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Time-frequency connectedness between energy and nonenergy commodity markets during COVID-19: Evidence from China

Hao Chen [a], Chao Xu [a,b,*], Yun Peng [a]

[a] School of Finance, Hubei University of Economics, Wuhan, 430205, China
[b] Collaborative Innovation Center for Emissions Trading System Co-constructed by the Province and Ministry, Wuhan, 430205, China

A R T I C L E I N F O

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A B S T R A C T

We aim to investigate the static and dynamic time-frequency connectedness between energy and nonenergy commodity markets in China during COVID-19 based on Baruník and Křehlík (2018) method. First, in this paper, we find that the short-term connectedness dominates the long-term one, and the total connectedness increases after the COVID-19 outbreak. Second, the energy commodity is the receiver and is influenced much by the spillovers of non-energy commodity markets (e.g. chemical commodities and non-ferrous metals) in the short run. At the same time, the impact is less at the long-term investment horizons. In addition, chemical commodities and soft commodities are the primary transmitters in this system in the short run. In contrast, chemical commodities and coal steel iron commodities are the main long-run primary transmitters. Third, the spillover role varies with the time-frequency domain during COVID-19. To be more specific, the energy commodity shows a net receiver role in the short and long run before the COVID-19 pandemic, but after it, the role of the net transmitter can be seen in the long run with ease. Finally, we show that COVID can reduce the hedging effectiveness at different investment horizons. The mineral policymakers should note our dynamic empirical results between energy and nonenergy commodity.

1. Introduction

The dynamic interdependence between energy and nonenergy commodities has attracted extensive attention from academia and industry (Meng et al., 2020). Especially during the COVID period, adverse external shocks can influence economic activities (Jiang et al., 2021a), financial instability (Albulescu, 2021), and social safety (Bitler et al., 2020), and portfolio management (Li and Meng, 2022). Meanwhile, the commodities experience a price fluctuation in the recent data,[1] and the different commodities sectors can show a strong comovement pattern (Jiang and Chen, 2022). Previous literature usually studies the relationship between commodities from the aggregate level, either from price volatility or return linkages (Jiang et al., 2019a). In addition, the macro- or micro-level dynamic links between oil and nonenergy commodities are investigated in the previous papers (see, e.g., Khalfaoui et al., 2021; Mo et al., 2022). However, few studies explore the price transmission mechanism between energy and nonenergy commodities from a time-frequency domain. There are *theoretic* channels, e.g., supply-demand channels. financial investments, behavioral channels, etc., for causing the spillovers between energy and nonenergy commodities are justified in much literature (Liu et al., 2018; Rehman et al., 2019; Bouri et al., 2021). In other words, most non-energy sectors depend on energy sectors, and energy prices can impact non-energy sectors in many lines. In this case, empirically detecting the transmission between energy and nonenergy commodities and the role of the commodity in the commodities system should be meaningful.

This paper targets China's commodities markets since China is the largest oil consummation country globally. In addition, China seeks to extend its clout in commodity markets.[2] To be more specific, China's commodity exchanges are now world-beating. The most important exchanges in China are in Dalian, Shanghai, and Zhengzhou. The number of contracts traded on these in 2020 was six times higher than on America's CME Group's exchanges (The Economist, 2021). Due to China's sugaring important role in the commodity markets and China's

* Corresponding author. School of Finance, Hubei University of Economics, Wuhan, 430205, China
E-mail address: contribute2022@163.com (C. Xu).

[1] In the first two quarters of 2021, Bloomberg's general commodity price index rallied more than 20%. There is a 44.5% rise in energy prices, a 20.5% rise in agricultural goods (20.5%), and a 17.6% rise in industrial metal, from the Blomberg database.

[2] For example, China consumes 55% of the world's supply of the coal from the IMF 2020 report.

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world-beating commodity exchanges, more and more attention is paid to China's commodity markets. With the rapid development in domestic commodities, the price fluctuation can be more inter-connected, leading to spillovers between energy and nonenergy sectors (Chen et al., 2021a). However, little literature has worked on the dynamic spillovers feature in China's commodity markets at the sector level (Ji and Fan, 2016) and even less from the frequency domain. Against this background, an accurate exploration of the time-frequency connectedness and hedging performance between energy and nonenergy commodity markets at different investment horizons can be helpful for policy design in China. Besides, investors can adjust the investment strategy with accurate dynamic spillovers.

In this context, we aim to capture the linkages relevant to application areas addressed in previous literature; we contribute to investigating the static and dynamic time-frequency connectedness; instead of the interdependence structure of the global commodity markets, we examine the connectedness between energy and nonenergy commodity markets in China during COVID-19 based on Baruník and Křehlík (2018) method. In addition, we design comprehensive portfolio strategies for investors. Finally, we address the effects of COVID-19 on the dynamic spillovers and hedging performance.

We provide the potential contributions of this paper in the following lines. First, much literature considers the dynamic spillovers and portfolio management from the time domain using Diebold and Yilmaz (2015) and Diebold and Yılmaz (2014) method (see, e.g., Magkonis and Tsouknidis, 2017; Jiang et al., 2019b; Antonakakis et al., 2020; Liu and Gong, 2020; Costa et al., 2022). However, this paper investigates the static and dynamic time-frequency connectedness between energy and nonenergy commodity markets in China during COVID-19 based on Baruník and Křehlík (2018) method. This method can allow us to revisit the same issues from different investment horizons. In addition, to align with Baruník and Křehlík (2018) method, we utilize the wavelet method to decompose the raw data to design portfolios from a frequency domain.

Second, we are closely related to Jiang et al. (2019a), Meng et al. (2020), and Chen et al. (2021a) to examine the time-varying relationship in the commodities markets in China. In this work, we are different in the following lines. For one thing, these works only consider the time domain; however, we investigate the dynamic relationship not only from a time-domain but also from a frequency domain. For another thing, our data are more comprehensive. Since we include all the primary commodities in the Wind database, the spillover system can be more complete relative to these papers. Besides, our data are long enough to explore the role of COVID in the dynamic relationship. Third, our comprehensive results provide a complete view of China's time-frequency connectedness and hedging performance between energy and nonenergy commodity markets. The results can guide policymakers in making decisions and investors to adjust the investment strategy varying to different market horizons.

Based on Baruník and Křehlík (2018) method, we find that the short-run spillovers dominate the long-run case, and the total connectedness increases a great deal after the COVID-19 outbreak. Second, the energy commodity is influenced much by the spillovers of non-energy commodity markets in the short run, while the impact is less at the long-term investment horizons. In addition, chemical commodities and soft commodities are the primary transmitters in this system in the short run, while chemical commodities and coal steel iron commodities are the main long-run primary transmitters. Third, the role of the connectedness system varies with the time-frequency domain during COVID-19. Finally, the portfolio results show that the portfolio strategy is efficient by including energy and nonenergy commodities. In addition, even though COVID can reduce the hedging effectiveness in the short and long run, the hedging ratio is always positive, and COVID cannot reverse it in the long run.

