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Research article

Dynamic spillover between crude oil, gold, and Chinese stock market sectors –analysis of spillovers during financial crisis data during the last two decades

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A R T I C L E I N F O

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A B S T R A C T

The present study investigates the presence of asymmetric return spillovers among crude oil futures, gold futures, and ten Chinese stock sector markets. Time-varying asymmetric spillovers between commodities and the 10 sectors are shown by utilizing the spillover index developed by Diebold and Yilmaz (2012, 2014). Our findings indicate that the industrial and discretionary consumer sectors generate and benefit the most from spillovers. Furthermore, it has been established that the basic materials sector exhibits a net positive impact on spillovers. In contrast, oil futures, gold futures, and other sectors demonstrate a net negative impact as recipients of spillovers. Moreover, the negative return spillovers outweigh the positive return spillovers. Our analysis spans from 2000 to 2023 to include various financial crises. The spillover effects of asymmetry are impacted by various factors, including the global financial crisis (GFC), the European sovereign debt crisis (ESDC), the decline in oil prices, and the outbreak of the COVID-19 pandemic. Including gold and oil in individual equity markets can benefit equity investors. Furthermore, implementing hedging strategies is susceptible to the global financial crisis, economic slowdown, oil price decline, and the recent COVID-19 pandemic. The oil futures exhibit the greatest hedging effectiveness during the COVID-19 spread. The findings indicate that gold exhibits comparable outcomes solely in the presence of positive spillover effects. At the same time, its performance reaches its peak during the recovery phase in the context of negative spillover effects.

1. Introduction

Global uncertainty and the rise of international commodity financialization have intensified scrutiny of commodity price fluctuations, particularly for oil and gold, from stock investors, hedge funds, and policymakers [1]. Research demonstrates the far-reaching economic impacts of oil price movements [2]. Past oil price changes triggered significant adjustments in stock markets [3], foreign exchange, and commodity prices.

Gold's allure as a safe-haven asset stems from its high purchasing power and low dollar correlation [4], attracting considerable investor interest in recent years. Both internationally traded commodities, gold and oil price fluctuations may synergistically affect

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other variables [5]. As global trade and financial liberalization accelerate, risk transmission intensifies, amplifying the speed at which economic signals traverse markets [6]. A growing body of research, including [7], explores the interconnectedness of oil, gold, and other markets. Their findings highlight spillovers' time-varying and frequency-dependent nature, with each crisis eliciting unique responses.

Recent global challenges, including the COVID-19 pandemic and ongoing regional conflicts like the Russia war, pose significant threats [8]. Numerous reports predict these escalating conflicts and uncertainties will impact the global economy [9–11] analyzed the pandemic's effects on oil, gold, and S&P500 markets, demonstrating the reduced hedging efficacy of oil and gold during this period [12]. examined pre- and during-pandemic correlations between oil, gold, and stock markets, revealing a low pre-pandemic intercorrelation that significantly increased afterward.

Increased interdependencies across industries facilitate the transmission of ups and downs from one sector to another, impacting the overall system and influencing market participants and policymakers [13]. While previous research predominantly focused on sector-level analysis [14], examining interdependencies and time-varying spillovers within sectors, this study deviates by:

Addressing high volatility: Given the frequent occurrence of energy and financial crises, coupled with the inherent volatility of oil, stock market, and commodity prices, studying spillover effects remains highly relevant.

Examining asymmetry: The presence of asymmetry has garnered limited attention in recent literature despite its significance. Understanding the extent and direction of return spillovers is crucial for investors seeking diversification benefits.

Providing actionable insights: This study sheds light on the interplay between commodity and stock markets, empowering participants to manage portfolio risk across diverse market conditions.

Moving beyond aggregate returns: Analyzing spillover using aggregate price returns may mask valuable risk management insights. Separating overall stock price returns into positive and negative components offers more precise insights into the effectiveness of hedging strategies during significant market downturns, as investor responses differ under upward and downward market pressures.

By addressing these areas, this study aims to offer valuable insights for portfolio diversification, risk management, and understanding market dynamics in the face of global uncertainties. This analysis investigates the asymmetric return spillovers between two commodities (gold and oil) and Chinese equities markets across various sectors. This focus is crucial due to the differing impacts of oil price fluctuations on individual sectors within the equity market [15]. For instance, the energy sector exhibits greater vulnerability to oil price shocks than the retail or medical industries due to its reliance on oil [16]. Considering Europe's steadily decreasing oil consumption, particularly within the energy sector, we explore the time-varying spillovers between oil and stock sectors. This research aims to provide valuable insights for investors on diversification strategies. Understanding the spillover effects between asset classes and sectors is crucial for making informed investment decisions, especially in dynamic markets like China. This analysis delves into the spillover dynamics between oil and gold in Chinese sector markets from 2000 to 2023, drawing upon pertinent academic literature.

Numerous studies have explored the spillover relationship between oil and gold in the Chinese context, revealing intriguing dynamics. While positive and negative spillovers exist, research indicates that negative spillovers from oil to other sectors generally outweigh positive ones [17]. This suggests that fluctuations in oil prices [18] often have a more significant and adverse impact on Chinese sectors than positive influences.

Furthermore, the impact of oil price shocks varies across sectors. Studies suggest that energy-intensive sectors, such as transportation and basic materials, are most susceptible to oil price fluctuations [5]. Conversely, defensive sectors like healthcare and consumer staples typically exhibit lower spillover effects [19].

It's important to note that spillover effects are not static and can evolve due to economic changes, policy interventions, and market developments [20]. Some studies observe an amplification of spillover effects following the 2008 global financial crisis, underscoring the necessity for dynamic analysis [21]. While gold may potentially act as a hedge against oil price volatility, its effectiveness appears limited in the Chinese context [22]. Research suggests that the hedging power of gold varies across sectors and economic conditions [23].

Furthermore, several studies advocate for including gold in equity portfolios to manage downside risk and diversify holdings, especially during periods of uncertainty when investors seek alternatives to the stock market [24]. The COVID-19 pandemic exemplifies how different equity sectors are impacted by crises, highlighting the importance of sectoral analysis in the gold-stock nexus. Therefore, we examine the diversification potential of gold compared to other Chinese stock sectors during times of instability or crisis [25].

In conclusion, the efficient flow of information within financial markets is paramount for stakeholders. However, understanding both positive and negative information spillovers is crucial for providing accurate insights. This analysis delves into the asymmetric return spillovers between commodities and Chinese equities markets, specifically focusing on the oil-stock and gold-stock nexuses [26]. Doing so, we aim to equip investors with valuable information on diversification and downside risk management strategies.

Our research contributes to the empirical literature in three notable ways. Firstly, we examine the impact of fluctuations in gold and crude oil prices on the Chinese stock market as a whole, as well as its sub-markets, while considering the asymmetric aspects by differentiating between negative and positive return spillovers across markets. Secondly, we conduct a quantitative analysis of commodity-stock sector portfolios' optimal composition, hedge ratio, and hedging efficiency. We analyze various periods throughout history, including before and after the Great Financial Crisis and European Debt Crisis, during the crises, the recovery phase, the oil price drop, and the spread of COVID-19, utilizing the spillover index developed by Ref. [8] for our empirical work.

The paper is novel in that it conducts a thorough analysis of the asymmetric return spillovers between ten Chinese stock sector markets, gold futures, and crude oil futures between 2000 and 2023. The analysis takes into account many financial crises, such as the global financial crisis (GFC), the European sovereign debt crisis (ESDC), the drop in oil prices, and the COVID-19 pandemic. This study differs from earlier studies by employing a time-varying spillover index to examine the dynamic spillover effects, with a specific emphasis on asymmetry and differentiating between positive and negative return spillovers. The report analyses how changes in gold and oil prices affect the Chinese stock market and its sub-markets, providing practical advice for diversifying portfolios, managing risks, and comprehending market dynamics in the face of global uncertainty. The paper explores the spillover effects between oil and gold in Chinese sector markets, focusing on the best mix, hedge ratio, and effectiveness of hedging commodity-stock sector portfolios under various economic situations and crisis times. This empirical technique reveals the direction and strength of spillovers and emphasizes the temporal relationship of spillover returns, offering significant insights for investors navigating various market circumstances.

By employing this empirical methodology, we can calculate the direction and magnitude of spillover from one market to another, examine whether a particular market is a net recipient of spillover, and identify the epidemic's origin [27]. Our findings show a temporal dependence on the spillover returns, with the industrial and discretionary consumer goods sectors being the primary generators and recipients of systemic spillover. Additionally, we found that commodities and seven of the ten other sectors are net recipients of spillovers, except for the industrial, materials, and consumer discretionary sectors. Furthermore, we discovered that the spillover effect between stock-sectors and fuel is more significant than the impact of stock market shocks on the gold market. There is also an asymmetry in the spillovers, with adverse effects outweighing the positive ones regarding returns. During the Great Financial Crisis, the European sovereign debt crisis, the current oil price falls in 2014–2015, and the COVID-19 pandemic, the disparity between positive and negative spillovers widened. As a result of the negative signals that COVID-19 broadcasts to the markets, negative spillovers have increased.

Moreover, our portfolio management study indicates that diversifying using commodities lowers overall portfolio risk. Regarding safeguarding against market risks, gold is a more productive option than oil, regardless of the prevailing economic conditions. The Global Financial Crisis and European Sovereign Debt Crisis period witnessed an upsurge in the cost of hedging, which necessitated a shift in the hedging approach in sync with the market dynamics, be it favorable or unfavorable. Lastly, it's important to note that the effectiveness of hedging strategies may vary depending on the specific economic context and the nature of the crises experienced.

The rest of the paper is structured as follows: Section 2 present methodology; Section 3 present data of the paper; Section 4 includes evidence-based findings of the paper; Section 5 presents the conclusion.

2. Method

Using the Generalized Vector Autoregression (GVAR) framework, we introduce a new spillover index matrix to measure return dynamics within the market. This framework accommodates potential non-stationarities and asymmetries in the data, making it more robust than traditional methods. Specifically, we employ the GVAR framework to model a joint process of asset returns (represented as Xt) as a covariance stationary VaR(p) process. This captures short- and long-term dynamics of spillovers between assets, offering a comprehensive understanding of their interconnectedness.

Analyzing spillover effects through this framework is vital for several reasons:

1. Enhanced Accuracy: The GVAR framework addresses potential non-stationarities and asymmetries in the data, leading to more precise spillover effects estimates than simpler models.
2. Dynamic Insights: The VaR(p) specification captures short- and long-term dependencies between assets, providing a deeper understanding of spillover dynamics.
3. The VAR method for DY spillover analysis is deliberate. The VAR method offers several advantages, including its ability to capture dynamic interactions among variables over time, its flexibility in handling multivariate data, and its widespread use in financial research literature. Additionally, the VAR method allows for a comprehensive examination of spillover effects across different investment horizons, offering a holistic understanding of market dynamics.
4. Market Understanding: Quantifying spillover effects through a well-defined index matrix facilitates a deeper comprehension of market structure and risk propagation mechanisms, as in Eq. (1).

$$X_t = \sum_{i=1}^{P} \Phi_i X_{t-i} + \varepsilon_t \tag{1}$$

X^t is a matrix of N x 1 exogenous variables, Φi is a matrix of N x N autoregressive coefficients, and $\varepsilon \sim (0, \Sigma)$ is an N1 identically distributed random variables matrix. The VAR mentioned above may be represented in the form of Eq. (2):

$$X_t = \sum_{i=1}^{\infty} B_i \varepsilon_{t-i} \tag{2}$$

With B0 as the N x N identity matrix and Bi = 0 for $i < 0$. The N x N constant matrices Bi follow a recursion of $Bi = \Phi 1Bi - 1 + \Phi 2Bi - 2 + \cdots + \Phi pBi - p$. We construct our variance elements and cross-variance sections, where the latter is the spillover index $\theta ij(H)$, using the "FEVD framework" for H-step forward forecasting errors [28] as in Eq. (3).

