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# HIGH-FREQUENCY VOLATILITY CONNECTEDNESS AND TIME- FREQUENCY CORRELATION AMONG CHINESE STOCK AND MAJOR COMMODITY MARKETS AROUND COVID-19

## Abstract

This study examines the connectedness and time-frequency correlation of price volatility across the Chinese stock market and major commodity markets. This paper applies a DCC-GARCH-based volatility connectedness model and the cross-wavelet transform to examine the transmission of risk patterns in these markets before and during the COVID-19 outbreak, as well as the leading lag relationship and synergistic movements between different time domains. First, the findings of the DCC-GARCH connectedness model show dynamic total spillovers are stronger after the COVID-19 outbreak. Chinese stocks and corn have been net spillovers in the system throughout the sample period, but the Chinese market plays the role of a net receiver of volatility relative to other markets (net pairwise directional connectedness) in the system as a whole. In terms of wavelet results, there is some connection to the connectedness results, with all commodity markets, except soybeans and wheat, showing significant dependence on Chinese equities in the medium/long term following the COVID-19 outbreak. Secondly, the medium-to long-term frequency of the crude oil market and copper market are highly dependent on the Chinese stock market, especially after the COVID-19 outbreak. Meanwhile, the copper market is the main source of risk for the Chinese stock market, while the wheat market sends the least shocks to the Chinese stock market. The findings of this paper will have a direct impact on a number of important decisions made by investors and policymakers.

## Keywords

DCC-GARCH, time-varying connectedness, leading-lag relationship, wavelet transform, COVID-19, realized volatility spillovers

## JEL Classification

G10, G13, F21, F10

## INTRODUCTION

COVID-19's outbreak in early 2020 had a significant influence on global financial markets, which suffered their worst setback since 2008 (Priya et al., 2021). With the overall level of risk in the markets skyrocketing, investors' desire to hedge their bets has skyrocketed as well. The local Chinese stock market appeared to be at the center of the financial turbulence when COVID-19 first erupted in Wuhan, China. Simultaneously, this serious health crisis is regarded as a source of systemic risk. This paper is particularly concerned about the impact of China on commodities markets during this global healthy crisis, because China is the world's largest importer of agricultural products and crude oil and the world's top consumer of gold and copper (The Economic Times, 2021). Furthermore, China is the world's largest emerging market and ranks second in total GDP behind the United States (World Bank, 2022), demonstrating the country's prominence in the global economy. This is why it is crucial to look into the con-

nectedness between the volatility of Chinese stocks and the commodity markets, as well as asset allocation in risk management.

This paper accomplishes research goals by capturing information not seen in daily data by utilizing 5-minute high frequency data. And this paper will employ a DCC-GARCH-based volatility connectedness method, which has several advantages over a VAR-based volatility connectedness approach (Diebold and Yilmaz, 2012, 2014). First, no rolling window size is required; second, the conditional volatility transmission mechanism may be estimated using only one model. In addition, using wavelet methods, this paper finds correlations between multiple time and scale domains of the time series of the selected markets, as well as lead-lag relationships. Kristofek (2015) finds that the ability of the wavelet method to be able to distinguish between short-term and long-term relationships across different financial markets is the most important benefit, as the wavelet method gives an overall picture of the relationships between time series over the entire sample period.

In the post-COVID-19 period, a new global economic situation has taken shape, and the dynamics of linkages between financial markets have changed accordingly. It is also important to examine China's inter-linkages with major commodity markets due to its status as a key market for major global commodities and its importance to the world economy and supply chains. This provides more insight into how the COVID-19 pandemic will affect the economy. Academics and investment professionals who are interested in the financial effects of COVID-19 on the dynamic and volatile relationship between China's equity and commodity futures markets will find the results of this paper helpful in finding the markets that interact with each other, so they can diversify their portfolios and reduce investment risk.

## 1. LITERATURE REVIEW

Gold, precious metals, and agricultural commodities are among the most important commodity assets (Chen et al., 2022; Naeem et al., 2021; Živkov et al., 2021; Farid et al., 2021; Mokni et al., 2021; Yıldırım et al., 2020). While many previous studies have looked at the correlation between Chinese stock markets and commodity markets (Awartani et al., 2016; Luo and Ji, 2018; Al-Yahyaee et al., 2019; Cai et al., 2020; Huynh et al., 2020; Lahiani et al., 2021), some studies have found significant volatility pass-through among Chinese stock markets and commodity markets, such as oil, agricultural products, and precious metals (Raza et al., 2016; Shahzad et al., 2019; Zhang et al., 2020; Kang & Yoon, 2020; Farid et al., 2021; Chatziantoniou et al., 2022). However, none of these studies looked into high-frequency volatility interdependencies between assets across time horizons throughout the COVID-19 pandemic. Three factors are critical: First, the definition of COVID-19 financial crisis contagion is based on spillover effects and high-frequency correlations of realized volatility data (Chevallier, 2020; Cuñado Eizaguirre, 2021; Davidovic, 2021; Li, 2021). Due to the close economic linkages between China and commodity

markets, Chinese stock markets and commodity markets form crisis spillovers after the COVID-19 outbreak (Corbet et al., 2020; Li et al., 2021; Zhang et al., 2021; Choi, 2022; Derbali et al., 2022); Second, changing the time horizon affects volatility linkages, resulting in volatility interdependence that varies over time (Singh et al., 2010; Najeeb et al., 2015; Ferrer et al., 2016; Zhang et al., 2021); And finally, market heterogeneity makes shock propagation according to time scale difficult (el Alaoui et al., 2015; Maghyreh & Abdoh, 2022; Raddant & Kenett, 2021; Ferrer et al., 2021; Ayadi et al., 2021).

