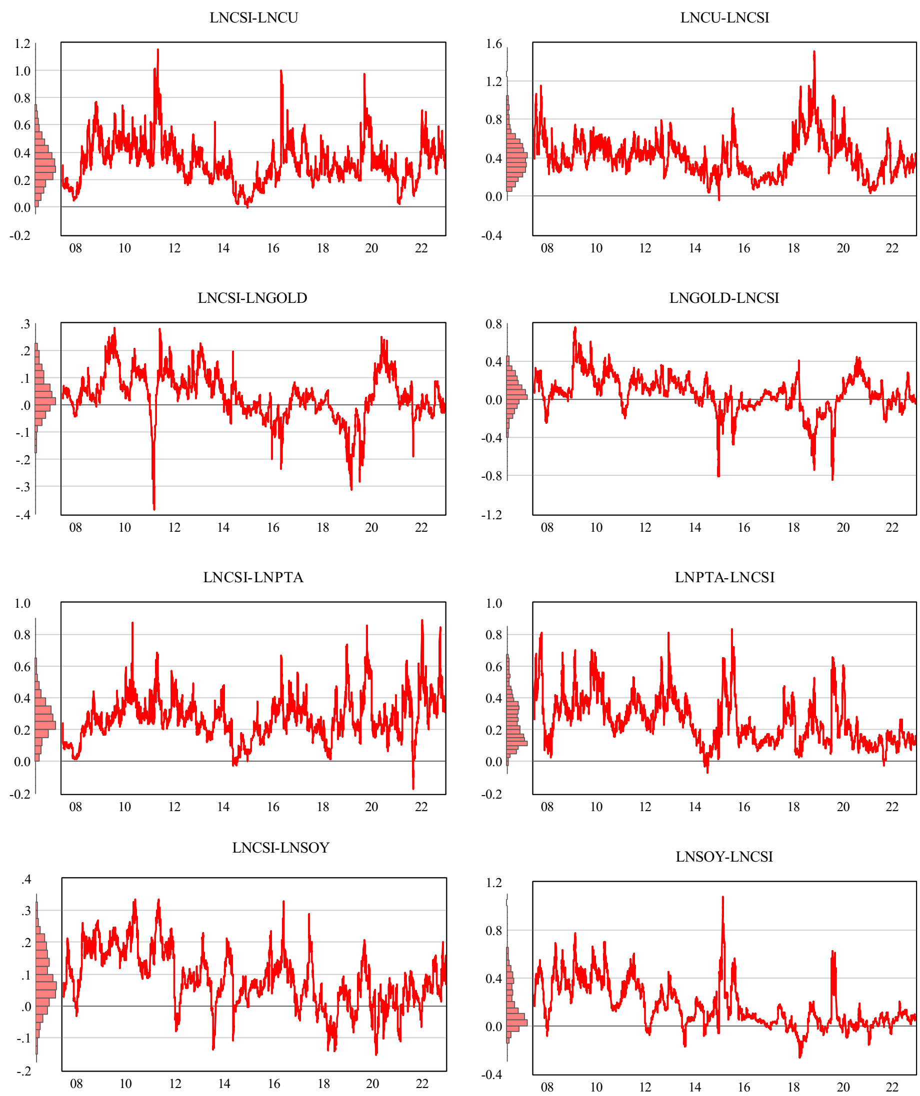

Fig. 8 Optimal hedge ratios (OHRs) of the CSI300-commodity pairs

short positions (the mean values of the OHRs are 0.330 and 0.415, respectively). The results are, to some extent, similar to those of Wen et al. (2021), who suggest that non-ferrous metals are associated with higher costs when hedging the Shanghai Composite Index (SHCI). In contrast, the OHRs of CSI300-gold and gold-CSI300 are lower than those of the other pairs (mean values are 0.033 and 0.060, respectively) and frequently oscillate between positive and negative. Hence, investors frequently incur higher costs when using copper as a hedging instrument. Gold appears to be more attractive for hedging CSI300 return risks for most of the financial and economic conditions analyzed. Second, in the post-COVID-19 period, the HE for hedging the CSI300 short position improved dramatically for both PTA and soybean returns. The OPWs of PTA-CSI300 increased to 0.787 compared to 0.5 in the pre-COVID-19 period, and the OPWs of Soybean-CSI300 increased to 0.475.