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} B_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} B_h \Sigma B_h^{'} e_i\right)} \tag{3}$$

The Σ is the covariance matrix of the error vector ε. In simpler terms, it measures how much the variables in the equation vary from their average value. σ_{jj} is the standard deviation of the error term in the *jth* equation, which tells us how much the data points deviate from their mean value along the *jth* axis. To further refine our observations, we employ a selection vector e_i, where the ith element is one, and the rest are zero. Finally, we normalize the observed spillover index in Eq. (3) to ensure that our data is within a reasonable range as in Eq. (4):

$$\widetilde{\theta}_{ij}(\mathrm{H}) = \theta_{ij}(H) \Big/ \sum_{j=1}^{N} \theta_{ij}(H) \tag{4}$$

Where $\sum_{j=1}^{N} \widetilde{\theta}_{ij}(H) = 1$ and $\sum_{ij=1}^{N} \widetilde{\theta}_{ij}(H) = N$ by structure $\widetilde{\theta}_{ij}(H)$ gives the degree to which "horizon H″ is linked in a pairwise direction from *j* to *i*. The overall spillover index, C(H), is calculated as follows using the "contributions from the variance decomposition method" as in Eq. (5):

$$C(H) = \frac{\sum_{ij=1,j\neq i}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{ij=1,j\neq 1}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100 \tag{5}$$

We aggregate partly "total spillover" in both the "FROM" and "TO" forms to examine the contributions of a specific sector. All equity returns Ci←*(H) are tied to commodity returns *i* through the directionality measure Ci←*(H) as in Eq. (6):

$$C_{i\leftarrow *}(H) = \frac{\sum_{j=1,j\neq i}^{N} \widetilde{\theta}_{ij}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq 1}^{N} \widetilde{\theta}_{ij}(H)}{N} \times 100 \tag{6}$$

Similarly, the trend of the relationship between all commodities *i* and the profit earned on all stocks is denoted by the symbol C*←i (H) as in Eq. (7).

$$C_{*\leftarrow i}(H) = \frac{\sum_{j=1,j\neq i}^{N} \widetilde{\theta}_{ji}(H)}{\sum_{ij=1}^{N} \widetilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1,j\neq 1}^{N} \widetilde{\theta}_{ji}(H)}{N} \times 100 \tag{7}$$

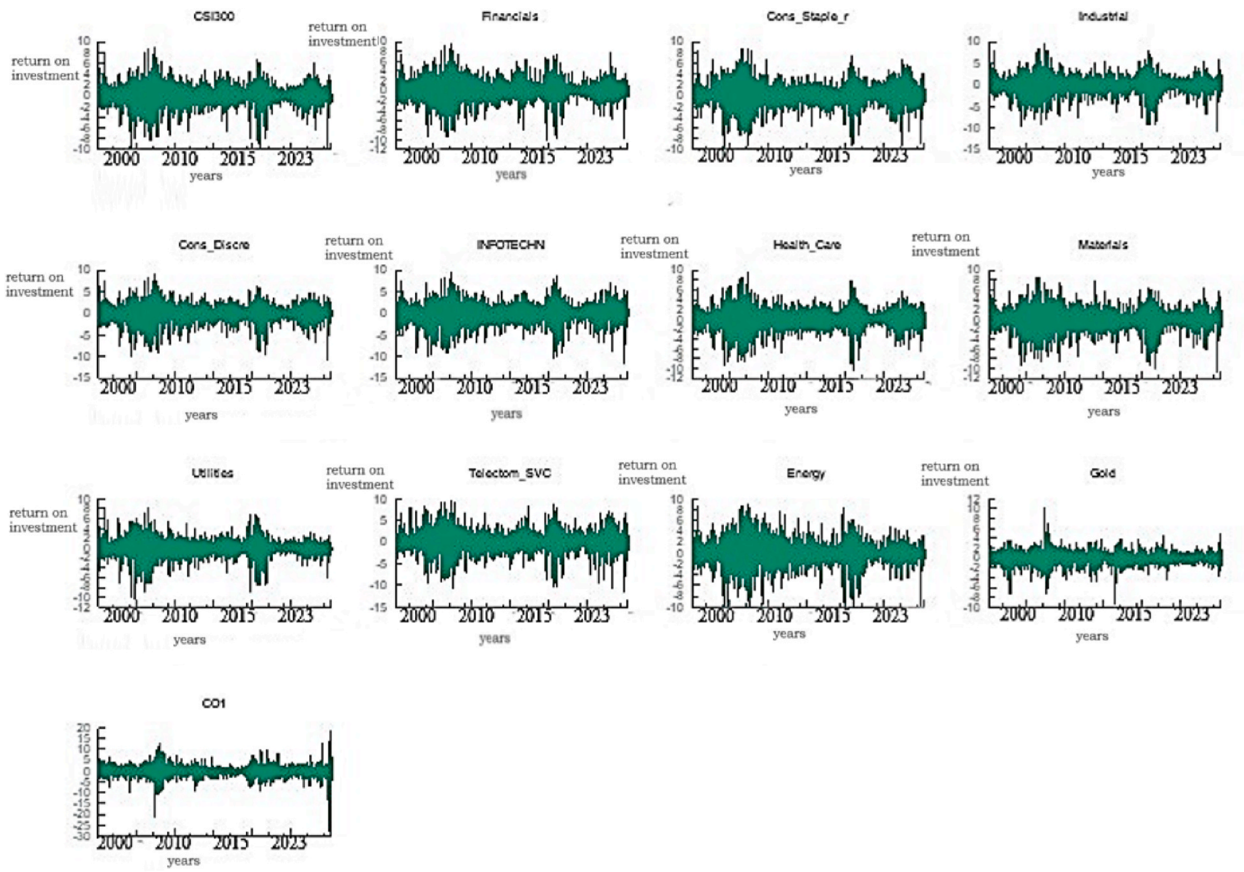

Fig. 1. Returns on investments in oil, gold, and stocks.

Table 1
Input data statistics and analysis of unit root test.

	CSI 300	Financials	Cons Staple	Industrials	Cons Discre	Info Techn	Hlth Care	Materials	Utilities	Telecom	Energy	Gold	CO1
Mean (%)	2.2411	1.1521	1.1881	1.1249	1.1495	1.1299	1.1717	1.1229	1.1176	1.135	1.1108	1.1376	−1.1062
maxi	5.581	3.388	3.4	4.498	8.554	4.402	3.391	2.267	4.308	2.252	3.394	14.44	13.22
Mini	−1.155	−13.38	−6.601	−14.46	−11.65	−12.23	−15.53	−12.27	−14.40	−13.35	−5.553	−6.612	−24.47
Std Deviation	3.3	3.36	5.536	2.299	2.207	3.324	2.286	3.322	2.764	3.336	5.517	2.239	6.604
Skewness	−2.245	−2.297	6.663	−2.272	−3.394	−2.238	−2.279	4.427	−2.292	−6.651	4.472	−2.612	−1.696
Kurtosis	2.267	3.321	6.607	5.526	5.575	2.263	5.343	6.631	3.873	8.849	4.314	4.454	17.7
Jarque − Bera	2521.***	1741.***	1359.***	2481.***	1789.***	973.3***	1528.***	1421.***	3840.***	1631.***	1652.***	6134.***	39.342.***
Q (30)	32.21**	32.23**	35.57**	32.21**	32.29**	22.22	48.80***	32.29***	32.32	21.17	31.19**	16.63	13.32
ADF	−32.24***	−32.27***	−34.47***	−34.42***	−33.38***	−33.35***	−32.24***	−31.13***	−36.63***	−35.56***	−35.54***	−36.66***	−36.66***
PP	−53.37***	−62.25***	−53.37***	−56.62***	−54.43***	−52.22***	−52.24***	−57.76***	−57.78***	63.31***	−53.37***	−67.76***	−65.59***
Zivot − Andrew	−28.83***	−62.23***	−34.41***	−26.63***	−22.21***	−32.24***	−33.39***	−22.27***	−25.57***	−43.34***	−28.20***	−62.22***	−26.64***

Notes: The assessment of “autocorrelation” of returns series is facilitated by the “Ljung-Box test”, which generates empirical evidence marked as Q (20). The empirical figures of the improved “Dickey-Fuller (1979) and Phillips-Perron (1988) unit root test” are indicated as “ADF (PP)”. “Zivot-Andrews’s (1992) technique” examines the unit root with structural break theory, with a 5 % and 1 % statistical significance.

Table 2
Unit roots of both positive and negative returns.