Several studies have documented some characteristics around the COVID-19 period's volatility spillover connections across Chinese stock and commodity markets. Wen et al. (2021) examine volatility spillovers among Chinese equities and commodities markets during the COVID-19 period, finding that stock market spillovers to commodity markets have increased dramatically since COVID-19's outbreak. The findings of Dai and Zhu (2022) explore the volatility spillovers and dynamics among WTI crude oil, natural gas, and BRI-related Chinese equity markets, and they imply that the assets studied are highly interdependent and that the COVID-19 outbreak

enhanced the risk of contagion impact. Shahzad et al. (2021) examine the stock market sectors of China during COVID-19 using 1-minute data from 2019 to 2020, concluding that a catastrophic COVID-19 event has a great and asymmetric impact on the volatility spillover network between sector indices, and that the energy sector should be monitored for the Chinese stock market's stability. The risk transmission between the Chinese stock market and commodity markets is investigated by Ding et al. (2021). Their findings show that different commodities markets react to stock market shocks in different ways, which might help policymakers better understand the consequences of policy transmission in China, given risk spillover channels and risk impact persistence mechanisms. Using DY and BK models, He et al. (2020) analyze the return and volatility dynamics of Chinese and US stock markets, as well as three commodities markets (natural gas, crude oil, and gold). Spillover dynamics in terms of time and frequency. First, crude oil has a net positive return spillover to the Chinese stock market in terms of time-domain outcomes, but gold has a net negative return spillover. The bulk of return spillovers occur in the short run in the frequency domain, whereas the majority of volatility spillovers occur in the long run. Using the DY approach of spillover indices, Mensi et al. (2021) investigate asymmetric return spillovers between crude oil futures, gold futures, and eleven sectors of the Chinese stock market. They claim that the spillover effect of all sectors on gold is nearly identical to the spillover effect on the oil market during the financial crisis, despite the fact that the spillover effect of oil on sectors is greatest during the financial crisis. During COVID-19, there was a stronger relationship between commodities and the Chinese stock market. Rather than returns, this paper focuses on the high frequency volatility analysis of commodities and the Chinese stock market in this study.

## 2. METHODS

### 2.1. DCC-GARCH connectedness approach

First, this paper will introduce the DCC-GARCH connectedness method introduced by Gabauer (2020a) and based on the VIRF, which repre-

sents the effect of a shock to variable  $i$  on the conditional volatility of variable  $j$ . The VIRF can be specified as:

$$\begin{aligned}\varnothing^g &= \text{VIRF}(J, \delta_{j,t}, F_{t-1}) = \\ &= E(H_{t+J} | \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - \\ &- E(H_{t+J} | \varepsilon_{j,t} = 0, F_{t-1}),\end{aligned}\quad (1)$$

where  $\delta_{j,t}$  is a selection vector with one at the  $j_{th}$  position, and zero otherwise.

Then, this paper will apply the DCC-GARCH model for conditional variance-covariance forecasting, a step that is a key step in calculating the VIRF.

Then this paper focused on calculating the generalized forecast error variance decomposition (GFEVD) on a VIRF basis. This means that all variables together explain 100% of the forecast error variance of variable  $i$ . The normalized variance share is calculated by the following equation:

$$\phi_{ij,t}^g(J) = \frac{\sum_{t=1}^{J-1} \varnothing_{ij,t}^{2,g}}{\sum_{j=1}^N \sum_{t=1}^{J-1} \varnothing_{ij,t}^{2,g}}, \quad (2)$$

where  $\sum_{j=1}^N \phi_{ij,t}^g(J) = 1$  and  $\sum_{i,j=1}^N \phi_{ij,t}^g(J) = N$ . The numerator indicates the cumulative effect of the  $i_{th}$  shock, while the denominator represents the cumulative effect of all shocks.

By using the GFEVD, the *total connectedness index* (TCI) can be constructed and the spillover from variable “ $i$ ” to variable “ $j$ ” (total directional connectedness) can be obtained by using the following equation:

$$C_i^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \phi_{ij,t}^g(J)}{N}. \quad (3)$$

In the next step, the total directional connectedness TO others from other variables is calculated by the following equation:

$$C_{i \rightarrow j,t}^g(J) = \frac{\sum_{j=1, i \neq j}^N \phi_{ji,t}^g(J)}{\sum_{j=1}^N \phi_{ji,t}^g(J)}. \quad (4)$$

Estimating the difference among the above two measures gives the NET directional connected-

ness, which can be interpreted as the effect of the influence variable  $i$  on the analysis network:

$$C_{i,t}^g = C_{i \rightarrow j,t}^g(J) - C_{i \leftarrow j,t}^g(J). \quad (5)$$

A positive (negative) net total directional connect-  
edness  $i$  of a variable, means that the variable  $i$  is a  
net transmitter (receiver) of shocks.

## 2.2. Wavelet analysis

Torrence and Compo (1998) proposed the fol-  
lowing equation for the cross wavelet spectrum  
of two-time series. The cross wavelet spectrums  
 $W_x(\tau, s)$  and  $W_y^*(\tau, s)$  of the continuous wave-  
let transform of the sum of two time series are as  
follows:

$$W_{x,y}(\tau, s) = W_x(\tau, s)W_y^*(\tau, s), \quad (6)$$

where  $\tau$  is the position parameter and  $s$  indicates  
the frequency parameter. The symbol  $*$  represents  
the complex conjugate of  $W_y^*(\tau, s)$ .