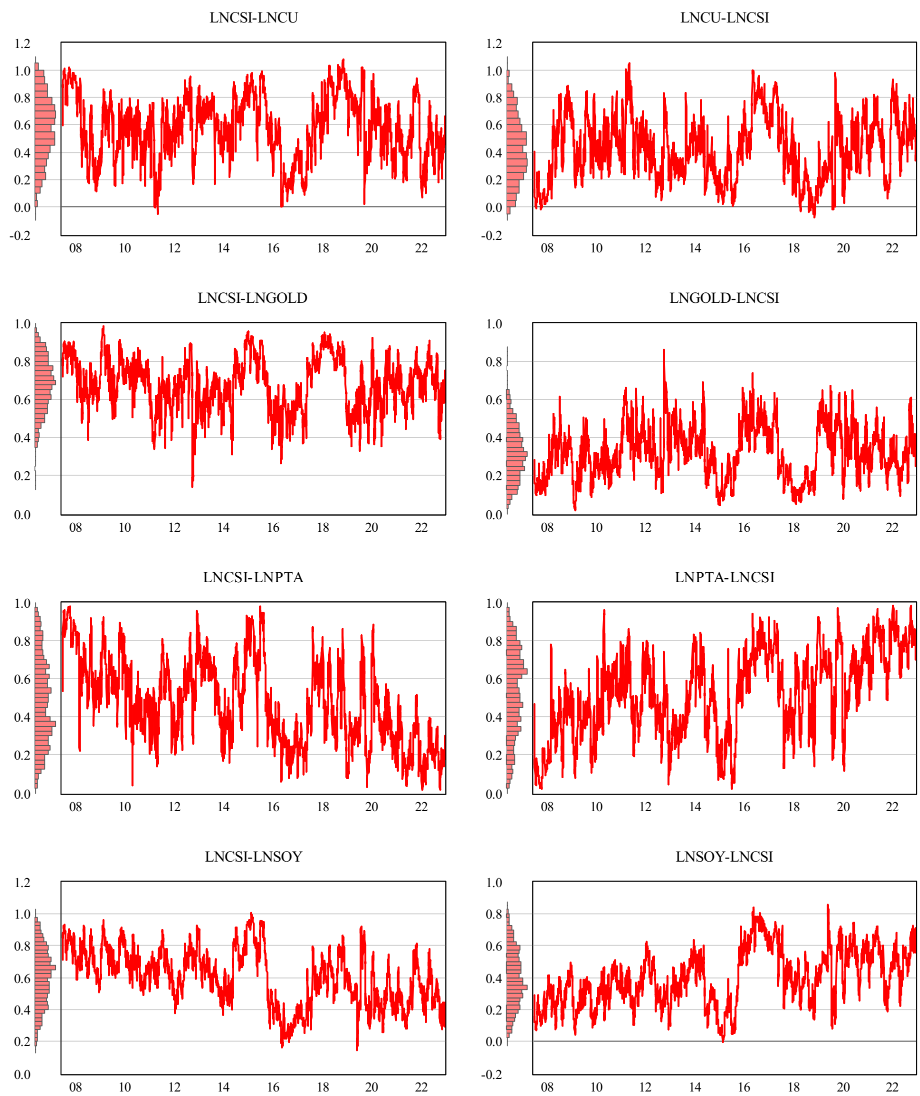

Fig. 9 Optimal portfolio weights (OPWs) of the CSI300-commodity pairs

Moreover, the mean values of the OHRs of CSI300-PTA increased to 0.373 in the post-COVID-19 period compared to 0.263 in the pre-COVID-19 sample. This result indicates that the hedging cost of the PTA has increased significantly because of its sensitivity to the combined impact of the pandemic and geopolitical war. During the Russia-Ukraine war, the safe haven role of gold in the CSI300 return increased dramatically because of this geopolitical event. The OHRs decreased from 0.067 (pre-COVID) to -0.018 for gold-CSI300 and from 0.036 (pre-COVID) to -0.004 for CSI300-gold. Third, in the entire sample period, the best hedging performance was achieved by the CSI300-gold pair, with the highest HE of 69.49%. An investment