	CSI 300	Financials	Cons Staple	Industrials	Cons Discre	Info Techn	Hlth Care	Materials	Utilities	telecom	Energy	Gold	Co1
Panel A : Positive returns													
Mean (%)	1.1284	2.2058	2.2085	2.2721	1.8079	2.2269	2.21	3.3352	2.2702	2.2896	2.2092	3.3171	3.6906
maximum	4.481	4.488	5.5	4.498	2.76	3.302	3.391	4.467	3.399	5.552	8.294	13.34	14.47
Minimum	1	1	1	1	1	1	1	1	1	1	1	1	1
Standard Deviation	3.313	3.302	2.211	2.285	4.48	4.44	2.216	2.247	2.868	4.411	3.301	2.283	2.331
Skewness	4.495	4.451	4.405	3.329	3.327	4.467	5.533	3.38	3.327	6.656	5.444	5.54	4.492
Kurtosis	12.2	12.29	12.22	13.3	5.597	6.62	14.45	5.51	14.43	12.2	12.21	24.43	25.52
Jarque − Bera	15,671. ***	14,489. ***	10,579. ***	16,317. ***	10,325. ***	7073. ***	11,670. ***	9321. ***	19,791. ***	14,552. ***	15,536. ***	60,943. ***	97,971. ***
Q (30)	102.2***	84.48***	63.39***	113.3***	102.2***	92.28***	103.3***	124.4**	124.4***	85.50***	102.2***	74.44***	54.47***
ADF	−23.36***	−22.25***	−5.57***	−23.30***	−2.345***	−21.19***	−26.64***	−25.51***	−23.39***	−26.62***	−23.36***	−23.32***	−23.31***
PP	−63.38***	−65.55***	−56.67***	−64.45***	−64.41***	−62.20***	−64.44***	−63.31***	−62.25***	−66.68***	−67.74***	−62.25***	−62.27***
Zivot − Andrew	−25.59***	−26.65***	−52.23***	−2.25***	−25.59***	−24.48***	−26.68***	−25.59***	−21.13***	−7.33***	−37.73***	−23.39***	−21.18***
Break − point	2/13/ 2008	December 3, 2008	13/26/ 2008	11/27/ 2015	4/13/ 2008	12/26/ 2011	13/21/ 2011	2/13/ 2008	9/28/ 2015	9/18/ 2009	04/20/ 2008	March 9, 2013	12/16/2007
Panel B : Negative returns													
Mean (%)	−2.2872	−2.2537	−3.3203	−2.2471	−4.4584	−4.4969	−3.3382	−3.3122	−3.3525	−3.3546	−3.3984	−4.4795	−1.1968
maximum	1	1	1	1	1	1	1	1	1	1	1	1	1
Minimum	−4.455	−12.28	−4.401	−14.46	−12.95	−12.53	−11.23	−12.27	−13.30	−12.25	−4.453	−5.512	−26.67
Standard Deviation	3.341	3.313	2.222	4.448	3.341	3.345	2.285	4.414	4.495	2.266	4.478	3.317	7.773
Skewness	−4.457	−4.418	−4.442	−5.522	−4.487	−1.149	−4.452	−4.458	−4.566	−2.253	−5.596	−4.439	−4.457
Kurtosis	16.61	16.68	16.66	15.55	16.63	4.4	13.34	13.15	15.57	16.68	13.38	22.26	67.76
Jarque − Bera	36,208. ***	31,174. ***	30,725. ***	33,793. ***	29,537. ***	18,178. ***	29,131. ***	24,424. ***	50,754. ***	30,134. ***	26,560. ***	72,213. ***	7.7798e+015***
Q (30)	462.2***	86.69***	61.11***	72.24***	71.11***	60.57***	71.10***	72.29***	77.78***	5.59***	85.50***	53.30***	62.28***
ADF	−22.29***	−23.31***	−213.31***	−23.36***	−26.65***	−27.69***	−26.69***	−21.19***	−28.81***	−22.20***	−23.38***	−25.53***	−2.48***
PP	−64.48***	−65.53***	−62.84***	−66.52***	−64.28***	−62.47***	−63.16***	−65.52***	−69.98***	−65.53***	−68.86***	−66.64***	−75.57***
Zivot − Andrew	−22.23***	−22.20***	−25.57***	−24.44***	−23.37***	−21.17***	−27.76***	−21.19***	24.41***	−23.33***	−25.56***	−27.71***	−21.14***

Note: The "Ljung-Box test for autocorrelation of returns series" provides empirical data, denoted by Q(20). The empirical statistics of the enhanced "Dickey-Fuller (1979) (Phillips-Perron (1988)) unit root test" is denoted by the abbreviation "ADF (PP)". The unit root with structural break theory is tested using "Zivot-Andrews's (1992) method", where 5 % and 1 % imply statistical significance.

We can write out the formula for the net directional connectivity from sector i to all other sectors, which is as in Eq. (8):

$$C_i(H) = C_{*\leftarrow i}(H) - C_{i\leftarrow *}(H) \tag{8}$$

To better understand the interconnectedness of global markets, we transform all sector interdependencies into networks. Ci←j(H) is the directional connectedness between any two nodes in the graph; $C_{i\leftarrow *}(H)$ is the directional connectedness "FROM" the graph; Ci←* (H) is the directional connectedness "TO" the graph; and C*←i(H) is the directional connectedness "FROM" the graph.

3. Data evaluation

This study considers the ten sub-indices of the "CSI 300 sector index", "namely the CSI 300 index (CSI 300), Consumer Discretionary index (CONS DISCRE), Consumer Staples index (CONS STAPLE), Energy index (ENERGY), Financials index (FINANCIALS), Health Care index (HLTH CARE), Industrial's index (INDUSTRIALS), Information Technology index (INFO TECHN), Materials index (MATERIALS), Telecommunications Services Index (TELECOM SVC), and utility index (UTILITIES)". We also consider the futures marketplaces for two essential commodities: "gold (GOLD) and West Texas Intermediate (CO1)". The commodities market is centered on the "Chicago Mercantile Exchange (CME)". Our samples' dates range from 2000 to 2023 from the DataStream database. Major economic downturns and pandemics like the one caused by the COVID-19 virus and the Great Recession of 2008–2009 are all represented in the sample. Daily compounded returns are determined using the logarithm of the percentage difference between two successive prices, expressed as $rt = ln\,(Pt/Pt-1) \times 100$. We also look at how the positive and negative returns in one market might affect the other market in a sector. It is well known that the reaction of asset returns to excellent and negative news is not uniform. We disaggregate the "aggregate returns" into positive and negative returns to quantify the asymmetric risk spillover. It is possible to define both positive and negative returns as in Eq. (9):

$$r(+) = \begin{cases} r_t, & if\, r_t > 0 \\ 0, & \text{otherwise} \end{cases}, r(-) = \begin{cases} r_t, & if\, r_t < 0 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

During the era of financial turmoil, where r (+) symbolizes fruitful returns and r (-) denotes unfruitful returns, the aftermath of the Great Financial Crisis (GFC) and European Debt Crisis (ESDC) was marked by the recovery of the financial markets. This resurgence was driven by the reduction in oil prices and persisted through the spread of the COVID-19 pandemic. In such an environment, the overall returns (rt) were determined by the summation of both positive and negative returns (r (+) and r (-)).

Fig. 1 illustrates the returns on oil, gold, and stock investments, offering a detailed breakdown across specific periods. These periods encompass the pre-financial crisis era, the financial crisis and the culmination of the economic supercycle, the subsequent recovery phase, the Great Oil Bust, and the onset of the COVID-19 pandemic. The depiction reveals notable instances of fat tails and clustering of unpredictability, particularly emphasized during economic distress, fuel devaluation, and the COVID-19 crisis.

The COVID-19 pandemic notably impacts the oil market more profoundly than the gold and healthcare industries. This observation underscores crude oil's susceptibility to pandemic-induced disruptions, such as reduced consumption stemming from measures like road closures. Conversely, the gold futures market experiences heightened investor reliance during times of uncertainty, thus exhibiting lesser susceptibility to the pandemic's effects.

Remarkably, the healthcare industry emerges as a standout amidst the current scenario. Medical professionals and healthcare facilities witness increased demand, driving profits through necessities like masks, medication, protective gear, and attire. Consequently, investor confidence in the healthcare sector strengthens, as evidenced by its resilient returns. The pandemic's spread impacts the healthcare and gold sectors less than crude oil, underscoring healthcare's resilience during crises.

Our analysis furnishes a comprehensive perspective on oil, gold, and stock investment returns across distinct temporal segments. The graphical representation vividly illustrates the heightened impact of the financial crisis, oil price downturns, and the COVID-19 pandemic, compared to pre- and post-crisis periods. Particularly, the propagation of the COVID-19 pandemic exerts a substantial influence on the oil market while exerting minimal effects on the gold market and the healthcare industry.

Our research indicates that prudent investors should carefully track the healthcare sector and the gold futures market, especially in times of uncertainty. The healthcare industry stands out as a resilient sector, demonstrating an ability to withstand the impacts of crises such as pandemics. On the other hand, the gold futures market is a secure haven for investors seeking stability during uncertain times, making it an appealing option for those averse to risks. It's crucial to emphasize that crude oil is notably susceptible to the repercussions of pandemics and other emergencies, highlighting the necessity of considering such vulnerabilities in investment decision-making. Returns on investments in oil, gold, and stocks are shown in Fig. 1.

Table 1 presents the statistical characteristics of gold, crude oil, and the ten industries comprising the CSI300 index. All markets except oil exhibit positive mean returns, with consumer staples boasting the highest average and power showcasing the lowest. The Oil and IT sectors are the riskiest, while gold ranks among the safest assets. Interestingly, all return series demonstrate negative skewness, indicating a left-tailed distribution and high kurtosis values, suggesting leptokurtosis (fatter tails than a normal distribution). However, the Jarque-Bera tests reject the normality hypothesis, confirming that the data deviates from a standard distribution. Moreover, the Ljung-Box test results validate the presence of autocorrelations within the stock and commodity sectors.

Moving to Table 2, the initial observations reveal larger standard deviations associated with negative returns across all sectors. The negative return series also display a higher degree of leptokurtosis than their positive counterparts. Importantly, both positive and negative return series exhibit stationarity of deviations, implying that while they may deviate from the normal distribution, their volatility remains stable. Oil and IT sectors pose the highest risk, while gold offers relative safety. Consumer staples enjoy the highest

Table 3
Spillover matrix of total returns across Chinese industries and commodities.

	CSI 400	Financials	CONS STAPLE	Industrials	CONS DISCRE	INFO TECHN	HLTH CARE	Materials	UTILITIES	TELECOM	ENERGY	GOLD	CO1	FROM
CSI 300	14.46	8.85	3.33	13.3	12.26	5.51	3.39	3.37	4.49	3.31	5.4	1.16	1.16	82.2
FINANCIALS	14.45	13.3	3.31	4.37	2.39	7.52	4.4	2.25	4.44	5.48	3.38	1.14	1.15	82.2
CONS STAPLE	12.28	7.71	13.26	4.38	13.49	5.55	5.5	2.22	4.44	7.65	7.5	1.15	1.1	835.5
INDUSTRIALS	12.29	4.3	3.37	13.7	14.49	5.53	3.38	12.27	4.49	8.51	4.49	1.14	1.14	85.5
CONS DISCRE	12.25	2.28	4.48	1.76	14.41	8.65	3.34	62.4	3.35	8.5	8.59	1.15	1.3	82.2
INFO TECHN	11.17	2.29	6.64	12.2	14.43	14.49	3.38	8.33	3.41	5.4	7.51	1.15	1.14	83.3
HLTH CARE	13.36	3.32	6.58	3.37	14.44	4.44	13.2	3.32	6.44	7.42	6.36	1.14	1.25	85.5
MATERIALS	13.37	5.52	5.58	3.33	4.59	9.51	3.37	12.26	7.45	3.38	8.3	1.27	2.21	85.5
UTILITIES	12.23	4.39	7.7	1.1	5.95	5.54	4.45	3.38	3.33	3.36	6.66	1.16	2.24	82.2
TELECOM SVC	12.28	6.51	5.46	1.15	8.4	7.68	4.42	5.5	4.37	13.34	8.22	1.13	2.24	81.1
ENERGY	12.28	7.73	4.56	12.2	9.9	4.42	5.5	14.47	5.45	2.29	14.4	2.25	2.21	81.1
GOLD	2.28	3.37	1.35	1.63	4.44	3.31	3.37	2.2	1.36	1.34	1.57	93.3	2.29	4.4
CO1	2.27	3.3	2	2.33	2.28	3.35	3.37	2.28	1.43	4.32	3.36	3.32	4.49	12.2
TO	113.3	73.3	74.35	123	144.1	84.4	73.3	2.12	3.21	79	82.2	6.6	8.3	961.1
ALL	121.1	94.4	93.3	116	123	4.34	95.5	102.2	2.11	83.3	95.5	4.33	3.22	
Net	22.2	−4.4	−7.5	13.3	14	−4.4	−3.3	3.3	−2.2	−12.2	−4.4	−4.3	−8.5	

Note: The subsequent chart has been formulated based on a universal dispersion analysis of inaccuracies in predicting 10 days through implementing “vector auto regressions” of order one, which were determined by the “Schwarz information criteria”.