2. Literature review

This paper is related to two strands of literature. The first one is the dynamic relationships between commodities (see, e.g., Mensi et al., 2014; Xiarchos and Burnett, 2018; Shah and Dar, 2021; Tan et al., 2020; Costa et al., 2022).[3] For example, Green et al. (2018) investigate volatility spillovers to electric power from large exogenous shocks in the prices of gas, coal, and carbon emission allowances in the German energy market. The results show that the magnitude of spillovers between commodities is vast and significant. Chuliá et al. (2019) check the links between energy markets using a broad data set consisting of a total of 17 series of prices for commodities such as electricity, natural gas, coal, oil, and carbon in European countries. Likewise, Barbaglia et al. (2020) examine volatility spillovers among energy, agriculture, and biofuel commodities, and the significant spillovers between energy and agricultural commodities are detected. Noting that the main research commodities are the developed indexes. However, the survey of the connectedness in China's commodities is still in its infancy (see Khalfaoui et al. (2021) for a comprehensive reading) even if China's commodities are more and more mature and international, and the composite indexes and products have also improved (Jiang at al. 2019a). Since China has become the second-largest economy globally, we aim to have an in-depth study on the spillovers between energy and nonenergy commodity markets in China.

In particular, among them, there are a few studies focusing on the commodities in China (Jiang et al., 2019a; Meng et al., 2020; Chen et al., 2021a). Jiang et al. (2019a) are closely related to this paper to examine the time-varying relationship in the commodities markets in China and provide discussion on the role financial crisis (GFC) on the hedging performance. The main results show that the volatility relationship is time varying and GFC can impact the hedging performance. In this paper, we are different to theirs in the following ways. On the one hand, these works only consider the time domain, however, we investigate the dynamic relationship not only from a time domain but also from a frequency domain. On the other hand, our data are more comprehensive. Since we include all the main commodities in the Wind database, the spillover system can be more complete relative to these papers since they only add four or six commodities in their work. Besides, our data are long enough to explore the role of COVID on the dynamic relationship.

The second one is the portfolio design. Many papers discuss the portfolio strategy and check the portfolio performance. For example, Li and Meng (2022) use the renewable energy stock markets and cryptocurrencies to show the dynamic nexus between these financial markets. It indicates that the stock markets can be partially hedged by cryptocurrencies. More importantly, they show that COVID-19 can revise the hedging performance. Likewise, there is literature using commodities to construct portfolios (see, e.g. Zhang and Chen, 2018; Ahmad and Rais, 2018; Bannigidadmath and Narayan, 2022). Aslet al. (2021) find diversification opportunities between S&P Global Clean Energy, Oil, energy, and crude oil distillation products. Similarly, Wang et al. (2021) study the impact of diversification with five energy futures, showing that the optimal portfolios can increase expected return and reduce the volatility simultaneously. In this paper, we speak to the previous papers to assess hedging performance between energy and nonenergy commodity markets. Besides, we aim to gauge the effects of COVID-19 on the constructed portfolio.

There are many connectedness approaches targeting to detect the nexus among financial markets. The first generation is Vector autoregression (VAR)-based method, i.e. the Diebold and Yilmaz (2015) and Diebold and Yılmaz (2014) method. Antonakakis et al. (2015) explore the dynamic connectedness between the business cycle and financial

[3] See Khalfaoui et al. (2021) for a comprehensive reading on the review of commodity spillover research.

cycles in the G7 countries. However, there are some shortcomings in this method. For example, it has an arbitrarily set problem. To overcome this, the Antonakakis and Gabauer (2017) method is developed to use the time-varying VAR method to replace the VAR method. Antonakakis et al. (2018) employ this Antonakakis and Gabauer (2017) method to detect the dynamic linkages between economics uncertainties in the developed countries. However, this method is still limited in the time domain. The recent Baruník and Křehlík (2018) method is widely used in recent academic papers since this method can allow us to investigate the static and dynamic time-frequency connectedness. For example, Liu et al. (2022) examine the risk spillovers between the global stock markets. Xia et al. (2020) study the dynamic time-frequency spillovers between the policy uncertainty and housing markets. To the best of our knowledge, this paper is the first to document the time-frequency connectedness and hedging performance between energy and nonenergy commodity markets in China using the Baruník and Křehlík (2018) method.

The review above demonstrated that the work related to the dynamic linkages between commodities has been increasing in recent years. However, the survey of the connectedness in China's commodities is still in its infancy even if China's commodities are more and more mature and international, and the composite indexes and products have also improved (Jiang et al., 2019a). In this way, we investigate the connectedness and portfolio design between energy and nonenergy commodity markets in China from the time-frequency perspective. Finally, due to the extensive influence of the COVID-19 in the financial markets (Jiang et al., 2021a), we further the effects of COVID.

The rest of this paper proceeds as follows. We will elaborate on the methods used in this paper in Section 3. Section 4 has a clear expression of the data and the way to deal with the data. In addition, introductory statistics and linear pairwise relationships are shown in this section. Section 5 provides the empirical results on the time-frequency connectedness and hedging performance between energy and nonenergy commodity markets in China during COVID-19. Section 6 concludes.

3. Model

This paper investigates the static and dynamic time-frequency connectedness between energy and nonenergy commodity markets in China during COVID-19 based on Baruník and Křehlík (2018) method. This method can allow us to revisit the same issues from different investment horizons. In addition, to be in line with Baruník and Křehlík (2018) method, we utilize the wavelet method to decompose the raw data to design portfolios from a frequency domain.

3.1. Time and frequency dynamic connectedness

VAR-based connectedness method is used to measure the dynamic spillovers between financial markets (Diebold and Yılmaz, 2014; Diebold and Yilmaz, 2015; Jena et al., 2021; Bouri et al., 2021).[4] Antonakakis and Gabauer (2017) then propose the seminal time-varying VAR connectedness and this method has been widely used since it can overcome the shortcoming of the conventional VAR model. Baruník and Křehlík (2018) further extend this model and in this paper, we use this model to detect dynamic relationship from different investment horizons.[5] We can compute the overall connectedness within the frequency band d as follows:

$$C^d = 1 - \frac{\sum_{j=1}(\widetilde{\Theta}_d)_{jk}}{\sum_{jk}(\widetilde{\Theta}_d)_{jk}}.$$

[4] See literature review part for details.

[5] For a textbook treatment, see Baruník and Křehlík (2018) for details.