of 0.68 yuan in the gold and 0.32 yuan in the CSI300 long position results in a hedging cost of 0.03 yuan. Compared with poverty commodity-CSI300, the PTA-CSI300 shows a higher HE, with a value of 44.1% for one unit of the CSI300 short position. The OPWs are estimated to be 0.53 yuan for the PTA long position and 0.47 yuan for the CSI300 short position, and the hedging cost of using

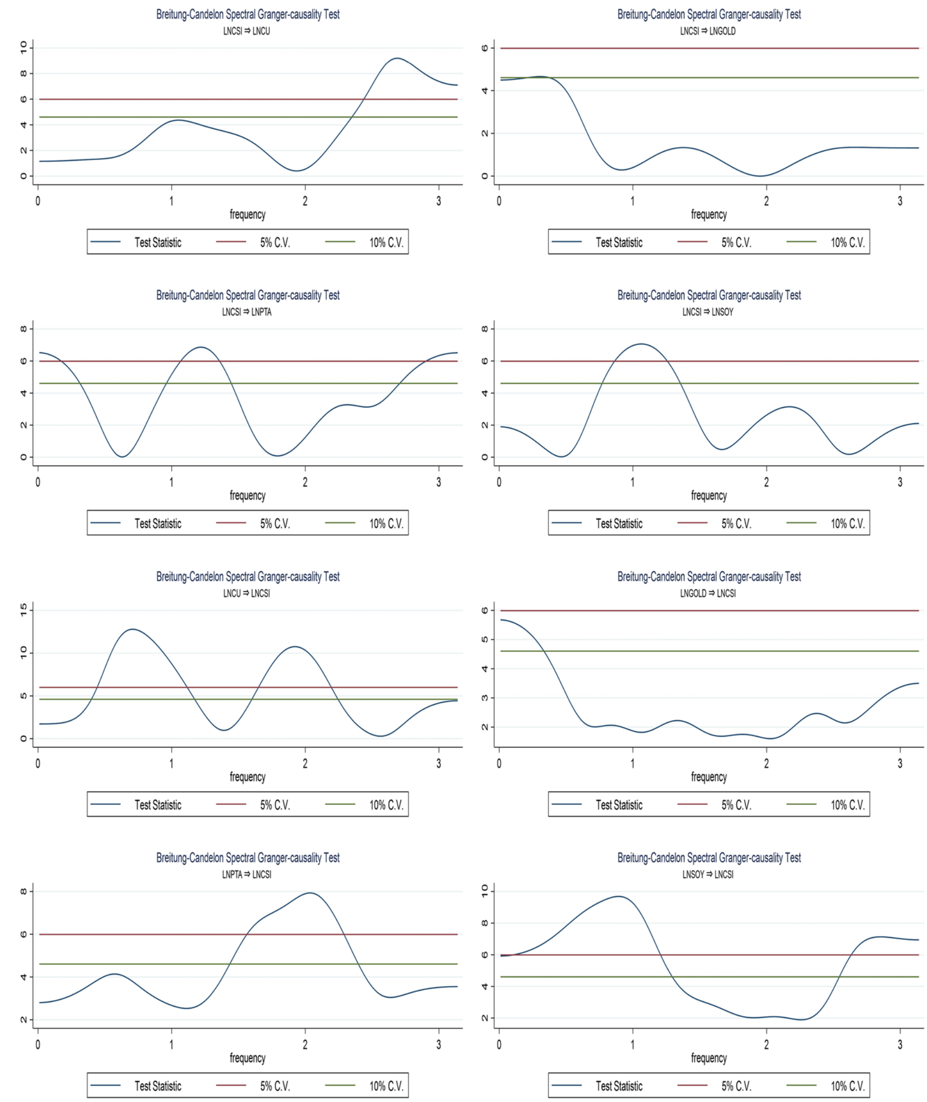

Fig. 10 Breitung-Candelon spectral Granger causality test (BC-SGc). The Wald statistical value and frequency (ω) are displayed on the vertical and horizontal axes, respectively

PTA is 0.26 yuan. Furthermore, soybeans offer a better instrument to hedge the CSI300 long position than copper and PTA, with an HE for SOY-CSI300 of 62.8%, whereas OHRs (0.084) are much cheaper than CSI300-copper and CSI300-PTA.