Table 4
A total spillover matrix for Chinese sectors and commodities.

	CSI 300	Financials	CONS STAPLE	Industrials	CONS DISCRE	INFO TECHN	HLTH CARE	Materials	Utilities	Telecom SVC	Energy	GOLD	CO1	From
CSI 300	12.21	12.28	3.38	12.23	12.23	4.48	2.2	8.84	8.85	4.43	5.53	1.19	2.26	82.2
FINANCIALS	12.25	12.22	2.24	2.29	3.31	4.32	4.38	3.38	3.36	4.42	9.9	1.19	2.24	82.2
CONS STAPLE	11.19	3.32	2.24	3.33	13.35	4.62	12.24	4.42	3.28	4.44	4.41	1.16	2.28	74.4
INDUSTRIALS	13.38	4.4	7.7	13.38	11.38	4.3	3.33	11.16	8.63	5.55	3.33	1.16	2.28	82.2
CONS DISCRE	13.31	3.36	2.25	13.34	13.2	3.37	4.45	4.49	4.43	7.76	3.38	1.18	2.21	82.2
INFO TECHN	13.37	3.36	3.32	12.22	12.24	15.53	4.37	9.37	3.39	8.84	2.29	1.14	2.27	81.9
HLTH CARE	11.13	6.6	3.35	4.42	12.21	7.78	15.56	4.49	2.23	7.71	2.26	1.16	2.29	81.2
MATERIALS	13.34	3.31	3.33	12.2	4.36	2.23	7.73	15.51	4.53	7.76	6.64	2.23	1.12	82.8
UTILITIES	13.38	3.29	4.39	13.31	8.45	5.45	5.58	3.37	18.34	6.62	2.21	1.19	1.23	82.66
TELECOM SVC	13.37	7.75	2.28	4.41	3.21	8.7	57.71	8.84	7.7	24.42	7.82	1.15	1.17	73.3
ENERGY	3.336	3.35	3.39	13.35	4.36	3.3	6.63	12.26	2.27	3.34	12.28	2.26	1.35	83.31
GOLD	3.37	3.23	1.3	2.22	1.33	1.16	1.17	2.22	1.26	2.22	2.89	2.25	1.77	3.3
CO1	3.34	3.32	1.28	3.39	1.4	1.14	1.34	2.31	1.23	2.23	1.87	5.59	82.2	12.2
TO	113.3	3.22	63.3	103.3	200	72.8	73.3	93.3	74.4	52.2	72.2	8.7	5.5	921.1
ALL	132.2	92.2	84.4	14.4	113.3	95.4	94.4	104.4	94.4	81.1	95	93.3	93.3	72.20
Net	32.2	−8.8	−11.6	13.4	16.6	−7.7	−8.4	6.6						

Table 5
Chinese sectors and commodity markets – Negative returns.

	CSI 400	FINANCIALS	CONS STAPLE	INDUSTRIALS	CONS DISCRE	INFO TECHN	HLTH CARE	MATERIALS	UTILITIES	TELECOM SVC	ENERGY	GOLD	CO1	FROM
CSI 300	3.39	5.52	3.32	12.26	11.13	3.33	2.22	4.47	2.29	8.32	9.92	1.22	1.31	82.2
FINANCIALS	13.33	14.46	6.64	6.66	2.29	2.23	7.41	8	3.32	3.31	3.32	1.25	1.38	82.2
CONS STAPLE	13.32	7.71	14.43	4.42	12.22	7.44	8.39	3.37	3.22	2.32	2.24	1.21	1.23	82.2
INDUSTRIALS	13.32	8.87	6.67	13.38	12.25	5.42	3.37	12.24	8.5	4.36	3.29	1.2	1.24	88.8
CONS DISCRE	13.33	4.48	3.3	13.38	13.32	8.45	2.31	7.4	3.39	5.46	8.3	1.22	1.25	84.4
INFO TECHN	8.8	5.5	4.35	8.83	13.35	15.57	9.91	3.31	8.89	9.44	2.26	1.21	1.28	83.3
HLTH CARE	4.41	3.34	3.24	3.24	14.48	8.52	13.44	3.22	9.45	4.34	3.34	1.18	1.1	86.6
MATERIALS	13.32	5.48	8.36	11.15	4.34	9.51	8.38	132.17	3.33	4.32	6.58	1.1	1.26	86.6
UTILITIES	13.39	4.35	3.33	12.26	3.39	8.83	8.44	3.32	23.65	3.3	4.47	1.12	1.3	83.3
TELECOM SVC	8.86	6.53	8.39	8.3	8.25	3.33	8.44	3.38	5.49	15.58	4.38	1.18	1.21	82.2
ENERGY	12.29	9.95	5.4	11.13	9.33	2.29	7.42	12.26	9.44	5.33	12.25	1.12	1.49	82.2
GOLD	1.15	3.46	2.25	1.88	3.21	1.73	1.49	2.27	2.29	1.37	2.25	82.22	5.53	12.2
CO1	2.26	4.22	2.81	2.71	2.33	2.8	1.6	2.76	2	2.3	2.32	4.4	74.41	22.3
TO	12.19	73.4	75.4	103.3	111	83.3	77.3	97	83.3	73.3	83.3	6	7.7	983.3
ALL	124.4	92.2	91.1	113.3	112.2	98.5	94.4	109.9	94.4	99	93.4	92.2	83.3	3.24 %
Net	24.4	−6.6	−8.8	12.2	11.1	−02.2	−4.4	5.5						

average returns, while power experiences the lowest. All markets exhibit left-skewness and leptokurtosis, suggesting unpredictability and potential for extreme events. Despite deviations from normality, return deviations exhibit stationarity, implying long-term stability.

4. Results and analysis

4.1. Total spillover index

Table 3 presents the static spillover index matrix for the Chinese, oil, and gold industries. The matrix's principal diagonal holds particular importance, as it showcases the impact of market shocks on the variance of each market's prediction inaccuracy. The off-diagonal column sums (To) and row sums (From) illustrate the bidirectional connections from the Chinese industry to all other variables in the system. Notably, the upper-right corner of the matrix is labeled "Total," symbolizing the comprehensive scope of the network's interactions. The "Net" column provides further insight, with negative (positive) values denoting markets that are net receivers (net transmitters) of spillovers, while positive values indicate net senders.

The table analysis indicates that inter-asset-class return spillovers contribute significantly, accounting for 74 % of prediction inaccuracy variance. Notably, industries play a pivotal role in these spillovers, with the industrial and consumer discretionary sectors emerging as primary sources of spillover for other assets. Shocks originating within the industrial sector exhibit the highest transmission compared to other stocks and commodities. Interestingly, while the industrial sector transmits shock proportions internally, the manufacturing sector shows minimal spillovers to commodity markets.

This observation aligns with the understanding that these industries are highly vulnerable to external shocks, as evidenced by their 87.4 % and 87.1 % exposure for the industrial and consumer discretionary sectors. Furthermore, Table 3 reinforces the theory of gold's relative decoupling, indicating minimal impact from equity and petroleum market shocks, thereby supporting the decoupling hypothesis.

It's crucial to acknowledge that our findings diverge from previous studies [29,30], which have identified a robust connection between gold and the Chinese stock market. Future research should aim to reconcile these discrepancies, possibly by considering the following factors:

Data timeframes and methodology: Variations in data periods or analytical methods could contribute to differing conclusions.

Specific shock types: Analyzing responses to shocks, such as global events or industry-specific news, may reveal nuanced dynamics.

Market conditions: Market volatility or specific economic contexts could influence observed spillover patterns.

Addressing these aspects in future research will enable a deeper understanding of the dynamics at play and provide more tailored guidance for investors seeking to diversify portfolios and manage risk effectively.

We also identify who is a net shock giver and a net shock taker. All other variables are net receivers of shocks except for the aggregate index, industrials, consumer discretionary, and essential materials sectors. The spillover impact between sectors and fuel is more significant than the equivalent between stock shocks and the gold market [31]. found that the energy sector has the most significant spillover to the markets for gold and petroleum, which is further supported by our results. The resulting index values are calculated to be 0.67 % and 1.66 %.

Our analysis revealed a 0.61 percent positive correlation between oil and energy markets. However [32], found only a unidirectional influence from the Chinese energy industry to the petroleum fuel market, and our new data suggests a bidirectional link instead. The extent to which sectoral returns and commodity prices fluctuate over time may account for this discrepancy. As a result, we redo the connectivity analysis for positive and negative returns, presented in Table 4 and Table 5.

Table 3 provides a comprehensive overview of the overall sample evaluation, while Table 4 displays the results of the total spillover matrix for positive returns. The most significant index values still stem from industrial, consumer discretionary, and basic materials shocks. Additionally, surprises in the telecommunications sector exert an 81.5 % more pronounced impact on other system parameters.

Our research has unearthed novel insights into assessing the severity of disruptions from equities to commodities. Specifically, we observe that the impacts of the banking, consumer, and healthcare sectors on gold are more pronounced than on oil. Furthermore, our analysis reveals that net transmitters and receivers maintain their positions within the system, indicating implications for the net spillover effect.

The energy industry continues to be the primary source of disruptions in the oil and gold markets, as corroborated by a comprehensive analysis of previous studies across the entire sample period.

Table 5 delves into negative returns and their implications. It becomes evident that oil is more susceptible to shocks in the equities market than gold. Additionally, the impact of negative returns on stocks outweighs that of positive returns, indicating a more significant spillover effect from negative returns. Our findings align with existing literature highlighting the role of information asymmetry in assessing contagious risks between the gold and stock markets, as suggested by prior studies [33]. These results also challenge previous claims regarding gold's efficacy as a hedge against stock markets in Brazil, Russia, India, and China [34].

However, our results diverge from those of [35] concerning the Chinese context. Shocks in the oil and gold markets exert a more substantial impact on market sectors than previously anticipated based solely on positive returns. The driving force behind equity markets no longer solely relies on profits derived from commodity markets.

A robust bidirectional relationship between crude oil and the energy industry is evident, as supported by numerous studies [36]. Furthermore, the gold and oil markets play disproportionately significant roles in constructing commodities-stock portfolios. However, investors must also remain vigilant regarding poor returns in Chinese equities markets, as they can serve as the primary source of spillover shocks in gold and petroleum markets. Consequently, researching the asymmetric spillover between Chinese equities and goods becomes imperative.

4.2. *Evaluation with rolling windows*

The traditional static spillover index faces a significant limitation: it assumes a fixed and permanent connection between the variables under examination. This overlooks the dynamic nature of financial markets, where correlations between stocks and commodities can fluctuate substantially during periods of volatility. Numerous studies emphasize that economic conditions are inherently dynamic, rendering static models with fixed parameters inaccurate and potentially misleading. This can result in skewed estimations of spillover effects.

We propose a rolling window analysis incorporating symmetric and asymmetric features to tackle this challenge. This approach investigates whether the directionality of return series influences spillover, offering a more nuanced understanding of market dynamics. Utilizing a 250-day rolling window ensures comprehensive coverage of diverse economic conditions. This enables us to capture and adjust to changes in the relationship between stocks and commodities over time, refining the spillover index calculation.