Following Baruník and Křehlík (2018), we estimate the directional connectedness from the financial market j to market k:

$$C^d_{j\to *} = \sum_{j=1, j\neq k} (\widetilde{\Theta}_d)_{jk}.$$

In addition, the contribution of directional connectedness from k to j is expressed as:

$$C^d_{*\to \mathrm{j}} = \sum_{j=1, j\neq k} (\widetilde{\Theta}_d)_{jk}.$$

In this way, we use the directional connectedness to yield the net connectedness:

$$C^d_{i,net} = C^d_{i\to *} - C^d_{*\to i}, \tag{1}$$

where the positive (negative) values of net directional connectedness signify whether a market is a transmitter (receiver) of connectedness.

3.2. Wavelet

The wavelet method is widely used in economic and financial research (Jiang et al., 2017, 2018; Lao et al., 2018) since it can allow us to decompose the raw data into different time horizons.[6] In this case, one can use this method to have a clear picture of the dependence structure of financial markets from the frequency domain. We follow Mo et al. (2019) to employ the maximal overlapped discrete wavelet transform (MODWT) to decompose the commodities time series in this paper. To be more specific, the return series of energy and nonenergy commodity markets are estimated as follows:

$$r_t = S_J(t) + \sum_{j=1}^{J} D_j(t),$$

where $S_J(t)$ is the smoothed version of r_t at scale J and $D_j(t)$ can be read as the wavelet scales, representing the decomposed part. As in Crowley (2007) and Jiang et al. (2020), we see that the wavelet method can boil the raw weekly data into different scales D1-D5.[7] In this paper, to be consistent with the time-frequency in Baruník and Křehlík (2018), we follow Li and Meng (2022) to utilize the sum of D1 and series corresponding to the periods of 2–4 weeks, whereas the sum of D2, D3, and D4 is used as the long-term horizon, corresponding to the periods 4–32 weeks.

3.2. Portfolio construction

We use the dynamic conditional correlation (DCC) model developed by Engle (2002) to estimate the dynamic relationship of our data.[8] This model has already attracted significant attention from economic and financial literature, investigating issues such as stock market interdependencies, portfolio construction and risk measurement.[9] Following Kroner and Ng (1998), the optimal portfolio weights $\omega_{cf,t}$ for nonenergy commodities at time t is defined in equation (2) [10]:

[6] By using the time horizon method, we can divide the investors into long-term investors or short-term investors. The long-run investors can usually refer to the institutional investors who are experienced in the financial markets. On the contrary, the short-run investors are the investors who usually focus on the short-run transactions.

[7] D1-D5 represent 2–4 weeks, 4–8 weeks, 8–16 weeks, 16–32 weeks and 32–64 weeks respectively.

[8] In this subsection, we leave out the DCC model for brevity. See Engle (2002) for a textbook treatment.

[9] See e.g. Mo et al. (2018), Nie et al. (2018), Akkoc and Civcir (2019), Chen et al. (2020).

[10] We assume the investors aim to hedge risks of the energy commodity by the inclusion of nonenergy commodity.

Table 1
Commodity index in China and detailed components.

Commodity index	Components	Symbol
Energy Index	Fuel, Coal Crude, Oil, LPG, Low-Sulfur Fuel	ENFI
Nonmetal Building Materials Index	Fiberboard, Plywood, Glass, PVC	NMBM
Noble Metals Index	Gold, Silver	NMFI
Oil Fat Index	Soybean Type I & II, Soybean Meal, Soybean Oil, Rapeseed, Palm Oil	OOFI
Soft Commodities Index	Cotton, White Sugar, Cotton Yarn	SOFT
Non-ferrous Metals Index	Copper, Aluminum, Zinc, Nickel, Tin, International Copper	NFFI
Coal Steel Iron Index	Coal, Iron Ore, Rebar, Hot Coil, Wire Rod, Ferrosilicon, Manganese Silicon, Stainless Steel	JJRI
Chemical Index	Rubber, Polypropylene, PTA, Methanol Pulp etc.	CIFI
Grain Index	Maize, Rice, Japonica etc.	CRFI
Agricultural Products Index	Eggs, Cornstarch, Apples, Pigs, Red dates	APFI

Table 2
Summary statistics.

	Mean	Max	Min	S. D.	Skew	Kurt	J-B	ADF
ENFI	0.0120	4.5191	−7.7272	0.7458	−1.0047	16.0669	7945.2400***	−32.3786***
NMBM	0.0288	3.0831	−2.4923	0.5795	0.5636	6.8733	739.7619***	−35.5238***
NMFI	0.0116	2.4162	−2.5353	0.4529	−0.4039	8.2911	1302.3030***	−31.7149***
OOFI	0.0070	2.2176	−2.1689	0.4130	−0.0141	5.9742	402.1635***	−33.0293***
SOFI	−0.0048	1.4262	−2.1863	0.3903	−0.3981	5.9438	422.7539***	−33.9447***
NFFI	0.0125	1.5933	−2.3480	0.4316	−0.3523	5.5331	314.2583***	−33.9655***
JJRI	0.0231	2.7545	−3.2967	0.7522	−0.1234	4.2908	78.5077***	−33.5862***
CIFI	−0.0033	2.3820	−3.1035	0.5484	−0.3515	5.5273	312.8057***	−33.0327***
CRFI	0.0207	1.4089	−1.2675	0.2842	0.0362	5.5003	284.4155***	−33.2048***
APFI	0.0039	2.4443	−2.5632	0.5555	0.3063	5.7642	364.4091***	−32.5255***

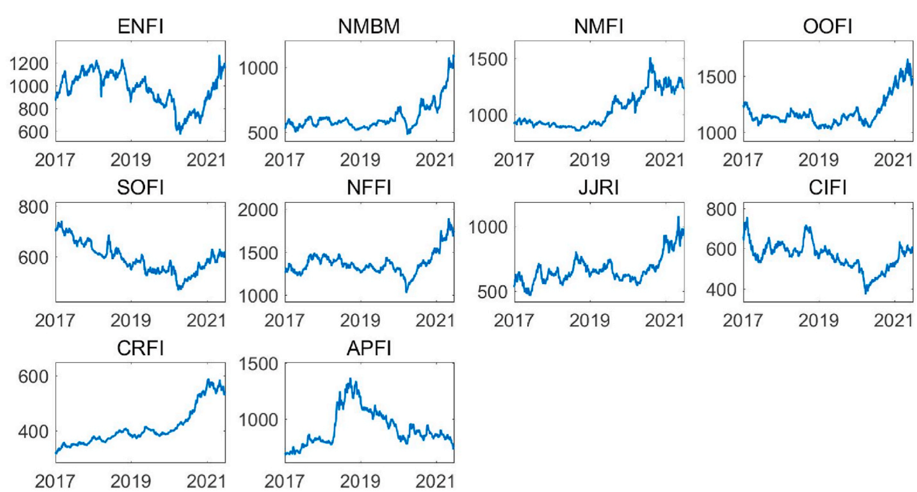


Fig. 1. Trend charts between energy and nonenergy commodity markets.