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{xy}(\tau, s))|^2}{S(s^{-1}|W_x(\tau, s)|^2)S(s^{-1}|W_y(\tau, s)|^2)}, \quad (7)$$

where  $S$  is represented as a temporal and scale  
smoothing operator,  $0 \leq R^2(u, s) \leq 1$ . Using a  
graphical representation based on wavelet squared  
coherence, this paper can recognize the simulta-  
neous motion of the two series in the frequen-  
cy and time domains. If the measured wavelet  
squared coherence is close to 1, the two series are  
more reliant on one another, and vice versa. In  
comparison to the standard correlation coefficient,  
the wavelet squared coherence contains only posi-  
tive values. In this situation, this paper cannot  
tell the difference between positive and negative  
correlations. To overcome this issue, Torrence and  
Webster (1999) proposed the wavelet coherence  
phase difference shown below:

$$\theta_{xy}(\tau, s) = \tan^{-1} \left( \frac{I \{ S(s^{-1}W_{xy}(\tau, s)) \}}{t \{ S(s^{-1}W_{xy}(\tau, s)) \}} \right), \quad (8)$$

where  $t$  and  $I$  indicate both actual and imagined  
elements, the phase difference is indicated by the  
black arrows in the wavelet coherence diagram.

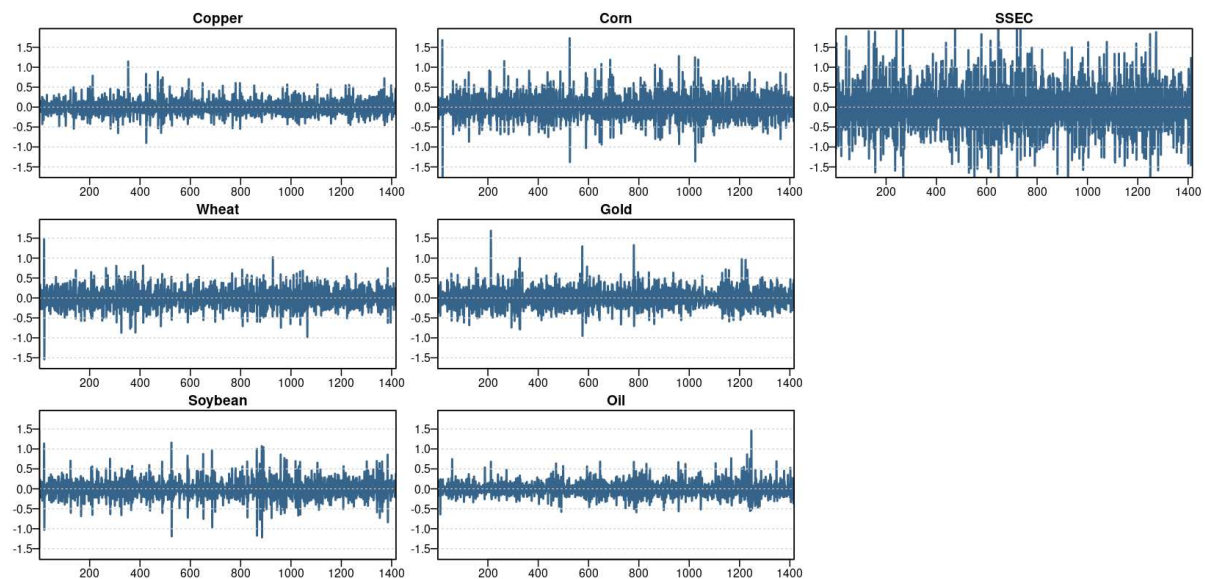
The two series are connected with each other at  
a specific frequency when they have a zero phase  
difference.

This paper uses realized volatility data from the  
Chinese stock market and the major commodity  
futures markets (soybeans, gold, corn, wheat, cop-  
per, crude oil) for the period from November 22,  
2011 to June 18, 2021. For each market data, the  
RV calculation technique utilized in this study is  
based on a 5-minute sampling frequency inter-  
val, which strikes a reasonable balance among ac-  
curate estimation and microstructural noise. To  
investigate COVID-19 shocks, this paper divides  
the sample into two sub-periods: the first sub-pe-  
riod has an interval from November 22, 2011 to  
January 22, 2020, representing the period before  
the COVID-19 outbreak, and the second sub-pe-  
riod has an interval from January 23, 2020 to  
June 18, 2021, corresponding to the period after  
the COVID-19 outbreak. This paper considers  
January 23, 2020, the first day of the COVID-19  
outbreak, which was the day the first major pre-  
vention and control measure against COVID-19  
occurred: the closure of Wuhan (Zeng and Lu,  
2022). All data is from the Thompson Reuter Tick  
History database. Following ABDL (i.e., Andersen  
et al., 2003), this paper considers the logarithm of  
the RV,  $R_t = 100 \cdot \ln(P_t / P_{t-1})$ , and  $P_t$  is the RV  
data at time  $t$ .

## 3. RESULTS

Figure 1 presents the logarithmic volatility of the  
RVs of the Chinese stock and the commodity mar-  
kets, and this paper can see that the volatility level  
of the Chinese stock market is significantly greater  
than that of the other markets. Based on the val-  
ues of the skewness and kurtosis statistics in Table  
1, the volatilities series for all markets are asym-  
metric and spiky, and the Jarque-Bera statistical  
test proves that the original hypothesis of a normal  
distribution is rejected for all markets. In summa-  
ry, the volatilities series for all markets has peaked,  
with high peaks and fat tails. The Ljung-Box Q sta-  
tistic for testing serial autocorrelation indicates that  
all variables have an autocorrelation feature when  
the return series of all variables are lagged by or-  
der 10. The ERS test statistic for the volatilities se-  
ries for all markets is significant, indicating that the