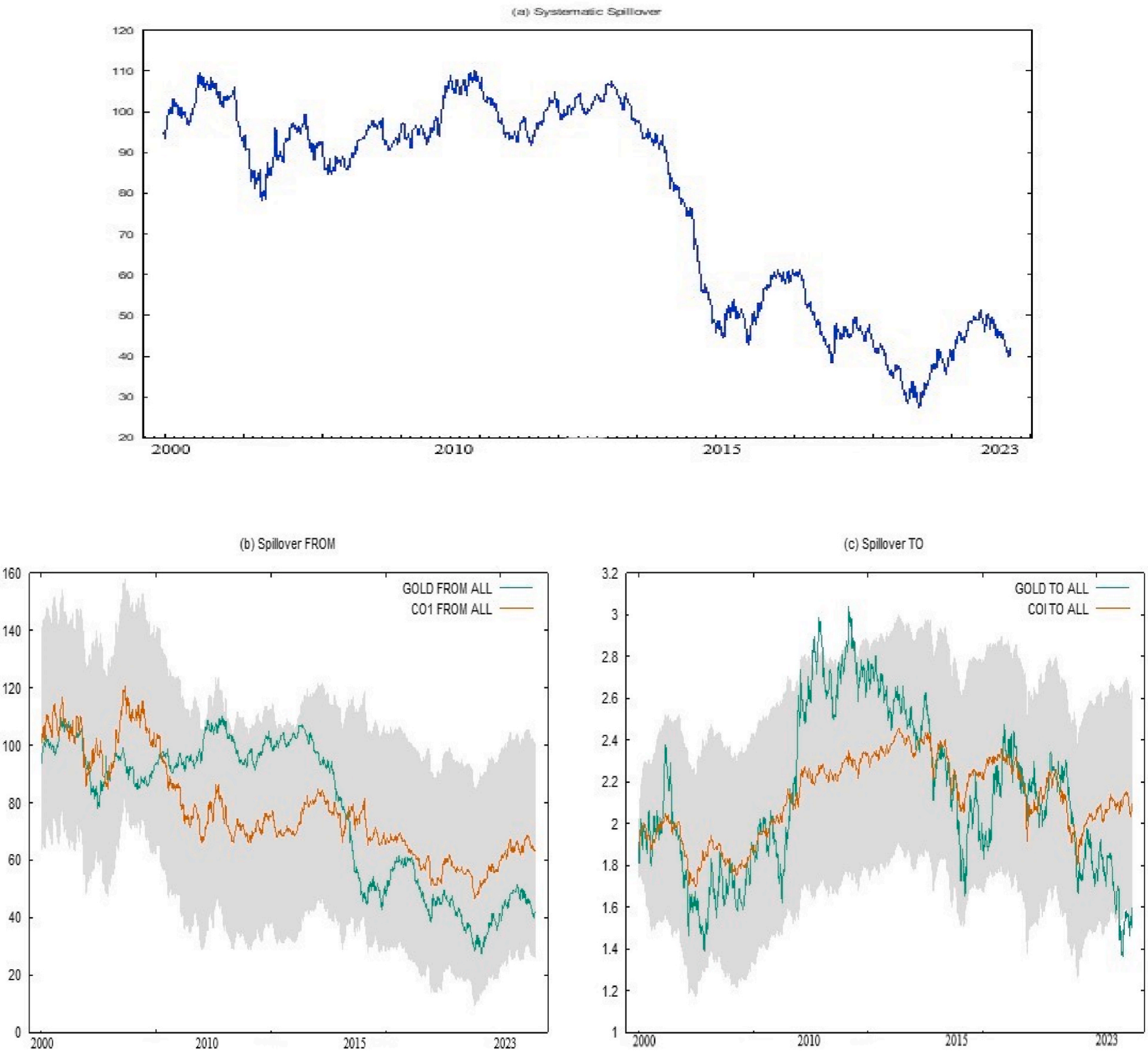

Fig. 2. Risk spillovers that work both ways.
Note: The estimation of all risk spillover indicators is carried out through the application of 250-day rolling windows. These windows facilitate the identification of spillovers on both sides and the overflow from the spillovers above and the overflow into them. The employment of this approach allows for a comprehensive assessment of risk spillovers, enabling a more thorough understanding of their impact.

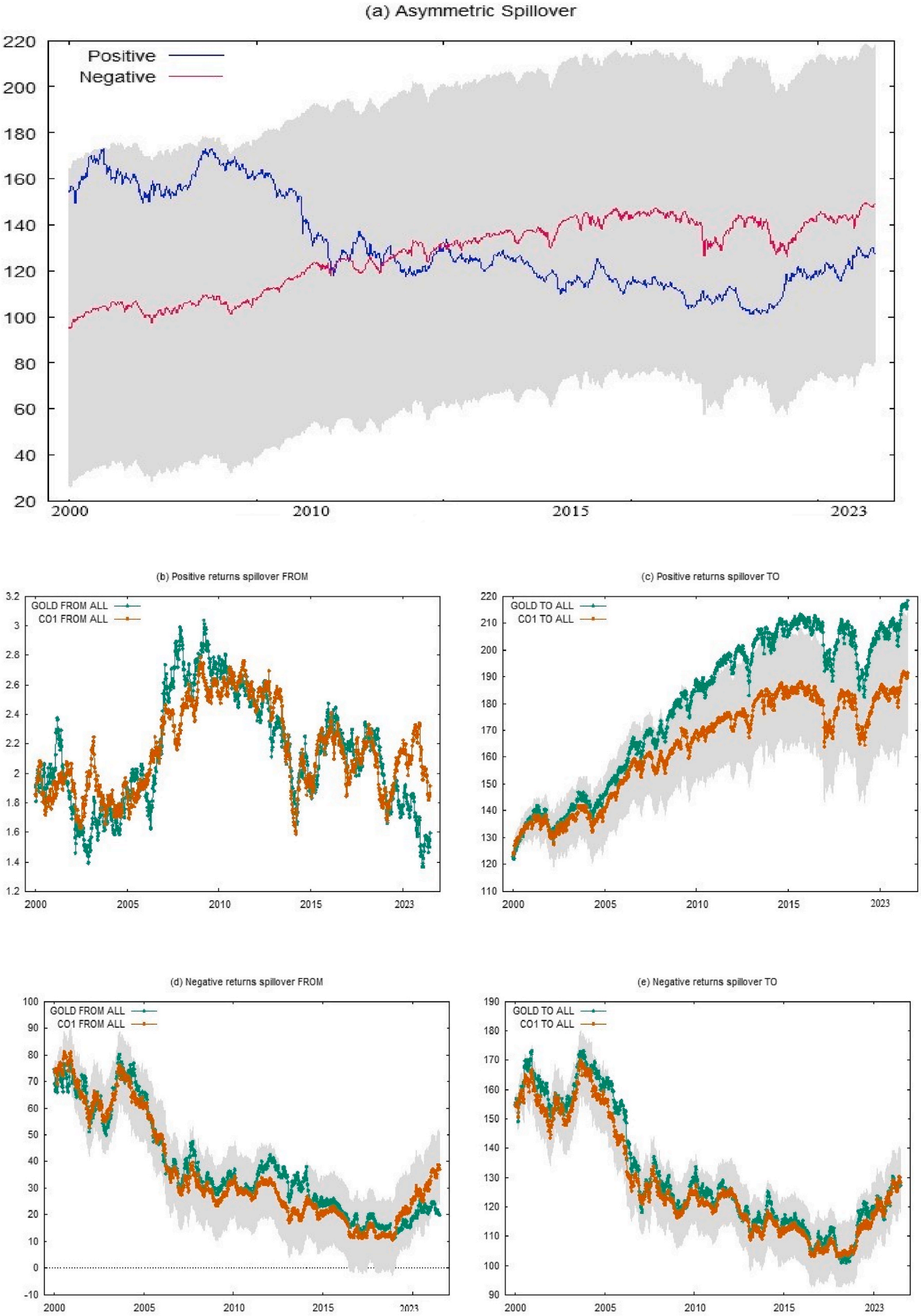

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Fig. 3. Risk spillovers with unequal impacts.
Notes: The utilization of 250-day moving windows proves to be an invaluable tool in estimating all risk spillover indicators. The spillover effect is not uniform, with varying outcomes observed for each indicator. Specifically, we note positive returns from the source and recipient for indicator (b), while the indicator displays negative returns from the source (c); the indicator shows pessimistic returns to the recipient (d). These findings are indicative of the complex and dynamic nature of risk spillovers.

Moreover, the rolling window method helps identify and accommodate significant shifts in correlations between the two markets, leading to a more precise representation of spillover effects. Compared to the static model, the rolling window analysis offers several advantages: it dynamically adapts to changes in the relationship between stocks and commodities, explicitly identifies and integrates significant correlation shifts, and incorporates both symmetric and asymmetric aspects, providing a more holistic perspective.

By addressing the limitations of the static index and leveraging these strengths, the rolling window analysis delivers a more robust and accurate assessment of spillover effects between stocks and commodities. This enhanced understanding can prove invaluable for investors and market participants navigating complex financial landscapes.

4.2.1. Symmetric risk spillovers

Fig. 2 illustrates the index of symmetric spillover for the Chinese stock markets and commodities over time. The interconnectedness between the two markets naturally intensified during the global financial crisis [37]. Subsequently, the index value decreased until 2016, when it stabilized at approximately 70 %, corresponding with the Chinese stock market crisis resolution. In 2017, the index value rose again and approached its historical peak [38]. Suggests that this is indicative of contagion effects. These swings led to a sharp decline in the spillover value in 2018, only for it to recover and reach a peak of approximately 80 % during the COVID-19 pandemic year.

According to Ref. [39], the financial contagion during the epidemic significantly impacted the stock markets. As a result, our conclusion aligns with theirs, indicating that various factors, including global economic crises and pandemics, have influenced the spillover index. Overall, the index provides valuable insights into the interconnectedness of the Chinese stock market and commodities market, and its fluctuations underscore the importance of closely monitoring these markets.

The findings depicted in Fig. 2(a) demonstrate that the COVID-19 recessionary periods and the global financial crisis of 2008 equally affected the Chinese commodities spillover pattern. This discovery highlights the importance of exercising caution and diversifying portfolios prudently in the face of both global financial and health crises. Directional spillovers are further investigated to examine the total spillover index changes. The study in Fig. 2(b) reveals that during the "GFC and ESDC" era, the spillover from all stocks to gold was remarkably similar to that of the oil market. However, after the crisis ended, these two products started responding differently. During the "Greater China Democratic Jasmine Revolution" in early 2011, there was a maximum overflow from equities into gold, and uncertainty in the Chinese economy peaked simultaneously as the correlation between stock prices and oil prices reached its highest. China is among the top five major oil producers globally and the second-largest oil consumer after the United States.

