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Relationship Assessment of COVID-19, Air Pollution, and Copper Demand from the Perspective of Copper Price

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Abstract: Copper in the international market has been priced by copper futures contracts from the London Metal Exchange (LME) and the New York Commodity Exchange (COMEX). Copper prices initially showed a downward trend until March 2020, but after the outbreak of COVID-19, they continued to rise and reached a record high in May 2021. The rise in copper demand also stimulated the continuous growth of copper production. However, a significant amount of smelting flue gas is produced in the copper smelting process. The main component of the flue gas is SO_2 and other acid gases, which pollute the environmental atmosphere. At the same time, due to the Chinese government's effective control of the pandemic, China's economy continued to grow. Therefore, as one of the world's largest copper consumers and producers, China's futures market has attracted attention for its influence on copper pricing and the pollution caused by copper smelting. In this paper, we used the grey entropy method to compare the influence of copper prices on the three futures markets and changes in China's air pollution in recent years. Our results show that before the pandemic, the influence of the LME futures copper price was the same as the COMEX but greater than the Shanghai Futures Exchange (SHFE). After the outbreak of the pandemic, the influence of the SHFE copper futures price significantly improved and slightly exceeded the LME and COMEX. This result echoes our finding that SO_2 has caused serious air pollution in recent years.

Keywords: copper prices; COVID-19; copper demand; grey entropy; SO_2

MSC: 91B76; 91G20

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Citation: Guo, R.; Hung, C.-C.; Lin, Z.-H.; Chen, W.-T. Relationship Assessment of COVID-19, Air Pollution, and Copper Demand from the Perspective of Copper Price. *Axioms* **2022**, *11*, 713. https://doi.org/10.3390/axioms11120713

Academic Editor: Palle E.T. Jorgensen

Received: 3 November 2022
Accepted: 7 December 2022
Published: 9 December 2022

1. Introduction

The price of copper has risen since March 2020 and set a new historical record of USD 10,747.5 per ton in May 2021. Due to the continued slowdown of global economic growth, increased geopolitical uncertainty, and many other factors, the consumption demand for copper is weak in major regions and countries worldwide. The international copper price has also fallen recently. The global copper income was about USD 248.78 billion in 2021 and is expected to reach USD 347.28 billion in 2028. In 2021, the market share of copper in the Asia–Pacific region was rated first in the world at over 37%, followed by North America and Europe. China is the world's largest copper consumer, accounting for over half of global copper consumption. However, copper prices are not set by contracts in the Chinese futures market. They are determined by contracts from the London Metal Exchange (LME) and the New York Commodity Exchange (COMEX). With the continued growth of China's copper demand and improvements to the futures market, whether the copper price of the Shanghai Futures Exchange becomes an international standard may be China's key to improving its position as a commodity pricing power.

Almost all commodities form a pricing centre in the international market, and the futures price determines the benchmark of international trade pricing. Issues related to the pricing power of bulk commodities, such as copper, crude oil, iron ore, and soybeans, have attracted attention from the Chinese government and relevant departments for their extensive impact. The United States has used its central position in the international futures market to dominate the pricing power of commodities for a long time, and China has been in a passive position to accept these prices [1–3]. To change this situation, China has developed many policies and studies on improving commodity pricing power. Some studies have focused on the international impact of China's futures market [4], the commodity price impact mechanism [5], and determining international pricing power [6]. These studies eventually tend to form a stable commodity market.

Since the COVID-19 pandemic at the beginning of 2020, the fluctuation of the commodity market and the pricing power of the international futures market have weakened. Due to the Chinese government's effective control of the pandemic, China's economy has grown rapidly and generated a huge market demand, further establishing the irreplaceable position of 'Chinese demand' in the international market of bulk commodities. Some scholars believe that "Chinese demand" is the main reason for the increase in commodity prices in the 21st century [7–9]. Nevertheless, the upward price trend will inevitably lead to a greater increase in copper production. As a result, the flue gas produced by copper smelting may also bring about air pollution.