$$\omega_{en,\ t} = \frac{h_{n,t} - h_{en,t}}{h_{n,t} - 2h_{en,t} + h_{e,t}},\ with\ \omega_{en,t} = \begin{cases} 0,\ if\ \omega_{en,\ t} < 0 \\ \omega_{en,t},\ if\ 0 < \omega_{en,t} < 1 \\ 1,\ if\ \omega_{en,t}\ > 1 \end{cases}, \tag{2}$$

where $h_{n,t}$ is the conditional variance of one type of nonenergy commodity in the GJR model, $h_{e,t}$ is the conditional variance of energy commodity in China, and $h_{en,t}$ is the conditional variance between energy and nonenergy commodity markets. Accordingly, the optimal weight of energy commodity is 1-$\omega_{en,t}$.

We further follow Kroner and Sultan (1993) to yield the hedge ratio β_{en} to minimize the risks in the designed portfolios, and the method is expressed in equation (3) [11]:

$$\beta_{en,t} = h_{en,\ t} / h_{e,t}. \tag{3}$$

To examine the effectiveness of the portfolio management, the hedging effectiveness (HE) index is introduced in this paper as in Mo et al. (2019), which is identified below[12]:

$$HE = 1 - \frac{Var_p}{Var_0},$$

where Var_p is the variance of the optimal portfolios defined in equations (2) and (3) and Var_0 is the variances of benchmark portfolio with the energy commodity only.

4. Data analysis

A variety of commodity markets data are employed in this paper to detect the time and frequency connectedness and hedging performance between energy and nonenergy commodity markets in China. Following Jiang et al. (2019a) and Meng et al. (2020), we select the most

[11] The hedge ratio means that the investors should take a long position of one unit in the energy commodity hedged by a short position of β_{en} units in nonenergy commodity.

[12] The hedging effectiveness is defined to compare the variance between the benchmark portfolio, which only includes the energy commodity, and the optimal portfolio outlined in equations (2) and (3).

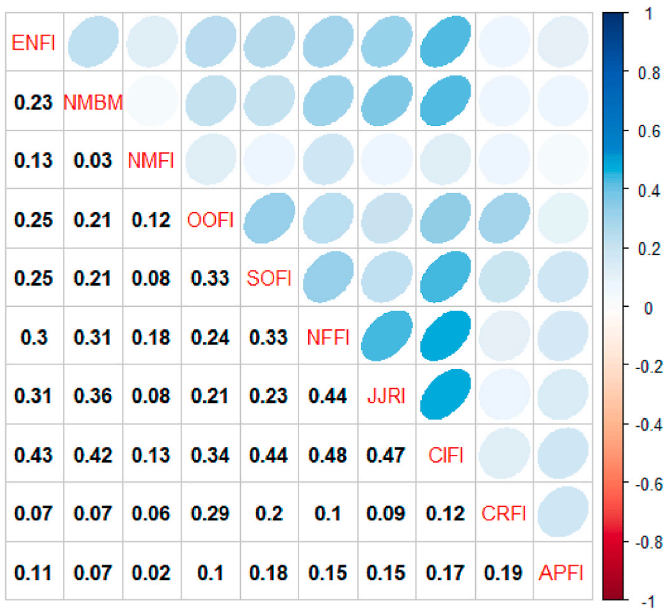


Fig. 2. Pairwise linear correlation between energy and nonenergy commodity markets.

with the Jarque–Bera (JB) statistics and are stationary significantly with the Augmented Dickey-Fuller (ADF) test.

We plot the time series innovation as in Fig. 1. It is clear that the sample data fluctuate enormously, and especially after the COVID-19 pandemic, the prices of these commodities vary a lot. This is also the reason in this paper why we focus on the event study with COVID-19. On the flip side, the pairwise linear relationship between energy and nonenergy commodities is shown in Fig. 2. It is seen that these commodities have a positive linear dependence structure, but the linear coeffects are not very strong. For example, the energy commodity and nonmetal building materials commodity show a linear relation with a Pearson parameter of 0.23, which can provide some preliminary results for us to study the portfolio management between energy and nonenergy commodity markets. The following section will address the dynamic connectedness and portfolio management between energy and nonenergy commodity markets.

5. Empirical analysis

5.1. Time-frequency dynamic connectedness

Table 3 shows static connectedness results between energy and nonenergy commodity markets in the short run.[14] It is observed that the total spillover of this system is 18.79% on average. We further find that the nonenergy commodities are the main net contributor to this commodity system. To be more specific, CIFI contributes the most to this system which is 4.07% on average, followed by JJRI (2.43%), NFFI (2.23%), and SOFI (2.14%). CIFI is also the primary recipient in this system which is 2.77%, followed by JJRI (2.59%), NFFI (2.51%), NMBM (2.14%), and ENFI (2.02%). The non-energy commodities are the main contributors and recipients, and it is observed that the energy commodity is influenced intensively by the non-energy commodities. We show that ENFI receives 31.66% of shocks from itself, 1.6% from NMBM, 6.96% from CIFI, 3.56% from JJRI, and others. In addition, ENFI contributes 4.06% of spillovers shocks to CIFI, 2.4% to JJRI, 2.37% to NFFI, and others.

Table 3
Connectedness between energy and nonenergy commodity markets at the short-term frequency bands.

	ENFI	NMBM	NMFI	OOFI	SOFI	NFFI	JJRI	CIFI	CRFI	APFI	FROM
ENFI	31.66	1.6	0.79	2.3	2.49	3.41	3.56	6.96	0.3	0.53	2.02
NMBM	1.71	35.54	0.47	1.78	1.72	3.59	4.27	6.59	0.18	0.2	2.14
NMFI	0.6	0.02	43.88	0.28	0.25	1.28	0.37	0.53	0.2	0.31	0.80
OOFI	1.64	1.76	1	33.24	4.12	2.09	1.47	4.1	2.59	0.33	1.80
SOFI	1.79	1.22	0.43	3.64	32.28	3.12	1.36	6.65	1.29	1.31	2.01
NFFI	2.37	2.72	0.63	1.57	3.22	28.9	5.43	6.74	0.38	0.75	2.51
JJRI	2.4	3.65	0.17	1.54	1.55	5.84	29.3	6.38	0.29	0.92	2.59
CIFI	4.09	3.81	0.87	2.58	4.55	5.18	4.76	23.42	0.36	0.72	2.77
CRFI	0.62	0.48	0.09	3.7	2.4	1.29	0.85	1.57	42	1.2	1.12
APFI	0.39	0.38	0.05	0.51	1.28	1.14	0.78	1.79	1.37	42.56	1.02
TO	1.67	1.99	0.77	1.70	2.14	2.23	2.43	4.07	0.91	0.87	Total:18.79
NET	−0.35	−0.15	−0.03	−0.10	0.13	−0.27	−0.16	1.29	−0.21	−0.15	