Similarly, Lu et al. (2023) provide cross-asset information transmission between Indian stock (BSESN) and commodities, including soybean, copper, and gold. There are some notable features when comparing the results for the two emerging economies. (i) Dynamic connectedness(spillovers) dramatically increased in the early phase of the COVID-19 period, followed by gradual weakening and leveling off for both the Indian and Chinese financial markets. On average, the TCI of the Indian asset class (BSESN and six commodities) is reported to be 35.78% between 2020 and 2022. In this study, the average TCI of the asset class from 2008 to 2023 is revealed to be 23.7% and exhibited a peak value of approximately 33% in 2020. (ii) The BSESN was a net recipient during

Table 7 The mean value of OHRs, OPW, and HE between CSI300 and commodities

CSI300-commodity		CSI300-copper	CSI300-gold	CSI300-PTA	CSI300-soybean
Full-sample	OHRs	0.330	0.033	0.274	0.084
	OPW	0.576	0.679	0.472	0.605
Pre-COVID	OHRs	0.328	0.036	0.263	0.086
	OPW	0.586	0.678	0.500	0.613
Post-COVID	OHRs	0.353	0.000	0.373	0.062
	OPW	0.487	0.692	0.212	0.521
Russia-Ukraine	OHRs	0.361	− 0.004	0.373	0.059
	OPW	0.487	0.694	0.213	0.525
	HE (%)	49.74%	69.49%	47.30%	62.62%
Commodity-CSI300		**Copper-CSI300**	**gold-CSI300**	**PTA-CSI300**	**Soybean-CSI300**
Full-sample	OHRs	0.415	0.060	0.255	0.162
	OPW	0.424	0.321	0.528	0.395
Pre-COVID	OHRs	0.423	0.067	0.269	0.172
	OPW	0.414	0.322	0.500	0.387
Post-COVID	OHRs	0.337	− 0.008	0.126	0.062
	OPW	0.513	0.308	0.788	0.479
Russia-Ukraine	OHRs	0.344	− 0.018	0.126	0.060
	OPW	0.513	0.306	0.787	0.475
	HE (%)	33.35%	29.68%	44.10%	32.70%

the pre-COVID-19 period and switched to a net transmitter between 2020 and 2022. CSI300 acted as a significant volatility transmitter for this asset class during most of the study period. (iii) Soybeans are a major net transmitter of volatility spillovers for asset classes in India's financial markets. In contrast, our findings reveal that soybean is a net recipient of the asset class (net connectedness: − 1.50), and the pairwise connectedness of soybean-CSI300 is weaker than that of the other asset pairs examined. (iv) Both BSESN and CSI300 have stronger dynamic linkages with copper, mainly because of India and China's imports and consumption in the global copper markets. Cu is a valuable asset for hedging and portfolio diversification. (v) In terms of the classical safe-haven property of gold, although gold is evidenced to be a valuable hedging instrument for global stock indices, such as: the US (S&P 500), Germany (DAX), Japan (Nikkei 2252) (Alshammari and Obeid 2023), and the African 7 stock indices (Naeem et al. 2022), gold is not confirmed to be hedging effectively for the Indian BSESN index. Our results indicate that gold achieves the best hedging performance for CSI300 long positions, with a hedging effectiveness of 69.49%. The role of the safe haven in hedging CSI300 long positions during the Russia-Ukraine war was significantly strengthened when compared to the pre-COVID-19 period.

Finally, comparing the results with other similar studies (e.gGençyürek and Ekinci 2023; Alshammari and Obeid 2023; Wen et al. 2021), this work may not only have superior risk management benefits for both the short and long hedgers, but the results also extend over a longer time period with the sample ending on June 30, 2023. More importantly, this asset class appears to be highly liquid, allowing investors to use the results of hedging strategies to easily buy or sell long/short positions without paying high transaction costs in China's financial markets (e.g., exchange-traded funds (ETFs), futures, etc.) (Table 7).