Therefore, in this study, we used the grey entropy method to test the pricing power influence on copper. We aimed to analyse the influence of the COVID-19 outbreak on the pricing process of copper and the change in SO_2 air pollution to determine whether the rise in copper price and production aggravates air pollution. This study is important for researching commodity pricing power and finding a new entry point for air pollution control.

2. Literature Review

2.1. Research on Copper Futures Price

Some scholars have used a grey correlation analysis and ripple analysis to study the fluctuation characteristics of copper futures and spot prices according to scale. They concluded that copper futures and spot prices are highly correlated and dynamic. Shanghai futures can be a haven in the mid and short terms, whereas New York and London futures can be a long-term haven [10,11]. There is an equilibrium relationship between the New York and Shanghai markets. China is closely related to the copper futures market in the United States. The two markets are more effective on a daily basis [12]. However, the copper spot market is inefficient and cannot provide an unbiased estimate of the future price of copper [13,14]. Some scholars have used nonlinear Granger causality and multifractal methods to study the nonlinear correlation between spot and futures prices in China's copper market. They also analysed the dynamic efficiency of China's copper futures market and concluded that its efficiency gradually improved over time [15]. The spot price can be predicted using the futures price and expected survey [16]. The futures price of copper reflects the expected price in a certain procedure, leading to changes in the spot price. Vigorously developing the futures market improves the price power of bulk commodities [17,18]. Copper's expected price change will impact relevant industries, such as construction, electricity, electronics, and manufacturing. Economic development is highly dependent on copper for many economies [19–21]. Some major macroeconomic events, such as Brexit, have also impacted the price fluctuation of copper futures. At the same time, the price structure of copper futures can be used for trading in adverse market environments. The expected copper price can be used as a basis for investment and risk management decisions [22,23].

2.2. Research on Commodity Pricing Power

In the early stages of research on commodity pricing power, scholars focused on the price discovery function of futures and discussed the relationship between futures and spot prices of various varieties [24–26]. In exploring the commodity pricing power method, many scholars have conducted empirical research on relevant futures varieties using cointegration tests [27–29]. Granger provided a noncausal theoretical framework widely used in the causal analysis of time series. On this basis, the multivariate time series unidirectional causal analysis method is widely used in financial and international trade markets [30–32]. Another research direction on commodity pricing power aims to study the volatility of market spillovers by applying the GARCH model and deriving more models. Some scholars have built a VECM–DCC–GARCH framework or UECCC–GARCH model to study the relationship between futures and spot market prices [33] or to analyse the structure of volatility spillovers [34]. In addition, some studies analysed the price discovery function of the futures market and its corresponding commodity pricing power through the spillover effect [35,36].

The scientific methodology of the grey system is mostly used in the fields of information science [37,38], natural science [39,40], and environmental pollution [41]. However, there is little research [42,43] in the social sciences. Therefore, we attempted to use the grey system method to predict the influence of China's copper futures price on the international market.

3. Experimental Materials and Methods

3.1. Historical Data of Copper Futures Price

The London Metal Exchange (LME), New York Commodity Exchange (COMEX), and the Shanghai Futures Exchange (SHFE) are three major copper futures markets. We selected copper futures prices from these three exchanges as the original empirical data. Considering the WHO's COVID-19 response and key action for 31 December 2019, as the dividing point of the pandemic, the data are divided into prepandemic from 2 January 2018 to 31 December 2019 and postpandemic from 2 January 2020 to 30 September 2021. The unit is unified as USD 1per ton at the daily middle rate of the US dollar to RMB. Meanwhile, China's $PM_{2.5}$, SO_2, CO, and NO_2 were used to evaluate air pollution. The annual data from 2017 to 2020 were selected from the CSMAR database to match the fluctuation cycle of copper prices.

3.2. Mathematical Model of Grey Relational Grade

We describe the mathematical foundation of grey relational grade as follows (The principle of grey entropy aims to weight variance degrees, and the highest value of weighting lambda represents the most important factor for all variances):

3.2.1. Factor Space

Suppose P(X) is one theme and Q is one relationship. If a feature possesses key factors, such as a countable intention factor, an expansion of factor, and an independence factor for the combination of {P(X); Q}, {P(X); Q}, then it can be called a factor space.