**Figure 1.** Time series plots of seven markets

**Table 1.** Descriptive statistics

Indicators Variables	Oil	Soybean	Wheat	Gold	Corn	Copper	SSEC
Mean	-0.006	0.041	0.028	-0.012	0.033	0.000	-0.025
Variance	345.264	591.196	603.371	629.216	1009.839	358.11	4040.76
Skewness	0.765	0.121	0.050	0.575	0.316	0.498	0.172
Kurtosis	7.213	6.452	5.579	5.731	6.141	5.713	4.643
JB	1186.336***	707.035***	393.217***	518.664***	606.265***	493.123***	166.411***
ERS	-12.413***	-23.990***	-7.435***	-8.442***	-8.592***	-11.405***	-23.186***
Q(10)	139.883***	264.518***	280.178***	219.395***	285.999***	167.754***	219.507***
Q <sup>2</sup> (10)	42.099***	218.427***	182.882***	47.545***	197.447***	77.228***	93.244***
ARCH-LM	55.146***	287.61***	236.83***	47.873***	260.86***	93.92***	95.27***

*Note:* JB = Jarque-Bera test, ARCH-LM is test for autoregressive conditional heteroskedasticity, calculated using 20 lags. ERS is a corrected ADF test for unit roots, testing the smoothness of the series. Ljung-Box Q tests for serial autocorrelation. \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% level, respectively.

return series for all markets is smooth. Finally, to verify the applicability of the DCC-GARCH model to the data, an ARCH effect test was conducted on the sample using LM, and the results showed the existence of conditional heteroskedasticity in the residuals of the sample series. The presence of an asymmetric distribution together with the ARCH effect strongly suggests that a GARCH-type model is suitable for modelling the sample data. In the next part, this paper reports the results of the DCC-GARCH connectedness approach.

The results of the static volatility spillover for the DCC-GARCH volatility connectedness model are presented in Table 2. Table 2 demonstrates that prior to the COVID-19 pandemic, the total connectedness index (TCI) was 25.28 %, while the

volatility connectedness index climbed to 28.43% during the pandemic. This means that in this paper's sample, spillovers account for 25.28% and 28.43% of the volatility projection error variation for all markets. This means that the Chinese stock market and the major commodity markets are moderately intertwined. Furthermore, prior to the COVID-19 epidemic, the maize market, followed by the Chinese stock market and wheat, was the highest contributor to overall system volatility. The crude oil market, on the other hand, made the least contribution to the system's volatility spillover. Following the COVID-19 outbreak, however, the maize market, followed by the Chinese stock market and the gold market, was once again the largest contributor to the overall volatility spillover in the system. This paper emphasizes the fact that before

**Table 2.** DCC-GARCH connectedness index

	Oil	Soybean	Wheat	Gold	Corn	Copper	SSEC	FROM
<b>Panel A. Before COVID-19</b>								
Oil	78.32	0.41	0.29	5.37	1.22	7.13	7.27	21.68
Soybean	0.32	44.52	13.71	1.16	37.68	0.99	1.61	55.48
Wheat	0.19	13.04	48.93	0.96	35.21	0.78	0.89	51.07
Gold	5.86	1.40	1.31	76.52	2.80	7.32	4.78	23.48
Corn	0.06	2.04	1.96	0.13	95.00	0.57	0.24	5.00
Copper	3.09	0.51	0.43	2.92	5.28	79.91	7.87	20.09
SSEC	0.03	0.01	0.01	0.02	0.02	0.06	99.86	0.14
Contribution TO others	9.54	17.42	17.70	10.56	82.21	16.85	22.66	176.94
NET directional connectedness	-12.13	-38.06	-33.37	-12.92	77.20	-3.24	22.52	TCI
NPDC transmitter	5.00	4.00	3.00	6.00	1.00	2.00	0.00	25.28%
<b>Panel B. During COVID-19</b>								
Oil	76.88	1.34	1.85	9.90	3.05	3.10	3.88	23.12
Soybean	3.63	48.72	9.64	1.86	27.39	2.18	6.58	51.28
Wheat	1.06	2.24	61.71	1.08	32.87	0.25	0.77	38.29
Gold	5.31	0.42	1.04	86.36	4.65	1.59	0.63	13.64
Corn	0.61	2.06	10.81	1.58	83.86	0.19	0.90	16.14
Copper	13.51	3.69	1.85	12.70	4.21	45.53	18.49	54.47
SSEC	0.44	0.32	0.13	0.10	0.53	0.54	97.94	2.06
Contribution TO others	24.57	10.07	25.33	27.21	72.70	7.85	31.25	198.99
NET directional connectedness	1.45	-41.20	-12.96	13.57	56.56	-46.61	29.19	TCI
NPDC transmitter	4.00	5.00	3.00	2.00	1.00	6.00	0.00	28.43%

Note: The results based on 100-day-ahead forecasts horizon from the DCC-GARCH models from Gabauer (2020b).