Robustness check

The frequency domain causality test (BC-SGc) allowed us to decompose the causality test statistics into different frequencies. The corresponding null hypotheses are specified as LNCSI (commodities returns) does not Granger-cause commodities returns (LNCSI) in the frequency domain. Figure 10 illustrates the empirical results for the frequency-domain causality changes from LNCSI (commodities returns) to commodities returns (LNCSI) with optimal lag orders. High frequencies (0–1) were interpreted as short-run Granger causality, whereas medium (1–2) and long frequencies (2–3) were interpreted as medium- and long-run Granger causalities, respectively.

The BC-SGc results are reported graphically to verify and assess the robustness of the main results. In general, the Granger causality relationships are all bidirectional for CSI300-commodity pairs, validating the possibility and feasibility of testing dynamic connectedness (spillovers) and hedging strategies between the CSI300 and commodities, as well as being suitable for an in-depth assessment of coherence (Zhu et al. 2023). Furthermore, different causal relationships of the CSI300-commodity pair and the commodity-CSI300 pair at different frequencies also confirm the results of time-varying volatility transmission, and investors with CSI300 long- or short positions should adjust their stock-commodity portfolios based on long-, medium-, and short-term investment goals.

As shown in Fig. 10, the LNCU Granger causes LNCSI over the short and long run within the (2,2.25) and (0.4, 1) frequency bands, respectively, while it causes LNCSI in the medium run within the (1, 1.17) and (1.6, 2) frequency bands. This pair shows a higher Wald test statistic (with a maximum value of approximately 13) than the other pairs, suggesting that the volatility of copper returns predicts the volatility of CSI300 returns for both shorter and longer cycle lengths. This finding verifies that the volatility of the copper return is more strongly linked to that of the CSI300 return than other commodities in the asset class and that the CSI300 return is the recipient of spillovers from the copper return across the sample period.

The changes in the LNCSI Granger cause changes in the LNGOLD over the long run within the (0.2, 0.4) frequency bands, whereas the LNGOLD Granger causes changes in the LNCSI in the long run within the (0.01, 0.3) frequency bands, with longer corresponding wavelengths. This finding validates that gold serves as a safe haven instrument for CSI300, as gold is less influenced by short-term periodicities and more influenced by long-term periodicities (Zhu et al. 2023).

Our reported evidence of Granger causality from the CSI300 return is the long- and medium-run causality of the soybean return, while the soybean return is confirmed to have a causal relationship with the CSI300 return at different frequencies. PTA is deemed to be an influential variable on CSI300 volatility, resulting from the bidirectional association between PTA and CSI300. However, the Granger causality association from PTA to CSI300 is confirmed in the medium and short runs, whereas the directional Granger causality from CSI300 to PTA is verified at different frequencies.

The reported results provide significant benefits for understanding the causality of the long-, medium-, and short-term linkages between CSI300 and commodities at different frequencies, allowing investors to adjust their portfolio components based on their risk tolerance and diversify their long-, medium-, and short-term portfolios. Consequently, investors are encouraged to adopt long-, short-, and medium-term portfolio management strategies to participate in China's stock and commodity markets.