The Chinese government's lockdown in January 2020, in response to the COVID-19 epidemic, has surprisingly contributed to the most significant directional spillover from stocks to oil. However, when the gold market is included, the evidence diminishes. The spillover effect from products to equities is seen in Fig. 2(c), where an inverted spillover effect is observed. With a few notable exceptions, the new findings are consistent with the old ones shown in Fig. 2(b). During the Great Financial Crisis, the oil spillover effect on all equities hit 29 %. This association had more peaks in 2011 and throughout the COVID-19 era. Although the oil industry did feel the effects of the viral epidemic, it did not experience them to the same extent as the stock market. As shown in Fig. 2(c), the spillover from gold to equities has risen since 2012, with the most significant value occurring in 2013. This evidence may be attributed to the increase in Chinese policy unpredictability after introducing "The 12th Five-Year Plan" in 2012. Additionally, measures such as deposit protection and an exit mechanism for financial firms in the market were implemented, which increased overall market volatility in China.

4.2.2. The spillover of asymmetrical returns

Fig. 3 depicts the dynamic nature of the asymmetric spillover index, highlighting fluctuating positive and negative returns. Both sub-indices exhibit clear time-variation, with the positive spillover consistently lower than its negative counterpart throughout the sample period. Notably, the frequency of adverse shocks has been declining since 2012.

However, a distinct post-sample period analysis reveals a crucial trend change coinciding with the COVID-19 pandemic. The difference between positive and negative index values widens significantly, suggesting a pronounced impact of negative shocks during this period. This supports the notion of increased information asymmetry in Chinese markets during the pandemic, as proposed by Ref. [40].

Furthermore, the spillover effect exhibits substantial variation across asset classes (stocks, oil, currency) as the pandemic intensifies. This may be attributed to local investors' early recognition of the virus threat, influencing their investment behavior. During epidemic progression, investors likely become more sensitive to negative news, prompting shifts between stock and commodity markets.

This finding aligns with [41] research on global risk transmission during the pandemic, highlighting the rapid spread of negative shocks across markets, potentially amplifying existing risks. Additionally [42], observed a pandemic-induced increase in risk-taking behaviors, potentially contributing to the surge in adverse shocks since the outbreak.

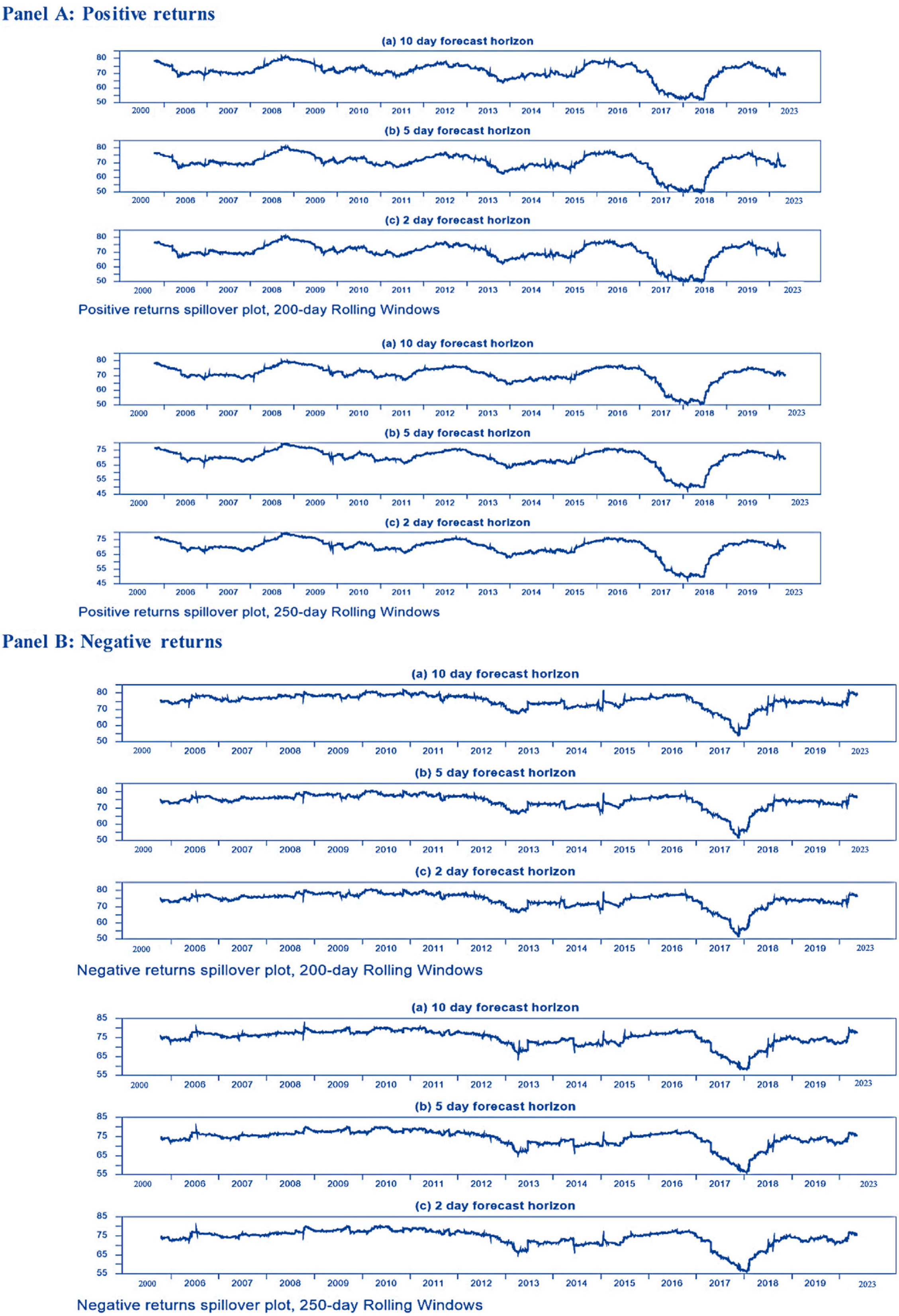

Fig. 4. Robustness analysis of positive (panel A) and negative returns (panel B).

Fig. 3(a) show Asymmetric Spillover, Fig. 3(b) and (c) reveal positive spillovers occurring roughly 20 % and 10 % of the time, respectively. These figures are noticeably lower than the negative spillover rates in 3(d) and 3(e). Notably, the oil market experienced significant sectoral adverse shocks during the 2008 global financial crisis and the 2016 Chinese financial crisis. We observe sharp oil return jumps following the influx of negative news. However, the most remarkable features emerged after 2020, reaching their peak afterward. Interestingly, the index remains at its lowest point between these two periods.

This finding highlights the crucial need to distinguish positive and negative shock impacts when analyzing the long-term relationship between sectoral market returns and commodities. Consequently, our results support the findings of [43] concerning the importance of external shocks in triggering asymmetric responses in stock market volatility. Additionally, our research reaffirms the unidirectional connection from (or to) the oil market, as previously suggested.

Furthermore, the stronger connection observed between oil supply and sectoral Chinese stock markets during the COVID-19 pandemic suggests the possibility of developing more effective trading strategies. This finding contradicts a recent study by Ref. [44], which concluded that announcing a potentially catastrophic infectious disease outbreak in the U.S. did not induce irrational trading on Wall Street.

4.3. Robustness analysis

Robustness analysis plays a vital role in ensuring the reliability and generalizability of our findings. It assesses how sensitive our conclusions are to assumptions, data, and methodologies variations. This helps confirm that our results hold under different conditions, strengthening their credibility and applicability.

This analysis is particularly crucial when dealing with complex systems like financial markets. Examining the robustness of our findings guarantees they are not solely due to specific characteristics of our chosen data or model. Additionally, it addresses potential limitations, such as data availability or methodological constraints, by demonstrating that the findings remain consistent even with alternative approaches.

Overall, robustness analysis enhances the trustworthiness and generalizability of our results. By demonstrating their credibility and applicability to a wider range of scenarios, we increase their value for the audience.

Fig. 4 presents robustness tests for “positive returns (Panel A) and negative returns (Panel B)" using 200- and 250-day rolling windows for H-step ahead forecasts of 10, 5, and 2-day periods. Notably, the total spillover indices for positive and negative returns exhibit similar trends, regardless of the forecasted days or timeframes employed. This suggests that variations in the rolling window size or forecast duration do not significantly impact the findings. This aligns with similar robustness tests conducted in previous studies [45], which also found comparable stability under alternative parameter values.

4.4. Portfolio study

Our research uncovers significant risk transfer between the commodities and stock markets, highlighting its importance for portfolio diversification and risk management. Accurately estimating the temporal covariance matrix is crucial for designing optimal portfolios that balance risk and return. This study leverages the projections from a multivariate DCC-GARCH model to provide practical guidance for investors seeking to manage risk in the commodity stock market. We offer quantitative strategies for determining portfolio weights and dynamic hedging ratios for positive and negative return scenarios. This empowers investors to develop optimal hedging strategies that mitigate risk while preserving potential returns. The scenario presented involves an investor with an existing equity portfolio seeking to protect their investment from potential losses by incorporating various commodities. As per [46], we adopt the following definition for the commodities assets' portfolio weight as in Eq. (10):

$$w^c = \frac{h_t^S - h_t^{C,S}}{h_t^C - 2h_t^{C,S} + h_t^S}, \text{with } w_t^C = \begin{cases} 0 & w_t^C < 1 \\ w_t^C & 0 \le w_t^C \le 1 \\ 1 & w_t^C > 1 \end{cases}, \tag{10}$$

The realm of commodities markets is known to be volatile at any given time t, while the stock market is highly unpredictable during the same time t. Additionally, the covariance between the commodities and stock markets, under specific conditions at time t, is represented as $h_t^{C,S}$. With the assistance of the DCC-GARCH model, all the relevant data required for determining the weight w_t^C for any combination of stocks and commodities can be obtained.

To mitigate the portfolio's susceptibility to risk, we have employed the beta hedge methodology, as suggested by Ref. [47], quantitatively. When we buy commodities assets worth one dollar, we simultaneously sell stocks worth β_t^C dollars to partially hedge our position. To determine the hedging ratio β_t^C (HR), we utilize the following formula as in Eq. (11):

$$\beta_t^C = \frac{h_t^{C,S}}{h_t^C} \tag{11}$$

Through an extensive evaluation of the genuine errors committed to hedging, it is plausible to ascertain the “efficacy of hedging (HE)” for the portfolios designed as in Eq. (12).

$$\mathrm{HE} = 1 - \frac{Var_{hedged}}{Var_{unhedged}} \tag{12}$$

The ($\mathrm{Var}_{\mathrm{hedged}}$) variable denotes the standard deviation of PF II, which is a well-balanced merger of stocks and commodities, whereas ($\mathrm{Var}_{\mathrm{unhedged}}$) refers to the “standard deviation” of PF I, the benchmark portfolio. When the hedging strategy is implemented, the portfolio’s volatility diminishes, leading to a rise in the “HEHE ratio”. This, in turn, indicates that the hedging strategy is successful to a greater extent.

Following our earlier investigation, we explore portfolio hedging strategies incorporating positive and negative stock returns. Table 6 presents the optimal weights, average hedging ratios (HRs), and hedging effectiveness (HE) for portfolios constructed with positive equity returns. We analyze these across the entire sample period and various sub-periods, including before the Global Financial Crisis (GFC) and European Sovereign Debt Crisis (ESDC), during the GFC/ESDC, the recovery phase, the recent oil price plunge, and the COVID-19 period.