Notes: This table displays the total spillover index of Baruník and Křehlík (2018) at the short-term frequency band 3.14 to 0.79.

representative and comprehensive commodities, i.e., Energy Index (ENFI), Nonmetal Building Materials Index (NMBM), Noble Metals Index (NMFI), Oil Fat Index (OOFI), Soft Commodities Index (SOFI), Non-ferrous Metals Index (NFFI), Coal Steel Iron Index (JJRI), Chemical Index (CIFI), Grain Index (CRFI), and Agricultural Products Index (APFI). The specific components of these commodities are elaborated in Table 1. In addition, we obtain the daily dataset from January 1st, 2017, to June 30th, 2021, in the Wind database, and the length of time is determined by data availability.[13] Our data is long enough for the consideration of the recent extreme events that as the COVID-19 pandemic. To align with the financial papers (see, e.g., Jiang et al., 2017; Jiang et al., 2021b), the raw time series is measured in log differences.

Table 2 shows the summary statistics of commodities. The data display the standard financial time series features. For example, the mean values of these series are minimal (near zero). The standard deviation of the energy commodity is quite significant, while the nonenergy commodities have relatively more minor standard deviations. The kurtosis is very high for the energy commodity, and skewness's heterogeneous effects appear. Besides, the data do not follow normality

On the flip side, we can obtain some interesting results from the net spillovers in the short run. It is observed that the SOFI and CIFI are the main net transmitters while other commodities are the net receivers, including the energy commodity. This result is in line with the results of Meng et al. (2020) and Yang et al. (2021), showing that the static spillovers of nonenergy commodity sectors are strong. To conclude, we find the static evidence that the energy commodity is influenced by the spillovers of non-energy commodity markets in the short run.

[13] Available at: https://www.wind.com.cn/en/edb.html.

[14] In this paper, we follow Li and Meng (2022) and Mo et al. (2022) to denote the short-run periods as 2–4 weeks, whereas the long-term horizon corresponds to the periods 4–32 weeks.

Table 4
Connectedness between energy and nonenergy commodity markets at the long-term frequency bands.

	ENFI	NMBM	NMFI	OOFI	SOFI	NFFI	JJRI	CIFI	CRFI	APFI	FROM
ENFI	25.28	1.26	0.3	1.53	1.23	1.75	2.23	4.04	0.25	0.29	1.46
NMBM	1.15	22.42	0.02	1.04	0.89	2.17	3.34	3.9	0.13	0.12	1.38
NMFI	0.75	0.28	36.73	1.35	0.31	1.15	0.2	0.8	0.22	0.23	0.79
OOFI	1.73	1.07	0.2	25.76	2.32	1.16	0.97	2.43	2.68	0.27	1.19
SOFI	1.54	1.14	0.2	2.32	23.3	2.57	1.34	3.99	1.42	0.7	1.51
NFFI	1.84	2.06	0.89	1.07	2.05	20.55	4.16	4.82	0.44	0.61	1.47
JJRI	2.45	3.04	0.15	0.72	1.04	3.91	21.42	5.01	0.32	0.59	1.61
CIFI	3.51	3.49	0.14	1.96	3.36	4.32	4.39	17.85	0.37	0.6	2.21
CRFI	0.08	0.04	0.19	2.74	0.96	0.11	0.16	0.21	31.9	1.21	0.77
APFI	0.61	0.06	0.15	0.31	1.17	0.76	0.97	0.8	1.27	34.09	0.86
TO	1.38	1.18	0.51	1.14	1.42	1.59	2.02	2.69	0.71	0.60	Total:13.24
NET	−0.08	−0.20	−0.28	−0.05	−0.09	0.13	0.41	0.48	−0.05	−0.26	

Notes: This table shows the spillover index at the long-term frequency band 0.79 to 0.1.

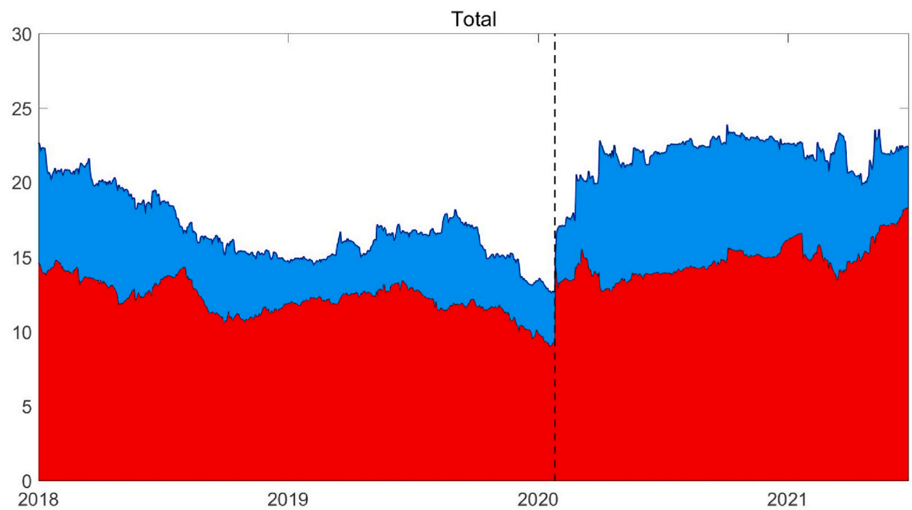


Fig. 3. Dynamic frequency total spillovers in commodity markets. Notes: The blue-colored area indicates the total spillover at the short-term investment period of up to 4 weeks. The red-colored area reflects the spillover at the long-term horizon of 4–32 weeks.