3.2.2. Comparison of Sequence

A sequence $x_i = (x_1(k), \cdot, \cdot\cdot, x_i(k)) \in X$; is assumed in Equation (1), as depicted below.

$$k = 1, 2, 3, \cdots, n \boxed{\in} N,\ i = 0, 1, 2, \cdots,\ m \in \boxed{I} \tag{1}$$

This sequence is comparable if the above equation meets three conditions: nondimensional, scaling, and polarization.

3.2.3. Four Axioms of Grey Relational Measurement

The grey relational space is $\{P(X); \Gamma\}$, in which $\{P(X)\}$ depicts the theme and Γ represents the measurement tool. This space is formed by acquiring factor space and comparability. The $\{P(X); \Gamma\}$ function contains four axioms: normality, duality symmetric, wholeness, and closeness. If all four of the above axioms are involved in a function of $\gamma(x_i, x_j) \in \Gamma, \gamma(x_i, x_j)$ is defined as a grey relational grade.

3.2.4. Grey Relational Grade

In a grey relational space, $\{P(X); \Gamma\}$ exists in the sequences $x_i = (x_1(k), \cdot, \cdot\cdot, x_i(k)) \in X$; where $k = 1, 2, 3, \cdots, n \boxed{\in} N,\ i = 0, 1, 2, \cdots,\ m \in \boxed{I}$. An equation is derived as follows, as shown in Equation (2).

$$\begin{array}{c} x_0 = (x_0(1), x_0(2), \cdot, \cdot\cdot, x_0(k)) \\ x_1 = (x_1(1), x_1(2), \cdot, \cdot\cdot, x_1(k)) \\ x_2 = (x_2(1), x_2(2), \cdot, \cdot\cdot, x_2(k)) \\ \vdots = \vdots \\ x_m = (x_m(1), x_m(2), \cdot, \cdot\cdot, x_m(k)) \end{array} \tag{2}$$

The function of $x_0(k)$ is the reference sequence (The method settings are all from the methods and tools provided by You, M.L. et al. (2012) [44]), whereas the other sequences are inspected sequences. These sequences are called "localization grey relational grade". Furthermore, a sequence can be defined as "globalization grey relational grade" if it meets the reference sequence. We used Nagai's grey relational grade [44] in this study.

3.2.5. Localization Grey Relational Grade

Equation (3) displays the expression of the grey relational grade, as follows:

$$\Gamma_{0i} = \Gamma(x_0(k),\ x_i(k)) = \frac{\overline{\Delta}_{\max.} - \overline{\Delta}_{0i}}{\overline{\Delta}_{\max.} - \overline{\Delta}_{\min.}} \tag{3}$$

in which $\overline{\Delta}_{0i} = \|x_{0i}\|_\rho = \left(\sum_{k=1}^{n} [\Delta_{0i}(k)]^{\ \rho} \right)^{\frac{1}{\rho}}$
where $k = 1, 2, 3, \cdots, n,\ i = 1, 2, 3, \cdots, m\ , j \in I$;

i. x_0: reference sequence;
ii. x_i: inspected sequences;
iii. $\Delta_{oi} = ||x_0(k) - x_i(k)||$: the difference between x_0 and x_i norm;
iv. $\Delta_{\min.} = \overset{\min.\min.}{\underset{j \in i}{\forall}}\ \forall k ||x_0(k) - x_j(k)||$;
v. $\Delta_{\max.} = \overset{\max.\max.}{\underset{j \in i}{\forall}}\ \forall k ||x_0(k) - x_j(k)||$.

3.2.6. Grey Relational Ordinal

The grey relational rank procedure is followed so that a sequence can be ranked after the value is calculated via the grey relational grade. For example, if a function expresses $\Gamma(x_0, x_i) \geq \Gamma(x_0, x_j)$, where x_0 and x_i depict reference and inspected sequences, respectively, and the grey relational rank of x_i is greater than that of x_j.