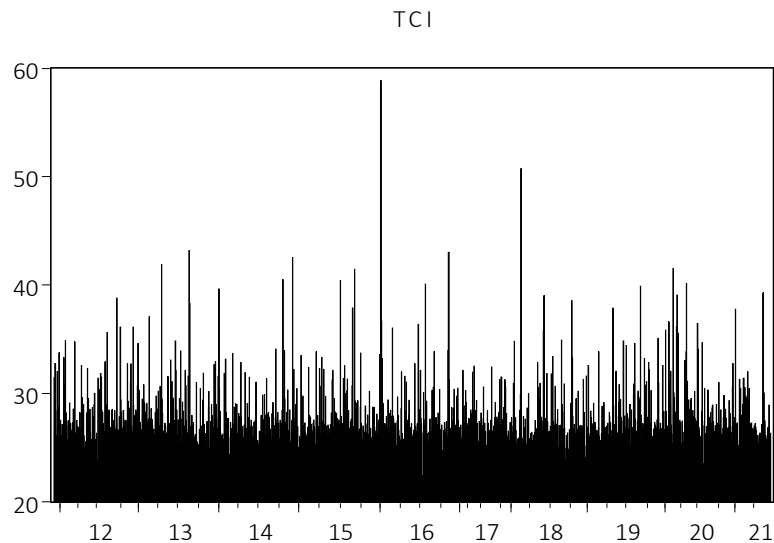
the COVID-19 outbreak, the Chinese stock market received 0.14% of the system's volatility spillover and 2.06% after the COVID-19 outbreak. This indicates that the interconnection of the investigated markets is stronger after the COVID-19 outbreak than before the outbreak, and that the volatility connectedness structure has altered.

Furthermore, through the sample period, this paper evaluates the time-varying behavior of total volatility connectedness. The cyclical movements and variations in volatility connectedness that cannot be anticipated from the Table 2 results are taken into account. Figure 2 depicts the dynamic connectedness index's time-varying swings, as well as the large jump in volatility connectedness, which ranges from 20%+ at the start of 2016 to close to 60% in mid-2015. More crucially, during the early stages of the COVID-19 epidemic, overall connectedness reached a nadir of 20%+ at the start of 2016, coinciding with a slowdown in Chinese economic fundamentals. Cyclical movements and connectedness erupted in response to the start of financial crises or policy shocks that resulted in market volatility. For the Chinese stock market crash in mid-2015, the Chinese stock market meltdown in early 2016, the Fed rate hike in

2017, and the outbreak of COVID-19 in 2020, this paper finds high volatility in the strength of current volatility contagion and total volatility connectedness indices.

This paper initially gives the net connectedness data for all markets across the sample period in order to determine whether markets are net transmitters or net recipients of spillover during the sample period. Figure 3 illustrates this. Positive numbers represent shocks' net pass-through, whereas negative values represent shocks' net receipts.

In most circumstances, the maize market and the Chinese stock market are net transmitters of volatility shocks in the system, as seen in Figure 3. Furthermore, for the majority of the time in the sample, the soybean, wheat, and copper markets are net recipients of volatility shocks in the system. On the other hand, the crude oil and gold markets play significant net receptive roles over the sample period, with some of these times acting as net transmitters in the system in the short term. The fact that the crude oil market has a definite peak after 1200 days, reaching a maximum level of roughly 10% or more during the COVID-19 period, is very noteworthy.



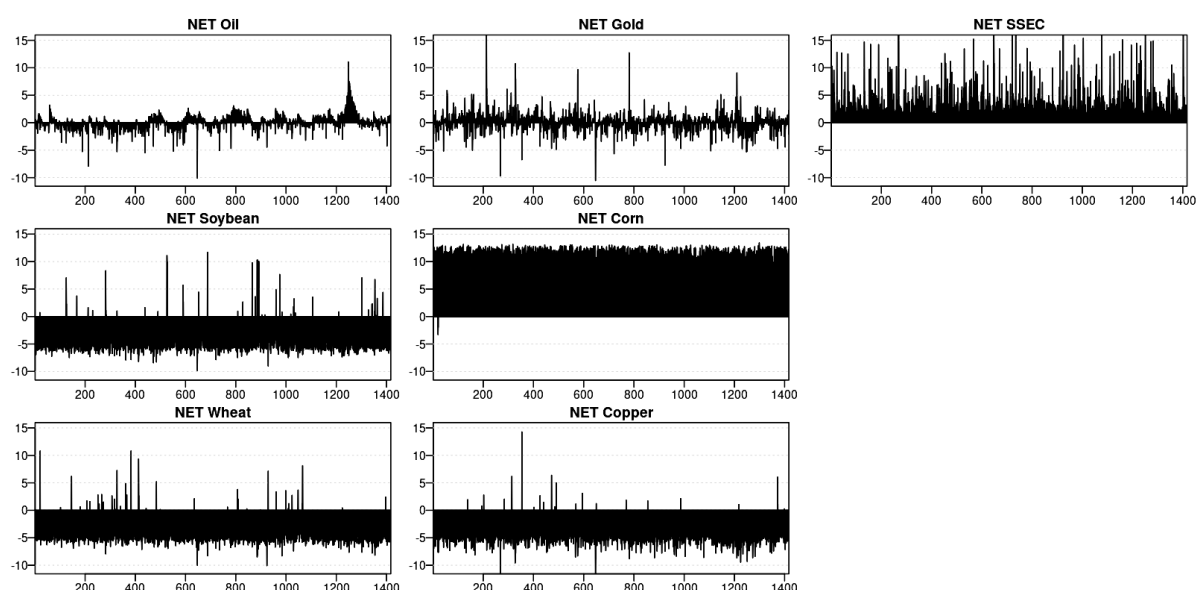
**Figure 2.** Dynamic total connectedness

To verify these findings, this paper looks at the net pairwise connectedness of the Chinese stock market to the key commodities futures markets in Figure 4 to see what role the Chinese market plays in the broader system compared to another.