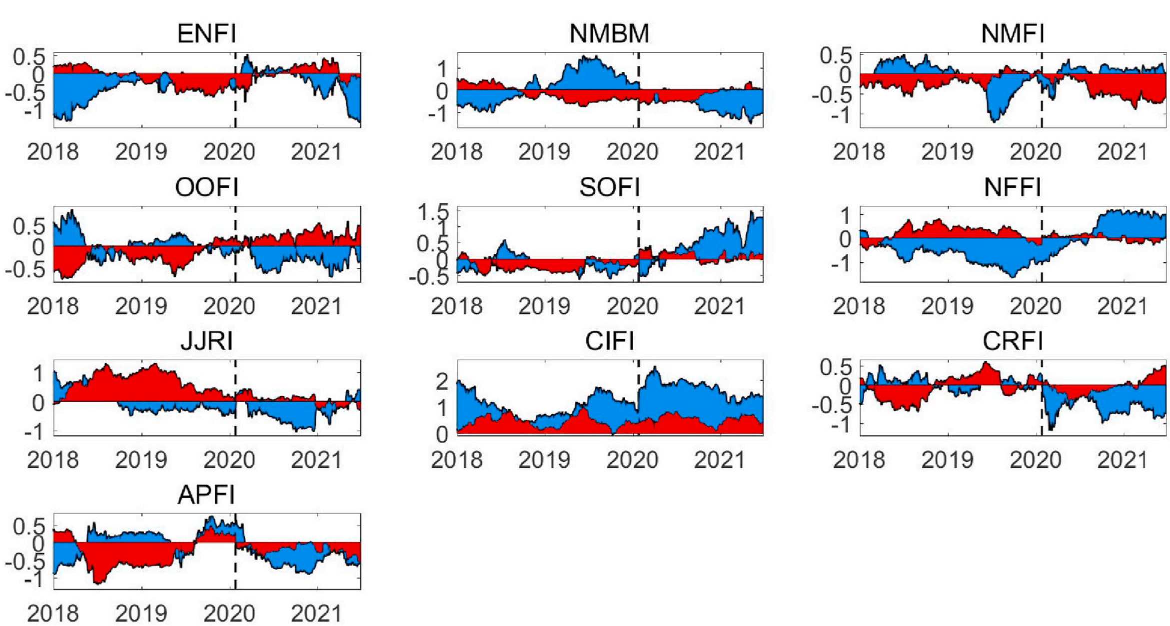
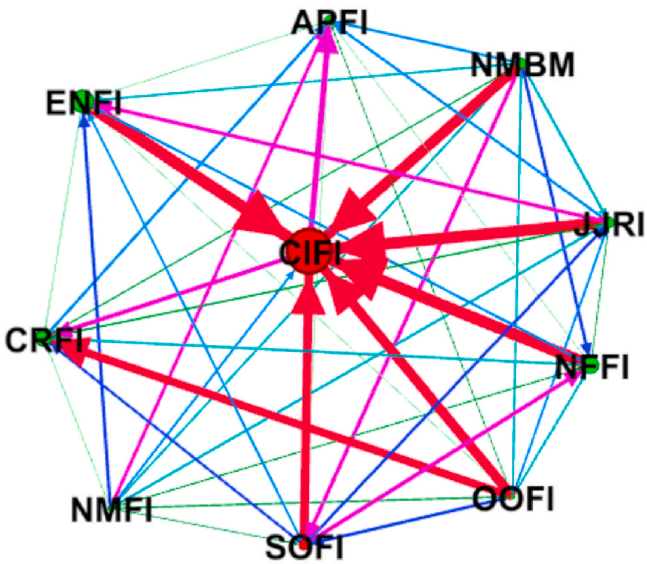
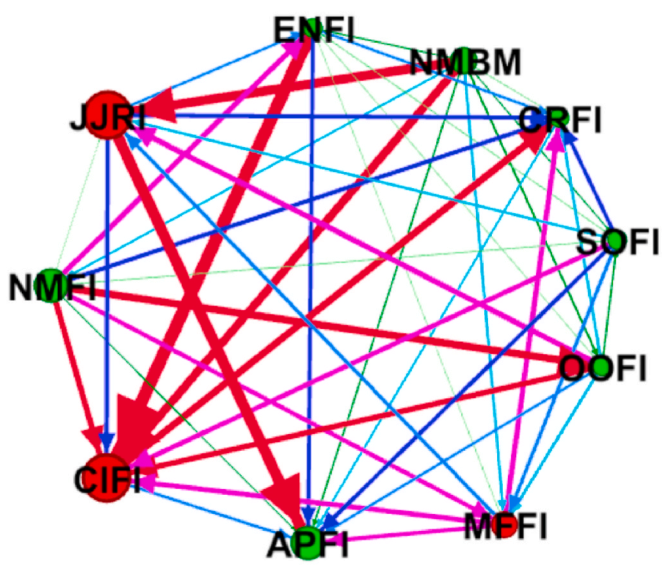


Fig. 4. Dynamic net spillover. See notes in Fig. 3.



(a) Short-term net pairwise spillover network



(b) Long-term net pairwise spillover network

Fig. 5. Net pairwise spillover at different frequency bands. Notes: A node's red (green) color indicates its most significant net transmitter (receiver) of spillover, respectively. The edge colors rank the strength of the pairwise directional spillover from red (strongest) to purple, pink, blue, light blue, and green (weakest). The edge arrow thickness also indicates the strength of the net pairwise spillover.

Table 4 shows the static connectedness results between energy and nonenergy commodity markets in the long run. The results are similar to those in the short run. First, the nonenergy commodities are still the main contributors and recipients in this system. For example, CIFI contributes 2.69% of spillovers to this connectedness system, followed by JJRI (2.02%), NFFI (1.59%), etc. CIFI is also the most prominent recipient with 2.21% of shocks in this system, followed by JJRI (1.61%), etc. Second, it is found that NFFI and JJRI are the net transmitters and other commodities are the net receivers. There are some different results from those in the short run. First, the total spillovers in this system are lower relative to the case in the short run, which is 13.24%. This result is in line with Li and Meng (2022). In addition, the long-run net spillovers are usually smaller than those in the short run. To put it differently, in the long run, the static spillovers are more minor, and the nonenergy commodities less influence the energy commodity. Finally, we find the role can alter from the short run to the long run, as in Chen et al. (2021b), who show the financial industry's role can be different. For example, in the short run, the role of SOFI is a net transmitter, while it becomes a net receiver in the long run. The role of financial markets can be changed in different timer horizons, as in Li and Meng et al. (2021).

The static results can provide us with a standard picture of the connectedness. Going one step further, we revisit the dynamics using time-frequency plots. Fig. 3 offers the total connectedness in these commodity markets. It is straightforward that the short-term connectedness dominates the long-term case, which is in line with Mandacı et al. (2020) and Saeed et al. (2021). However, the fluctuation feature is similar in both the short and long run. In particular, the role of COVID-19 is evident in this figure. It can be seen that after the COVID, the total spillovers increase a great deal. Similar features share in Lin and Su (2021) and Jiang and Chen (2022). This explains why this paper focuses on studying the effects of COVID as in Li and Meng et al. (2021).

Fig. 4 shows the dynamic net connectedness at different time spans. It is observed that the spillovers pattern varies with the time-frequency domain. For example, the energy commodity (ENFI) shows a net receiver role in the short and long run before the COVID-19 pandemic, but after it, the role of the net transmitter can be seen in the long run with ease. Similar results can be observed in the nonenergy commodities. This result can echo the recent empirical evidence in the financial markets to prove the varying role of transmitter/receiver as in Akyildirim et al. (2022), Farid et al. (2022), Umar et al. (2022). In addition, we find that the net spillovers wave sharply during the period.