Each long/short pair in the table represents the HR for a $1 long position in the stock market (specific sector) and a $1 short position in the gold market. The data suggests that allocating more funds to gold often generates higher returns than equities.

For instance, consider the telecommunications industry and gold across the entire period. The optimal weight of 0.94 implies that a $1 investment in this portfolio should be 94 % allocated to gold and 6 % to telecommunications equities. In other words, for every $1, investors should invest $94.20 in gold and $5.80 in telecommunications stocks. This highlights the general preference for gold, regardless of market conditions.

Considering hedging costs, the ideal HR ranges from 1.3257 (telecommunications during the oil crash era) to 0.435 (utilities during COVID-19). A hedging ratio 0.435 indicates that a $1 long position in gold requires a short position of about $0.43 in utilities. Based on these data points, a high HR value implies an expensive hedge. This suggests that, in such cases, investors may be better off increasing their long position in stocks and decreasing their short position in gold.

Table 6 presents an interesting finding: adhering to the utilities’ gold investment plan results in a lower allocation to the gold market, increased HR, and improved hedging efficacy in all market situations. However, this was only true after the “Global Financial Crisis and the ESDC”, when investors had to devote 75.13 percent of their portfolios to gold to achieve the lowest HR. Furthermore, the consistency of the table points towards the necessity of investing in the “telecommunications-gold” portfolio to attain maximum hedging efficacy. Before the “Great Financial Crisis”, the highest HE% was associated with the industrial-gold combination, but this new evidence again contradicts this notion. Tables 6 and 7 collectively suggest that as stock values decline, investors are more likely to include gold in their portfolios [48]. This unexpected conclusion can be explained by investor risk appetite in the equities market and significant uncertainty during crises. Table 6 also reveals similar findings about investing in the utility sector and the gold market to achieve the lowest HR and maximum HE. However, this was not true before the worldwide and European disorders [49]. At these times, investors may find optimism in the consumer staples and gold combination to achieve the lowest (highest) HR (HE%).

The analysis of hedging for portfolios concerning the oil market is presented in Table 8 and Table 9, where positive and negative returns are utilized. The results indicate that oil storage should not be given priority over stock holdings. This trend is particularly

Table 6
Portfolio analysis of positive returns for sector-gold pair.

Portfolio pairs	**Whole period**			**Pre − GFC & ESDC**			**GFC & ESDC**		
	w_t^C	β_t^C	HE (%)	w_t^C	β_t^C	HE (%)	w_t^C	β_t^C	HE (%)
CSI 300/ GOLD	1.1987	1.8068	13.35 %	1.8513	1.7654	**28.23 %**	1.2366	2.8189	3.81 %
FINANCIALS/ GOLD	1.1231	1.8601	3.37 %	1.7709	2.2779	13.31 %	1.2051	2.9466	NA
CONS STAPLE/ GOLD	1.7726	2.9168	3.87 %	1.7669	2.2635	13.37 %	1.2461	2.8347	3.83 %
INDUSTRIALS/ GOLD	1.7312	1.8613	5.51 %	1.868	2.8966	23.39 %	2.251	2.7367	3.76 %
CONS DISCRE/ GOLD	1.7566	1.8736	5.45 %	1.7069	2.7522	3.24 %	2.2679	2.7636	3.76 %
INFO TECHN/ GOLD	1.7135	2.2365	7.79 %	1.6422	2.2516	23.38 %	2.8089	2.7326	NA
HLTH CARE/ GOLD	1.6489	2.2026	7.78 %	1.7247	2.2424	23.22 %	2.7636	2.8938	3.73 %
MATERIALS/ GOLD	1.7805	2.9335	2.29 %	1.661	2.2203	16.66 %	2.248	2.7067	NA
UTILITIES/ GOLD	1.6766	2.7338	2.61 %	1.5024	2.2416	26.67 %	2.792	2.7723	3.85 %
TELECOM SVC/ GOLD	1.8413	2.2832	**26.52 %**	1.5956	2.2805	26.67 %	2.8252	2.6755	**83.34 %**
ENERGY/ GOLD	1.7894	2.2589	2.13 %	1.6557	2.2086	6.56 %	2.8433	2.293	NA
Portfolio pairs	**Recovery period**			**Great oil bustt**			**COVID − 19**		
	1.8545	1.6708	23.38 %	1.9046	1.8208	12.27 %	1.5232	1.7232	25.56 %
CSI 400/ GOLD	1.819	2.6189	3.39 %	1.995	2.9583	102.29 %	1.5326	1.7412	35.57 %
FINANCIALS/ GOLD	1.6686	2.6628	33.35 %	1.8295	2.2536	53.32 %	1.7343	1.7013	4.45 %
CONS STAPLE/ GOLD	1.6763	2.6801	21.11 %	1.7598	2.2311	13.31 %	1.6248	1.6033	23.38 %
INDUSTRIALS/ GOLD	1.7101	2.6012	21.11 %	1.6956	2.9061	4.34 %	1.6504	1.6454	14.41 %
CONS DISCRE/ GOLD	1.8452	2.8852	1.93 %	1.6404	3.3737	5.10 %	1.6308	2.2721	4.49 %
INFO TECHN/ GOLD	1.7183	2.7285	17.70 %	1.7573	3.3513	13.32 %	1.8787	1.6751	5.45 %
HLTH CARE/ GOLD	1.5536	2.566	1.23 %	1.8074	5.5444	2.24 %	1.2086	1.2358	3.22 %
MATERIALS/ GOLD	1.602	2.6921	23.30 %	1.7167	5.5684	6.33 %	1.7106	1.6808	4.40 %
UTILITIES/ GOLD	1.873	2.7582	**32.24 %**	1.7679	5.4257	**22.22 %**	1.8668	2.2125	**63.39 %**
TELECOM SVC/ GOLD	1.6972	2.8953	22.25 %	1.7958	5.4008	6.67 %	1.4459	4.4789	34.45 %

Notes: The ideal weights and hedging ratios are summarized below. The bolded figures represent the “portfolio” that benefits most from “hedging”.

Table 7
Portfolio analysis of positive returns for sector-gold pair.

Portfolio pairs	Whole period			Pre – GFC & ESDC			GFC & ESDC		
	w_t^c	β_t^c	HE (%)	w_t^c	β_t^c	HE (%)	w_t^c	β_t^c	HE (%)
CSI 300/ GOLD	2.2377	1.1288	12.25 %	1.8371	2.8821	27.77 %	2.9735	2.244	4.52 %
FINANCIALS/ GOLD	1.9543	2.2862	12.29 %	2.2781	3.3641	22.25 %	2.7817	2.2861	5.58 %
CONS STAPLE/ GOLD	1.9433	2.2366	**18.31 %**	2.6014	2.2659	**34.44 %**	3.3664	3.3832	3.36 %
INDUSTRIALS/ GOLD	1.9942	3.3253	13.30 %	1.7083	2.2523	19.93 %	1.8082	2.8179	2.79 %
CONS DISCRE/ GOLD	1.9971	3.3322	14.46 %	3.3184	4.4953	14.40 %	3.8143	3.3225	1.65 %
INFO TECHN/ GOLD	1.7578	3.3604	2.33 %	1.8186	1.8362	1.78 %	1.871	2.2889	1.69 %
HLTH CARE/ GOLD	1.7396	2.2759	14.44 %	5.5685	3.308	2.22 %	1.7895	4.4046	7.71 %
MATERIALS/ GOLD	1.7887	3.3361	21.92 %	1.9072	4.4728	24.48 %	4.8138	2.8828	**23.31 %**
UTILITIES/ GOLD	1.8121	3.3091	3.32 %	3.3957	3.3733	23.32 %	3.3521	3.3558	2.30 %
TELECOM SVC/ GOLD	2.2273	3.3875	13.33 %	3.3168	2.2394	22.23 %	1.8458	3.3687	3.39 %
ENERGY/ GOLD	2.2993	3.3735	13.32 %	3.3871	2.202	25.54 %	1.8493	3.3474	3.35 %
Portfolio pairs	**Recovery period**			**Great oil bustt**			**COVID – 19**		
	1.7242	1.6467	33.87 %	1.7654	3.3535	23.38 %	1.2051	1.7232	5.51 %
CSI 400/ GOLD	2.8234	1.7387	45.51 %	2.2779	3.3801	23.22 %	1.2461	1.7412	5.51 %
FINANCIALS/ GOLD	2.7137	1.6689	55.45 %	2.2635	3.3389	16.66 %	2.251	1.7013	5.56 %
CONS STAPLE/ GOLD	2.8174	1.7261	37.79 %	2.8966	13.89	26.67 %	1	1.6033	5.07 %
INDUSTRIALS/ GOLD	2.8383	1.6538	73.78 %	2.7522	2.7725	26.67 %	2.8089	1.6454	2.25 %
CONS DISCRE/ GOLD	2.9406	1.6864	23.29 %	2.2516	2.3752	6.56 %	2.7636	2.2721	1
INFO TECHN/ GOLD	2.7224	1.6512	22.61 %	2.2424	2.7255	15.52 %	1.8173	1.6751	5.56 %
HLTH CARE/ GOLD	2.5583	1.5251	**49.99 %**	2.2203	2.2241	**22.80 %**	1.6968	1.2358	**26.71 %**
MATERIALS/ GOLD	2.8453	1.7573	24.47 %	2.2416	2.5591	3.34 %	1.8421	1.6808	4.46 %
UTILITIES/ GOLD	2.8971	1.6232	24.43 %	2.2805	2.8992	4.46 %	1.8883	2.2125	1
TELECOM SVC/ GOLD	2.819	1.9469	24.46 %	2.2086	2.6745	6.63 %	1.6357	4.4789	8.70 %

Table 8
Portfolio analysis of positive returns for sector-CO1 pair.