The net pairwise directional connectedness from several commodities to the Chinese equity market is depicted in Figure 4. Throughout the sample period, the Chinese stock market was clearly a net recipient of volatility shocks in the net pairwise spillover portfolios of the major commodities futures markets. This paper found similar results to those found by Wen et al. (2021). This paper identi-

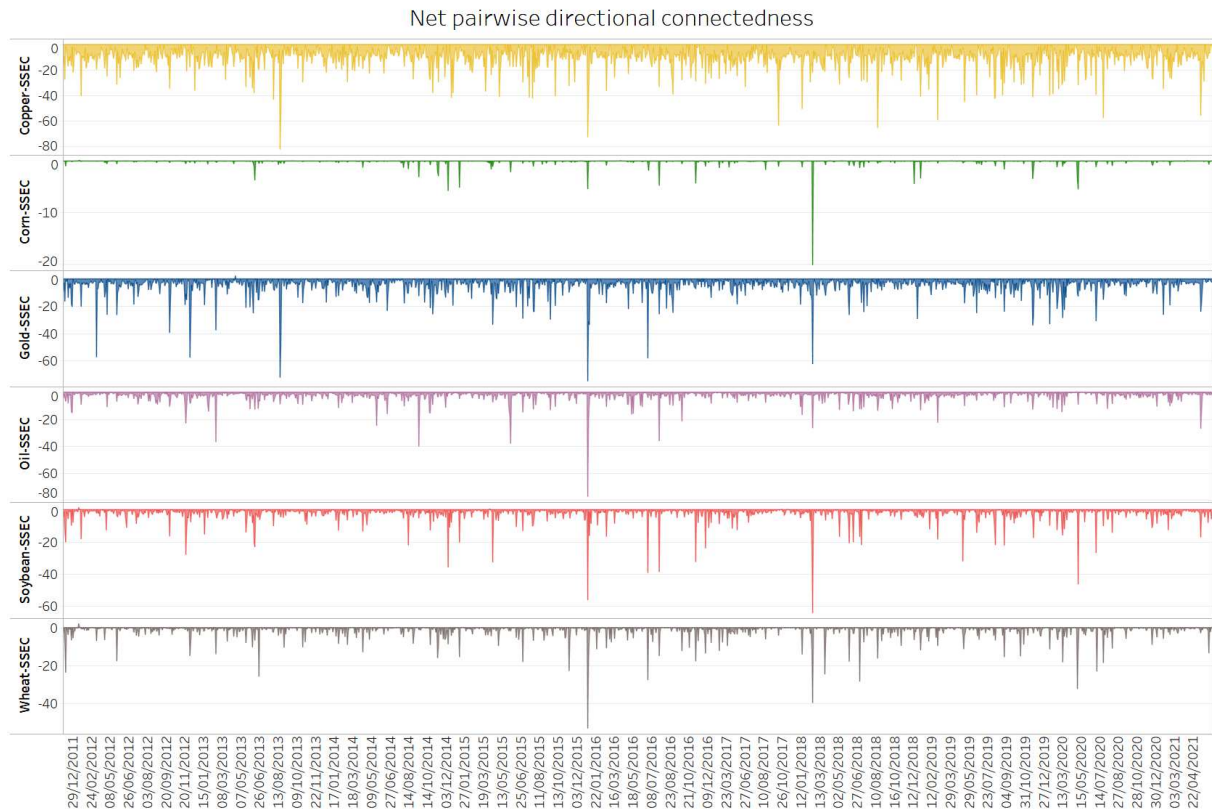
fies some notable spikes that are closely associated with market turbulence, such as the Chinese stock market meltdown in 2015, the US-China trade war in 2018 (especially for agricultural futures markets), and the COVID-19 pandemic in 2020.

In the meantime, this paper focuses on the values of spillovers on the left-hand side of Figure 4. This paper can note that the copper and crude oil markets have the strongest positive spillover influence on the Chinese equity market in the pairwise connectedness combination before the COVID-19 epidemic over the whole sample period. Furthermore, when combined with Table



**Figure 3.** Net directional connectedness





**Figure 4.** Net pairwise directional connectedness

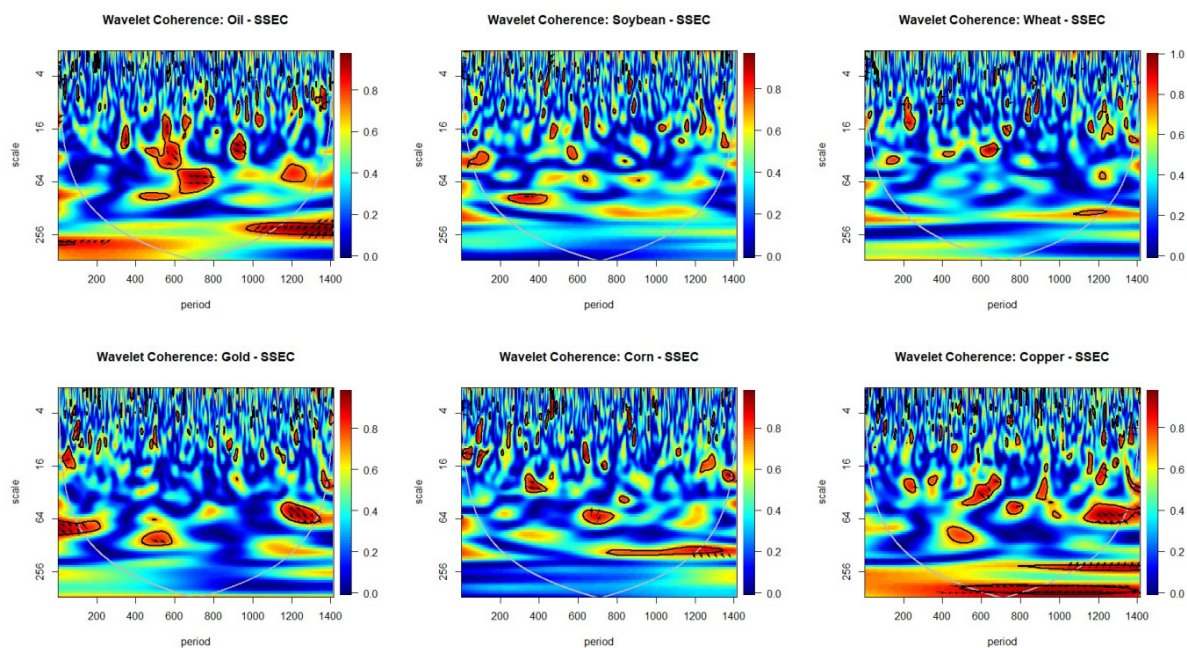
2, this paper find that the copper and crude oil markets were the strongest positive spillovers to the Chinese market in the paired spillover portfolio before the COVID-19 epidemic, followed by gold; while after the COVID-19, the copper market stayed the strongest positive spillover to the Chinese stock market and increased sharply (22.52% to 29.19%), while crude oil was replaced by soybeans. Undeniably, the role of the gold market as a major origin of transmission and spillover to the Chinese stock market was significantly weakened after the COVID-19 outbreak.