Fig. 5 plots the net pairwise spillover in the short-run (panel a) and long-run (panel b). At the short-term investment horizons, the specific role of this commodity is evident in this figure. For example, CIFI is the center of the system, and it receives spillovers shocks from other commodities. OOFI contributes the most to the CRFI and CIFI. In the long run, CIFI and JJRI receive the main spillovers shocks in this system.

Interestingly, ENFI contributes the most to CIFI. The primary risk source of ENFI is NMFI. In this way, this figure can give us a complete picture of the net pairwise relationship.

To better evaluate the role of COVID-19 on the dynamic net spillovers, we divide the full sample into two different samples to compare the net pairwise spillover during COVID-19 at different horizons shown in Fig. 6. In the short run, the results are similar in the short and long run. For example, CIFI is the most recipient, and the primary sources of risk are NMBM, JJRI, and ENFI. However, after the COVID-19 pandemic, the role of the receiver becomes evident in NFFI.

In the long run, before COVID, JJRI is the main contributor to APFI and ENFI is the main risk source of CIFI. CIFI and APFI are the most recipients. Similarly, in the long term, CIFI and OOFI are also the most recipients, and the main risk sources are NMFI and NMBM. ENFI contributes the most to CIFI, and the main risk source is NMFI.

5.2. Portfolio management

Following Jiang et al. (2019a) and Mensi et al. (2021), the wavelet-DCC model is used to construct portfolio specifications for investors. This section aims to hedge the energy commodity risks by including the nonenergy commodity and provide optimal portfolios' weights and hedge ratios. And then, the hedging effectiveness (HE) index is employed to evaluate the hedging performance. It is seen that the COVID-19 pandemic can increase the total spillovers and make the net dynamic connectedness wave intensively in the previous analysis. Finally, we divide the total sample into two subsamples to check the role of COVID-19 on the hedging performance.[15] Tables 5 and 6 show the

[15] The COVID-19 pandemic time is determined by the outbreak point as in Li and Meng (2022), which is the first week of February 2020.

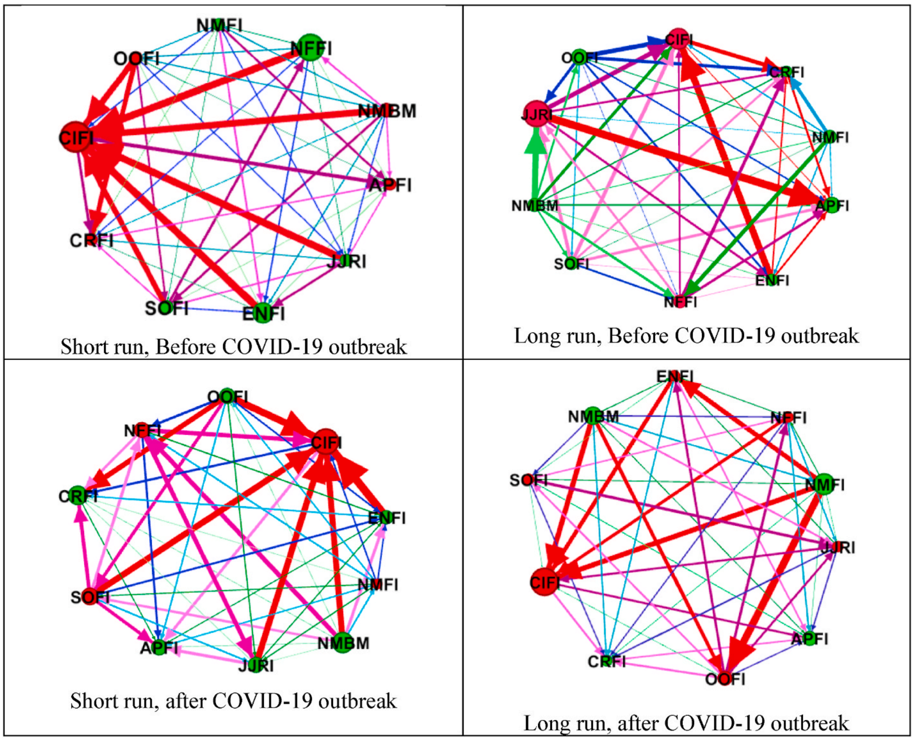


Fig. 6. Net pairwise spillover during COVID-19 at different investment horizons. Notes: See Fig. 5.

Table 5
Optimal portfolios' weights, hedge ratios, and hedging effectiveness between energy and nonenergy commodity markets at the short-term frequency bands.

	Pre COVID-19			Post COVID-19			Full Sample		
	$W_{en,t}$	$B_{en,t}$	HE (%)	$W_{en,t}$	$B_{en,t}$	HE (%)	$W_{en,t}$	$B_{en,t}$	HE (%)
NMBM	0.6194	0.2620	50.79%	0.6206	0.3331	47.16%	0.6198	0.2844	49.09%
NMFI	0.7670	0.3681	42.11%	0.5691	0.0969	53.12%	0.7046	0.2826	50.64%
OOFI	0.7133	0.2895	34.68%	0.7267	0.6180	33.10%	0.7176	0.3931	33.77%
SOFI	0.7211	0.2554	43.68%	0.8082	0.3419	18.39%	0.7486	0.2827	34.06%
NFFI	0.6673	0.3450	35.02%	0.7703	0.5648	38.33%	0.6997	0.4143	36.30%
JJRI	0.3728	0.2045	66.31%	0.5964	0.3680	42.91%	0.4433	0.2560	59.65%
CIFI	0.5680	0.3304	48.91%	0.7301	0.7830	21.03%	0.6191	0.4731	39.02%
CRFI	0.8151	0.2080	42.48%	0.8192	−0.3342	42.08%	0.8164	0.0371	42.31%
APFI	0.5545	−0.0266	69.79%	0.7478	0.4457	30.57%	0.6155	0.1223	59.67%

Note: see note in Table 3.

Table 6
Optimal portfolios' weights, hedge ratios, and hedging effectiveness between energy and nonenergy commodity markets at the long-term frequency bands.