Portfolio pairs	Whole period			Pre – GFC & ESDC			GFC & ESDC		
	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c
CSI 400/ CO1	1.7726	2.2734	63.36 %	1.1867	1.1038	**43.51 %**	1.2107	2.2247	52.25 %
FINANCIALS/ CO1	1.7312	2.2586	56.62 %	1.1945	1.1229	32.21 %	1.2272	2.2952	42.27 %
CONS STAPLE/ CO1	1.7566	3.3309	57.78 %	1.1026	2.2805	3.22 %	1.2396	4.4358	53.60 %
INDUSTRIALS/ CO1	1.7135	2.8972	57.66 %	1.1203	2.2213	42.24 %	1.2381	4.4373	47.78 %
CONS DISCRE/ CO1	1.6489	2.2071	57.66 %	1.1705	2.2535	32.26 %	1.2538	4.4485	44.45 %
INFO TECHN/ CO1	1.7805	5.86	55.52 %	1.1659	2.2976	34.47 %	1.2325	3.3896	42.27 %
HLTH CARE/ CO1	2.2273	5.3253	55.52 %	1.1573	2.2624	45.68 %	1.2777	3.3713	42.22 %
MATERIALS/ CO1	2.2993	2.2335	**62.25 %**	4.533	2.2286	34.40 %	1.222	1.3624	**66.64 %**
UTILITIES/ CO1	1.6766	2.7338	3.31 %	1.5024	3.3416	22.27 %	2.792	2.7723	6.55 %
TELECOM SVC/ CO1	1.4142	1.5172	53.32 %	1.3917	5.5328	32.22 %	3.3769	3.3181	42.26 %
ENERGY/ CO1	1.2209	1.2535	53.33 %	1.231	5.583	31.12 %	2.8679	2.4184	36.69 %
Portfolio pairs	**Recovery period**			**Great oil bustt**			***COVID* – 19**		
	1.6913	2.7962	2.23 %	1.279	1.1939	62.21 %	1.1971	2.2417	92.21 %
CSI 400/ CO1	1.736	1.6869	12.21 %	1.1894	2.2572	54.41 %	4.4273	3.3517	93.23 %
FINANCIALS/ CO1	1.2943	1.4922	**25.15 %**	2.8674	2.8033	52.27 %	2.2978	2.2083	96.63 %
CONS STAPLE/ CO1	3.307	3.3039	18.64 %	3.3327	3.3344	53.39 %	3.3516	3.3763	96.69 %
INDUSTRIALS/ CO1	4.4492	5.5228	16.69 %	5.5465	6.631	65.51 %	3.3848	2.3921	92.80 %
CONS DISCRE/ CO1	1.9324	1.8818	2.22 %	2.2262	2.2392	42.29 %	2.2721	2.2229	82.26 %
INFO TECHN/ CO1	2.8655	2.7448	22.27 %	2.2708	5.5483	56.68 %	6.6004	6.6019	93.39 %
HLTH CARE/ CO1	2.2438	2.4155	18.80 %	3.3046	3.255	**67.72 %**	1.1215	1.2717	**99.25 %**
MATERIALS/ CO1	1.5342	1.5198	23.39 %	2.2917	1.3598	52.29 %	2.2931	2.7066	94.44 %
UTILITIES/ CO1	1.8024	1.7278	3.36 %	1.5741	1.6661	42.28 %	2.8724	2.8379	84.49 %
TELECOM SVC/ CO1	2.2389	1.5184	23.33 %	1.1383	1.5271	52.85 %	2.2835	2.3253	97.75 %

evident during COVID-19, which can be attributed to the sharp decline in oil prices due to reduced oil demand. Upon closer examination of the data, it becomes apparent that adding oil provides the highest HE ratio during the pandemic, accompanied by negative return spillover. Moreover, regardless of the direction of stock returns, hedging costs are at their lowest during an oil collapse [50,51]. Observed a significant correlation between stock prices and oil prices during the oil crisis. However, when negative returns are considered, hedging becomes the most expensive option during the “GFC and ESDC” period. There is usually more evidence of favorable returns after a financial crisis. Our findings are consistent with those of [52,53], who found that changes in oil market shocks explain BRICs stock returns oil. Market conditional value-at-risk can be used to represent this phenomenon [54]. study also supports a

Table 9
Portfolio analysis of negative returns for sector-CO1 pair.

Portfolio pairs	Whole period			Pre − GFC & ESDC			GFC & ESDC		
	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c	β_t^c	w_t^c
CSI 400/ CO1	1.1159	1.1807	64.45 %	1.1188	1.5871	38.22 %	2.3201	2.244	4.52 %
FINANCIALS/ CO1	1.1561	1.1145	54.45 %	1.1576	1.1278	33.38 %	4.4481	2.2861	5.58 %
CONS STAPLE/ CO1	1.1222	1.1814	64.44 %	1.1658	1.5677	**43.34 %**	4.4866	3.3832	3.36 %
INDUSTRIALS/ CO1	1.1841	1.1304	54.49 %	1.1518	1.1305	22.27 %	4.4846	2.8179	2.79 %
CONS DISCRE/ CO1	1.2993	1.1353	54.41 %	1.1096	1.6631	22.70 %	2.2851	3.3225	46.48 %
INFO TECHN/ CO1	1.4789	1.1508	44.45 %	1.1442	1.8929	12.21 %	2.2439	2.2889	44.44 %
HLTH CARE/ CO1	1.2645	1.1083	64.44 %	1.1373	1.6097	33.38 %	2.2761	4.4046	53.38 %
MATERIALS/ CO1	1.153	1.1354	**64.44 %**	1.1925	2.2884	32.22 %	2.2548	2.8828	**64.41 %**
UTILITIES/ CO1	2.251	1.1748	53.39 %	1.1641	2.2415	32.26 %	2.299	3.3558	42.24 %
TELECOM SVC/ CO1	2.7996	1.1022	52.28 %	1.1378	2.2675	22.27 %	2.2442	3.3687	42.24 %
ENERGY/ CO1	2.2309	1.1691	52.21 %	1.187	2.2517	32.21 %	1.762	3.3474	32.24 %
Portfolio pairs	**Recovery period**			**Great oil bustt**			***COVID* − 19**		
	4.4242	1.1989	12.21 %	2.2854	2.2885	44.42 %	1.1143	1.1054	92.27 %
CSI 400/ CO1	4.4234	1.193	2.19 %	1.1086	2.2003	2.27 %	1.1195	1.1168	92.24 %
FINANCIALS/ CO1	4.4137	1.1971	**22.31 %**	1.1383	2.212	42.24 %	1.1193	1.1017	92.26 %
CONS STAPLE/ CO1	4.4174	1.1668	13.38 %	1.1471	3.3429	43.33 %	1.1341	1.1229	92.27 %
INDUSTRIALS/ CO1	4.4383	2.2871	13.37 %	1.153	3.3364	43.37 %	1.1231	4.4401	82.24 %
CONS DISCRE/ CO1	3.3406	2.2079	3.35 %	1.1395	3.3618	3.35 %	1.1884	4.4038	82.22 %
INFO TECHN/ CO1	5.5224	2.2932	13.35 %	1.1357	3.3114	43.33 %	1.1143	3.3612	92.21 %
HLTH CARE/ CO1	5.5583	2.2865	15.57 %	1.2277	3.3252	**53.31 %**	1.1116	2.2105	**96.65 %**
MATERIALS/ CO1	5.5453	2.2017	3.22 %	2.231	3.37	33.36 %	1.1576	1.1465	83.34 %
UTILITIES/ CO1	5.5971	2.2478	13.39 %	2.2279	3.3717	34.47 %	2.2049	1.1917	83.37 %
TELECOM SVC/ CO1	4.49	2.6893	12.24 %	2.2564	3.2399	44.41 %	2.2221	1.1005	92.26 %

higher hedging ratio during the global crisis, confirming the oil-stock market's historical performance fluctuations [55]. also supports the notion of a time-varying relationship between stock and oil prices. Similar results can be found in the literature, such as [56] observation of a flight-to-quality from oil to bonds during the crisis regime.

A deeper analysis of the oil-stock data yields some intriguing findings. Specifically, traders may anticipate the smallest hedge ratio by allocating more (or less) capital into the fundamental utilities (oil) market. This approach has demonstrated greater success in hedging than observed hedging practices, particularly following global and European crises. These findings should reinforce the seven years of evidence indicating that the Chinese primary utilities sector is a preferred hedging vehicle for traders.

However, hedging against negative returns has become the costliest option when investing in the IT industry, even considering the entire sample period. Lastly, comparing the costs and efficacy of hedging in the oil and gold markets reveals compelling trends, as highlighted in Tables 6–9.

5. Conclusion and policy implications

The present study delves into the spillovers of asymmetric returns between various Chinese sector stocks such as “Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunications Services, Utilities”, and two commodity futures markets-gold futures and WTI crude oil futures employing the DY methodology. The findings suggest significant spillovers that tend to fluctuate with time. The industrial and discretionary consumer sectors are the primary generators and beneficiaries of systemic spillover. Commodities and seven of the ten other sectors are net recipients of spillovers except for the industrial, materials, and consumer discretionary sectors. The spillover impact between sectors and crude oil is larger when compared to the effects of shocks in stocks and gold. Including asymmetry spillovers in the study helps dig further by considering both positive and negative spillovers in terms of returns. Negative spillovers are more common than positive ones, suggesting leverage effects. The study also provides data on asymmetric spillovers across markets and demonstrates the need to be aware of asymmetric spillovers and the market's reaction to positive and negative returns. The industrial and discretionary service sectors benefit the most from spillovers of all types, while the telecoms and consumer staples sectors benefit the least. The intricacy of the examined market interactions is reflected in the wide range of net spillover receipt sizes. The symmetric spillovers across markets tend to increase during the Great Financial Crisis, the European sovereign debt crisis, the COVID-19 outbreak, and a downward trend following the 2016 Chinese stock market fall. The oil industry spillovers are at their peak during economic downturns. Asymmetric return spillover data demonstrate that the positive spillover seems worth somewhat less than the negative counterpart throughout the sample period.

The quantity of adverse occurrences has been on the decline since 2012. The difference between positive and negative impacts increased during the Great Financial Crisis, the European sovereign debt crisis, the oil price drop of 2014–2015, and the COVID-19 pandemic. Because of the virus outbreak, there was a rise in negative impacts since it gave negative signals to the markets. The chance of positive spillovers is less than negative ones when a region develops. The interdependence of commodities and Chinese stock markets has increased, leading to the development of more effective trading methods during COVID-19. A study conducted during the COVID-19 pandemic shows that the gold market is still linked to certain sectors' returns each week. Portfolio management analysis reveals that diversifying an equities portfolio with commodities reduces the portfolio's overall risk. Gold has a greater hedging efficiency than oil in calm and turbulent times.

The cost of hedging increased during the Great Financial Crisis and the European sovereign debt crisis, and hedging strategies changed when market conditions altered. During the COVID-19 outbreak, incorporating oil futures into an equity portfolio maximizes hedging efficiency. Gold has a similar effect when positive spillovers occur, but its value increases during the recovery phase when unfavorable spillovers occur. These results have significant implications for traders. First, recognizing the spillover property across stocks and commodities sectors may provide valuable information for portfolio diversification. Second, the efficacy of hedging with commodities varies over time, with the oil market seeing its greatest effectiveness during the COVID-19 era. Third, investing in a combination of basic commodities and utilities instead of only one asset class may result in greater long-term returns (at lower costs) after the European debt crisis. When selecting the best position and making a profit, Chinese stock market players may utilize crude oil price volatility as part of their strategic research, given that negative returns on Chinese stock markets can produce excess crude oil market volatility. Policymakers and portfolio managers may react to the results in various ways. Unorthodox measures are required to reduce the impact of spillovers during the pandemic. Allowing for extensive short-selling may be a solution to anticipate future asset prices better, yet it may also lead to long-term issues.

Nonetheless, this approach could result in enhanced pricing opportunities and decreased herd behavior in the stock and commodities markets. In addition, while oil may serve as a valuable hedging tool, it is only beneficial under certain conditions, and portfolio managers should keep this in mind. It may be more advantageous to heavily invest in sectors less susceptible to spillover effects to maximize profits. Finally, portfolio managers should evaluate the market capitalization of companies in the most affected sectors and the potential spillover at the company level to determine if smaller firms are at greater risk of suffering from the pandemic's negative impacts.

Ethics approval and consent to participate

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Data availability

We collected relevant data from World Bank open data available at https://data.worldbank.org/. For any further query on data, corresponding author at email address zoelfc@hotmail.com may be approached.

CRediT authorship contribution statement

YingTian Wu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chun Mai:** Writing – review & editing, Writing – original draft, Project administration, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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