The results of dynamic connectedness demonstrate that the transmission of net pairing spillovers among the Chinese stock and commodity markets and how the volatilities change over time. And the results of the wavelet analysis are reported in the following section.

In Figure 5, to accurately describe the dependency structure between major commodity markets and the Chinese stock market, this paper uses wavelet coherence to explore the co-movement of different commodity markets and the Chinese

stock market in the time-frequency domain. The blue color in the graph indicates a weak dependence among commodity and stock markets, while the red color indicates high dependence. The short-term frequency domain is defined by a minimum scale ranging from 4 to 16 days, the medium term is defined as a medium scale of 16-64 days; and the long term is defined as a scale of 64-256 days. The horizontal coordinates are the time domain intervals of the samples, defined as 200, 400, 600, 800, 1000, 1200, and 1400 days, corresponding to the dates 13/03/2013, 18/06/2014, 01/09/2015, 16/12/2016, 07/08/2018, 04/12/2019, and 11/05/2021. As shown in the figure, the ( $\rightarrow$ ) arrow shows that the two variables in the returns are correlated in-phase, while ( $\leftarrow$ ) indicates that the two variables are linked in-phase. Also, ( $\nearrow$ ) = the former variable leads; ( $\searrow$ ) = the latter variable leads; ( $\nwarrow$ ) = the latter variable leads; ( $\swarrow$ ) = the former variable leads.

The results for wavelet coherence are shown in Figure 5. For both oil and SSEC, this paper explores that the correlation is strongest in the medium-term frequency domain (16-64 days)



**Figure 5.** The wavelet coherency between major commodity and Chinese stock markets

and in the sample interval 400-800 days (i.e., 18 June 2014 to 16 December 2016), where the crude oil market and the Chinese stock market have a significant correlation and the Chinese stock market leads the crude oil market (bottom right of the arrow). This is linked to the Chinese stock market crash in mid-2015 and the Chinese stock market meltdown in early 2016. The findings of this paper also show that the Chinese stock market's volatility has spread to the crude oil market in the medium run. Furthermore, the crude oil market and the Chinese stock market show a constant high level of reliance at long-term frequencies (64-256 days) starting around August 7, 2018, and especially after the COVID-19 outbreak, and the crude oil market volatilities lead the Chinese stock market volatilities (arrow top right).

Next, for soybean and SSEC, there is a significant in phase connection among the soybean and the Chinese equity market in the medium-to long-term frequency domain (64-256 days) and in the sample interval 200-400 days (time domain). This paper believes that the possible reason for this is that the global economic fundamentals were in decline or in turmoil during the period of rising world soybean prices (Oladosu & Msangi, 2013) due to the lower yield expectations caused by the South American

drought and the mid-year US drought, which led to a spike in soybean volatilities, thus triggering the co-movement of the two markets.

For wheat and SSEC, this paper finds a short-lived linkage in the short-term frequency domain of 4-16 days and a sample interval of 200-400 days (time domain) with the arrow on the left, demonstrating that Chinese stock market volatilities are ahead of wheat market returns. This is due to the increase in Chinese imports of US wheat as a result of the growth in China's domestic wheat demand, with wheat price volatility following Chinese stock market movements in the short term. In contrast, after the outbreak of COVID-19, this paper observes that the dependent between wheat and the Chinese stock market was not significant.

For gold and SSEC, this paper finds a significant correlation over the medium- to long-term frequency domain of 64-256 days and a sample interval of 0-200 days (time domain), and the upper left of the arrow illustrates that Chinese stock market volatilities lead gold market returns until around 13/03/2013, which this paper considers meaningfully due to the Fed rate hike causing gold prices to plummet during this period. This is partly because the safe-haven value of gold stimulates investor demand to buy gold in times of market uncertain-

ty; and partly because China is the world's largest market for gold, and the fall in the volatilities of gold has led to a significant increase in demand from the Chinese gold market consumer market. Simultaneously, this paper finds that in the same frequency domain, after the COVID-19 outbreak, i.e., around 1200 days (time domain), there is again a clear linkage between Chinese stock market and gold market returns, and the bottom right of the arrow indicates that Chinese stock market returns lead gold market volatilities. This implies that during COVID-19, investors could rely on positive volatilities in the gold market to compensate for losses in the Chinese stock market.

For corn and SSEC, this paper discovers a significant linkage between the two in the medium and long-term frequency domain of 64-256 days and the sample interval of 800-1400 days (time domain), with the lower right arrow indicating that Chinese stock market volatilities lead the corn market. This paper's analysis of possible reasons for this is that the US-China trade war affected corn prices as China is an important buyer of US corn and, during the trade war, China increased tariffs on bulk agricultural products imported from the US (Lee & Westhoff, 2020). However, following the outbreak of COVID-19, this paper observes that Chinese equities outperformed corn market volatilities in the long-term frequency domain (64-256 days), which was associated with an increase in sown area and an easing of supply and demand in the corn market.