3.3. Mathematical Model of Grey Entropy

The following contents describe the fundamental concept of grey entropy and random number. A function was defined as $f_i : [0, 1] \to [0, 1]$, $i = 1, 2, 3, \ldots, n$, if a finite set "$\hat{A}$" existed in the whole set. This function met three conditions listed as $f_i(0) = 0$, $f_i(x) = f_i(1 - x)$, and $f_i(x)$ was monotonic in the range $x \in (0, 0.5)$. These three conditions are monotonic in the range of $x \in (0, 0.5)$, and Equation (4) derives from the above statements:

$$d(A) = g[\sum_{i=1}^{n} c_i f_i(\hat{A}(u_i))] \tag{4}$$

where

i. $g(x)$ is monotonic in the range of $[0, a] \to [0, 1]$;
ii. is real and let Equation (4) transfer to Equation (5) because of the above conditions;
iii. $d(A)$ is defined as the entropy of set $\hat{A}$.

$$a = \sum_{i=1}^{m} c_i f_i(0.5) \tag{5}$$

According to the conditions mentioned above, the new entropy comes from the original entropy called grey entropy, as shown in Equation (6):

$$W(\hat{A}) = \frac{1}{0.6478} \sum_{i=1}^{m} W_e(X_i) \tag{6}$$

where

i. the value of $\frac{1}{0.6478}$, called the normalization coefficient, originates and adopts $c_1 = c_2 = c_3 = \ldots = c_m = 1$ into Equation (5), which corresponds to the factor number;

ii. the condition of $W(x)$ is satisfied by the following: $W(x) = [xe^{(1-x)} + (1-x)e^x - 1]$.

The calculation process of grey entropy consists of seven steps, as shown below.

(1) Set the sequences;

$$x_i = (x_i(1), x_i(2), x_i(3), \ldots\ldots, x_i(k)) \text{ where : } i = 1, 2, 3, \ldots, m, k = 1, 2, 3, \ldots, n \tag{7}$$

(2) Calculate the total sum of the attribute of each factor;

$$D_k = \sum_{i=1}^{m} x_k(i) \tag{8}$$

(3) Calculate the normalization coefficient;

$$k = \frac{1}{0.6478 \times m} \tag{9}$$

(4) Calculate the entropy of each factor;

$$e_k = \frac{1}{0.6478 \times m} \sum_{i=1}^{m} W_e\left(\frac{x_i(k)}{D_k}\right) \tag{10}$$

(5) Calculate of the sum of entropy;

$$E = \sum_{i=1}^{n} e_k \tag{11}$$

(6) Calculate the relative weighting;

$$\lambda_k = \frac{1}{m - E}[1 - e_k] \tag{12}$$

(7) Normalize the weighting: The value of β_k represents the weighting of each factor.

$$\beta_k = \frac{\lambda_k}{\sum\limits_{i=1}^{n} \lambda_i}$$

After application of the grey entropy calculation in the sample data, the relative weighting values of variables could be analyzed for realization of the weighting influence of variables.

4. Results and Discussion

4.1. Changes in Copper Price Influence

After March 2020, the epidemic in China was under control, and the price of copper futures began to rise. In October 2020, China's copper consumption represented more than 60% of the world's consumption. The upward trend in copper prices will certainly affect China's interests and urge it to create countermeasures. With improvements in China's futures market in recent years, whether or not the influence of the SHFE copper futures price has increased after the outbreak of the epidemic will be determined by comparing the copper futures prices of three exchanges before and after the pandemic. Our results are as shown in Tables 1–4:

Table 1. Values of attribute "D" calculated using grey entropy and by importing data from three copper futures markets before the COVID-19 outbreak.