	Pre COVID-19			Post COVID-19			Full Sample		
	$W_{en,t}$	$B_{en,t}$	HE (%)	$W_{en,t}$	$B_{en,t}$	HE (%)	$W_{en,t}$	$B_{en,t}$	HE (%)
NMBM	0.6118	0.2852	40.99%	0.6254	0.2715	37.49%	0.6161	0.2809	39.17%
NMFI	0.7980	0.1028	40.34%	0.6495	0.2168	23.40%	0.7512	0.1387	29.65%
OOFI	0.7635	0.3574	27.03%	0.7682	0.4794	10.47%	0.7650	0.3959	18.10%
SOFI	0.7939	0.4247	31.65%	0.8082	0.5577	4.60%	0.7984	0.4666	18.71%
NFFI	0.7450	0.4198	24.10%	0.7760	0.5653	12.35%	0.7548	0.4657	18.54%
JJRI	0.3928	0.2479	57.87%	0.5356	0.2841	31.94%	0.4378	0.2593	49.59%
CIFI	0.6258	0.4413	31.02%	0.7485	0.6537	5.58%	0.6645	0.5083	21.19%
CRFI	0.8518	0.2100	19.83%	0.8619	0.3593	15.00%	0.8550	0.2571	17.62%
APFI	0.5757	0.1553	50.68%	0.6874	0.1688	28.74%	0.6109	0.1596	43.97%

Note: see note in Table 4.

main results of our portfolio management.

Table 5 shows the optimal portfolios' weights, hedge ratios, and hedging effectiveness between energy and nonenergy commodity markets at the short-term frequency bands. This table has some main takeaways: first, the optimal weights for different nonenergy commodities are pretty different. For example, the pre-COVID weight for NMBM is relatively high (0.6194), while the weight for JJRI is meager. In this case, we need to put 0.6194 units of assets in the NMBM and 0.3805 units in the energy commodity market. Second, we find that most pairs have a positive hedging ratio. That means we should take a short position in the nonenergy commodities but a long position in the energy commodity. For example, the pre COVID hedging ratio for NMBM is 0.2620, indicating we should take 0.2620 units long part in the energy commodity and 0.7380 units short position in the NMBM. Third, one can see that the HE index is positive in all cases, meaning that the portfolios are efficient in reducing the variance (risks), and this result is in line with Jiang et al. (2019a) and Mo et al. (2022). For example, the HE index for NMBM is 50.79%, which means the portfolios can decrease 50.79% of the total variance of the single energy commodity variance.

Finally, the COVID-19 can work on the hedging performance. On the one hand, after the COVID-19, the hedging performance measured by the HE index is worse relative to the case pre-COVID. For example, we see that the HE index for OOFI is 34.68% before COVID-19, but it is lower to 33.10% after COVID. This result is in line with Li and Meng (2022), who also show that the COVID-19 pandemic can change the hedging effectiveness in the energy stock markets. On the other hand, COVID can change the hedging ratio. For example, pre-COVID, the hedging ratio is negative for APFI, but it turns positive after COVID. A similar case can be found in CRFI.

Table 6 shows the optimal portfolios' weights, hedge ratios, and hedging effectiveness between energy and nonenergy commodity markets at the long-term frequency bands. The main results are very similar to the case in the short run. First, the weight for the nonenergy commodities is positive, implying that we need to have a portion of nonenergy commodities in the portfolio construction. For example, the weight for NMBM pre-COVID is 0.6118, and which means that we need to include 0.6118 units of NMBM in our portfolio. Second, it is revealed that the hedging ration β is positive in most cases which means we need to have a long position in the energy commodity. For example, the pre COVID hedging ratio is 0.2852 for NMBM. We should hold a long position in the energy commodity but 0.2852 units short position in NMBM. Third, the HE index is always positive, and it shows the portfolio is efficient, as in Meng et al. (2020). Fourth, the COVID-19 pandemic can change the hedging effectiveness, but it cannot reverse the ratio.

There are some interesting results when comparing the short and long run cases. The COVID pandemic has a different role in the hedging ratio. Even though COVID can reduce the hedging effectiveness in the short and long run, the hedging ratio is always positive, and COVID cannot reverse it. This result can complement the main development in Li and Meng (2022), where the hedging effectiveness is investigated with COVID. We further find that the HE index is smaller relative to the short-run portfolios in the long run. For example, the HE index for NMBM in the total sample is 49.09% in the short run, but it reduces to 39.17% in the long run.

6. Conclusions

This paper revisits the dynamic connectedness and portfolio management between China's energy and nonenergy commodities. To have a better evaluation, we address this question from the time-frequency domain, and daily data spanning from January 1st, 2017 to June 30th, 2021 are employed. Since the COVID-19 pandemic has caused extensive impacts on the financial markets, as in Bouri et al. (2021), we further document the effects of COVID on the dynamic spillovers.

We find the static evidence that the energy commodity is influenced by the spillovers of non-energy commodity markets in the short run. The static spillovers are more minor in the long run, and the energy commodity is less influenced by the nonenergy commodities, implying that the short-term connectedness dominates the long-term case. COVID-19 can impact the dynamic spillovers: first, the total spillovers increase a great deal; second, it can be observed that the spillovers pattern varies with the time-frequency domain during COVID-19. To be more specific, the energy commodity (ENFI) shows a net receiver role in the short and long run before the COVID-19 pandemic, but after it, the role of the net transmitter can be seen in the long run with ease. In addition, chemical commodities and soft commodities are the primary transmitters in this system in the short run, while chemical commodities and coal steel iron commodities are the main long-run primary transmitters. The portfolio results indicate that the portfolio between energy and non-energy commodities is efficient, as Meng et al. (2020). Even though COVID can reduce the hedging effectiveness in the short and long run, the hedging ratio is always positive, and COVID cannot reverse it in the long run.

Our empirical results highlight implications for both mineral policymakers and investors. From the policymakers' perspective, it is clear that the spillover transamination is dynamic and different from different time horizons. A wise mineral policy should be designed to consider all these situations to try to calm down the strong fluctuations of the spillovers to keep economic stability. On the other hand, since the commodities are necessary primary inputs for business and production, the product price and goods price may be sensitive to the wave of commodities prices. Policymakers need to consider the dynamic nexus between commodities to make suitable policies to reduce the price fluctuation. The comprehensive portfolio results can provide ample information for investors who target the commodities markets in China. In addition, COVID-19 can impact the relationship between energy and non-energy commodities through the time-frequency perspective, and it can also increase the total connectedness. Policymakers should make a note of this relationship. The comprehensive portfolio results can provide ample information for investors who target the commodities markets in China. First, it is beneficial for investors to construct portfolios by including energy and nonenergy commodities. Second, the results vary with the time-frequency domain. Investors need to adjust the portfolio design accordingly based on the dynamic connectedness results to reduce risks. Third, since the COVID-19 pandemic can influence the hedging performance, it is suggested that investors should have a detailed view of this type of extreme external event. In this paper, we target the Chinese commodities markets to examine the relationship between energy and nonenergy commodity markets. The potential future avenue is that we can try to incorporate the primary global commodities and regional commodities into our framework to show more complete results.

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.

Data availability

Data will be made available on request.

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