For copper and SSEC, this paper can find a significant linkage in the medium-term frequency domain of 16-256 days, with a sample interval of 1200-1400 days (time domain), and the lower right of the arrow illustrates that Chinese stock market volatilities lead copper market volatilities. Within the same time domain, a significant linkage occurs in the frequency domain after 256 days, and the arrow points upwards to the right, indicating that copper market returns are ahead of Chinese stock market returns. This paper also finds a strong linkage between the copper and Chinese equity markets after 256 days in the same sample interval and frequency domain, which establishes a link with the previous volatility contingency results. The arrow is on the left, indicating that Chinese stock market returns are ahead of the

copper market. This paper attempts to further explain the possible reason for this based on the results of the cross-wavelet transform, which is the supply and demand in the copper market that led to a shortage of copper after the COVID-19 outbreak, which allowed the price of copper to surge. In the aftermath of the COVID-19 outbreak, and China's being the world's largest producer, trader, and consumer of copper, the relationship among the Chinese stock market and copper futures volatilities in the aftermath of the frequency lead was affected as supply and demand in the Chinese copper-related and consumer markets differed across time scales, as well as generating different market expectations.

## 4. DISCUSSION

The results on volatility connectedness suggest that the dependence between Chinese stock markets and commodity markets grew after the COVID-19 outbreak and that there exists a significant degree of correlation between Chinese stock markets and specific commodity markets. In general, the Chinese stock and corn markets are net senders of volatility shocks. The different commodity markets behave in roughly the same way as the Chinese stock market on the net pairwise spillover, with the Chinese stock market being a net recipient of volatility shocks on the net pair spillover throughout the sample period. Prior to the outbreak of COVID-19, copper had the highest spillover strength among Chinese stocks, followed by crude oil. And crude oil was replaced by soybeans after the COVID-19 outbreak. Therefore, it is important to keep an eye on the impact on the Chinese stock market when commodity market prices experience shocks after a major health crisis. The dynamic total volatility connectedness indicates that the degree of aggregate volatility spillover varies across time. Overall, the occurrence of main economic disasters and political catastrophes tends to raise the total volatility connectedness index, such as the Chinese stock market meltdown and the US-China trade war prior to the COVID-19 health crisis. In addition, the gold's ability to hedge Chinese stock market risk was significantly reduced after the COVID-19 outbreak.

The results on the cross wavelet transform revealed that the copper and crude oil markets exhibited higher correlations with the Chinese stock market throughout the sample period, particularly in the medium and long-term frequencies. In contrast, no significant correlations were observed for the soybean and wheat markets. In the case of gold and corn markets, the dependence on the Chinese stock market is weaker in the short term, but increases in the medium and long term. In particular, the Chinese stock market leads them in the medium and long term after the COVID-19 outbreak. Finally, at the end of the sample period (specifically from January 2020 onwards), the medium/long-term integration of the Chinese stock market with most commodity markets increases significantly, highlighting the dependence characteristics of the Chinese stock market with most commodity market returns during the 2019 coronavirus pandemic.

This paper goes on to explain the possible reasons for the results, China's current demand for copper is increasing, and in addition, non-ferrous metal futures, such as copper futures, are now developing very rapidly, with many domestic copper spot companies in China participating in hedging in the commodities market. Therefore, the copper market is increased transmission effects and linkages to the Chinese stock market (Wen et al., 2021). According to Su et al. (2021), the crude oil market also has a greater impact on the Chinese stock market in the aftermath of the epidemic, due to China's

status as the largest importer of crude oil. But the Chinese government can also use crude oil reserves or regulatory instruments to mitigate the shock of international oil prices during the crisis. Possible reasons for the spike in soybean market spillover to the Chinese stock market following the COVID-19 outbreak are China's high import dependence on soybeans as the world's largest soybean importer, as well as short-term supply constraints triggered by the epidemic, such as measures to restrict traffic and movement in soybean exporting regions as the epidemic develops, combined with a delayed harvest in the main soybean-producing regions. These factors have impacted the Chinese stock market through downstream industries and market fears.

This paper's findings suggest that, during a pandemic, the risk of investing in the Chinese market rises due to increased volatility interdependence, but that the corn market retains its role as a volatility contributor. Based on this paper's results of leading-lag correlations between the key commodity markets in the Chinese stock market in different time and frequency domains, investors can construct value-investing strategies based on risk appetite to effectively hedge against financial risks caused by the pandemic. Furthermore, recent research that revealed weak correlation qualities between commodities markets or among commodity markets and stock markets during the epidemic has been confirmed by this paper's results (Mensi et al., 2021).

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## CONCLUSION

The results of dynamic connectedness demonstrate that the volatility of Chinese equities and the major commodity indices is highly correlated. And the results of the cross wavelet transform revealed that the copper and crude oil markets exhibited higher correlations with the Chinese stock market throughout the sample period, particularly in the medium and long-term frequencies. In particular, the Chinese stock market leads them in the medium and long term after the COVID-19 outbreak.

In conclusion, by considering the spillovers among these markets, investors can improve their investment strategies in extreme events. Furthermore, analysis of the different frequencies suggests that investors are more likely to achieve optimal volatilities over the medium and long term. This research will also provide useful information to assist policymakers in the development of alternative futures contracts to reduce the influence of major commodities markets on the Chinese stock market.



## AUTHOR CONTRIBUTIONS

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