Conclusions and policy implications

Investing in China's financial market requires a disciplined investment process to systematically identify and capture the underlying inefficiencies, thereby exploring unique investment opportunities in China's stock and commodity futures markets. In this regard, the results of this study supplement existing studies by providing new insights into the dynamic connectedness between the CSI300 and China's commodity futures contracts for the period from January 09, 2008 (the launch date for gold futures trading) to June 30, 2023. The econometric modeling framework combines TVP-VAR connectedness and cDCC-FIAPARCH to analyze dynamic connectedness and hedging opportunities. Robustness analysis was performed using the BC-SGc test, which indicates long-, medium-, and short-term causality relationships. The following conclusions were drawn from this study. First, the TCI experienced a significant uptrend, reaching 30–50%, triggered by the 2008 GFC and 2011 ESDC. It has also effectively captured the COVID-19 shock and peaking at 33% by 2020. Copper returns are the most dominant volatility transmitter, while CSI300, gold, and soybeans are net recipients. The spillover effect from PTA and gold returns intensified after the Russia-Ukraine war. Second, the DCCs of the CSI300-copper pair peaked in response to the pandemic and were much higher than those of the other pairs. During the Russia-Ukraine war, DCCs on CSI gold dropped to -0.009, suggesting a strengthened safe haven role. This war also dramatically increased the DCCs of the copper-PTA and gold-PTA pairs. Finally, CSI300-gold achieves the best hedging performance, with a hedging effectiveness of 69.49%. PTA-CSI300 had the highest hedging effectiveness (44.1%). Thus, investors with CSI300 long positions are likely to profit from prioritizing gold for hedging, whereas those with CSI300 short positions benefit more from allocating gold to the PTA.

The empirical evidence also shows that the spillovers between commodities and CSI300 are not homogeneous. The properties of each commodity can partly explain this, its market size and liquidity, the level of financialization, and other factors outlined by Ahmed and Huo (2021). Given the size and complexity of financial markets, the transmission mechanisms and hedging strategies between commodities and stock markets tend to differ across countries. Soybeans have been reported to be a major net transmitter of volatility spillovers for the asset class in India's financial markets. By contrast, our findings reveal that soybean is a net recipient of the asset class and offers a hedging instrument to hedge the CSI300 long position. Gold achieved the best hedging performance for CSI300 long positions, with a hedging effectiveness of 69.49%, despite not being confirmed as an effective hedge for the Indian BSESN index.

These findings are expected to guide investors in managing their portfolios' risk exposure by implementing various hedging strategies while investing in China's stock and commodity markets. The gains are likely to be differentiated by the portfolio structure and investors' risk preferences. In addition, this study may not only provide superior risk management benefits, but this asset class also appears to be highly liquid, allowing investors to use the results of exploring short-term trading and investment strategies (medium- and long-term investment) without incurring high transaction costs. Furthermore, this study recommends that investors closely monitor both domestic and external disturbances to make adaptive decisions and flexibly adjust their hedging practices in China's financial markets. Finally, the findings on cross-asset information transmission mechanisms have practical implications for monitoring the dynamics of risk spillovers in China's financial markets and enable policymakers to formulate preventive and supportive measures to reduce systemic risk.

Like all scientific works, however, this study has limitations. China's crude oil futures market was formally launched and traded in March 2018. Moreover, China's crude oil futures are confirmed as net recipients of global oil prices, requiring an improvement in its influence on the international market and price discovery function (Sun et al. 2023). As the priority here is the dynamic connectedness between the CSI300 and China's commodity futures contracts between 2008 and 2023, China's crude oil futures are not included to ensure an unbiased estimation. Future studies may incorporate international oil indices, such as WTI oil futures or Brent oil futures, into asset classes. Furthermore, we encourage extensive empirical analysis to investigate the emerging assets of bitcoin and carbon credit futures to enrich the literature and thus help investors and regulators reduce systemic risk while investing in China's financial markets.

Abbreviations

ADF	Augmented Dickey–Fuller
BC-SGc	Breitung–Candelon spectral Granger causality
cDCC	Corrected dynamic conditional correlation
CSI300	China Securities Index 300
DCC	Dynamic conditional correlations
ESDC	European sovereign debt crisis
FIAPARCH	Fractionally integrated asymmetric power ARCH
GARCH	Generalized autoregressive conditional heteroscedasticity
GFEVD	Generalized forecast error variance decomposition
GFC	Global financial crisis
HE	Hedging effectiveness
OHRs	Optimal hedge ratios
OPWs	Optimal portfolio weight
PTA	Purified terephthalic acid
NDDC	Net directional dynamic connectedness
NPDC	Net pairwise directional connectedness
TCI	Total connectedness index
TVP-VAR	Time-varying parameter vector autoregression
VMA	Vector moving average

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Author contributions

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Availability of data and materials

This work uses publicly accessible data that can be accessed following the references provided in the manuscript. The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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