x_1 SHFE	x_2 LME	x_3 COMEX
8423.14	6879.25	6850.76
8361.97	6824.73	6793.84
8113.07	6879.91	6801.46
8103.64	7029.22	6972.98
8049.77	6492.68	6523.03
8143.22	6156.95	6099.53
7375.42	5962.00	5865.75
7146.91	6212.59	6106.61
7098.61	6155.31	6042.87
7237.71	6195.61	6076.31
7119.63	5997.64	5922.97
7090.64	6061.75	5990.29
6991.90	6373.95	6366.65
7306.41	6423.10	6390.98
7326.12	6411.79	6398.60
7341.58	5972.10	6007.81
6918.56	5908.60	5903.26
6771.29	5961.61	5940.76
6810.66	5722.11	5700.05
6615.65	5774.43	5749.86
6656.77	5790.43	5773.14
6650.77	5875.58	5855.91
6714.17	6052.29	6047.70
6948.02	6129.89	6133.41
Attribute D =		
175,315.63	149,243.5	148,314.52

Normalization coefficient k = 0.5146.

According to the relative weight value calculated by the grey entropy formula, the weights of the LME and COMEX futures copper prices were both 0.3334, and the weight of the SHFE was 0.3332 before the pandemic, as shown in Table 2. Before the pandemic, the influence of the LME futures copper price was the same as the COMEX but greater than the SHFE. After the outbreak of the pandemic, the weights of the LME, COMEX, and SHFE futures copper prices were 0.3333, 0.3332, and 0.3335, respectively, as shown in Table 4. The weight of the SHFE futures copper price was the largest, and the COMEX futures copper price was the smallest, which further explained the influence of China's copper price after the pandemic.

Table 2. Values from the processing of each factor after weighted analysis using grey entropy before the COVID-19 outbreak.

SHFE	LME	COMEX
0.0634	0.061	0.0611
0.063	0.0605	0.0606
0.0612	0.061	0.0607
0.0612	0.0623	0.0622
0.0608	0.0578	0.0584
0.0614	0.0549	0.0548
0.056	0.0533	0.0528
0.0543	0.0554	0.0548
0.054	0.0549	0.0543
0.055	0.0552	0.0546
0.0541	0.0536	0.0533
0.0539	0.0541	0.0538
0.0532	0.0568	0.057
0.0555	0.0572	0.0572
0.0556	0.0571	0.0573
0.0557	0.0534	0.054
0.0527	0.0528	0.0531
0.0516	0.0533	0.0534
0.0519	0.0512	0.0513
0.0505	0.0517	0.0518
0.0508	0.0518	0.052
0.0507	0.0525	0.0527
0.0512	0.054	0.0543
0.0529	0.0547	0.055
entropy E =		
1.3302	1.3304	1.3304
relative weighting lambda =		
0.3332	0.3334	0.3334
Rank = 2 = 3 > 1		

Table 3. Values of attribute "D" calculated using grey entropy and importing data from three copper futures markets after the COVID-19 outbreak.

x_1 SHFE	x_2 LME	x_3 COMEX
7073.97	5710.00	5682.83
6541.34	5499.35	5435.94
5953.76	4932.59	4935.90
5862.95	5227.48	5212.67
6119.09	5598.19	5548.61
6573.16	6123.78	6063.70
7280.51	6431.04	6380.13
7381.43	6671.98	6631.98
7593.08	6650.32	6655.86
7687.11	6832.94	6858.79
8035.46	7353.33	7346.69
8849.25	7902.04	7905.44
9077.19	8023.93	7989.83
9664.81	8973.40	8947.17
10,226.09	8944.50	8973.92
10,517.81	9734.52	9580.19
11,534.99	10,101.44	10,216.53
10,891.94	9486.29	9596.51
10,739.05	9514.20	9608.35
10,707.31	9341.59	9451.17
10,719.26	9279.15	9420.96
Attribute D =		
179,029.54	158,332.06	158,443.15

Normalization coefficient k = 0.5146.

Table 4. Values from the processing of each factor after weighted analysis using grey entropy after the COVID-19 outbreak.

SHFE	LME	COMEX
0.0527	0.0483	0.0481
0.0489	0.0466	0.0461
0.0447	0.042	0.042
0.044	0.0444	0.0442
0.0459	0.0474	0.047
0.0491	0.0517	0.0511
0.0542	0.0541	0.0537
0.0549	0.056	0.0557
0.0564	0.0559	0.0559
0.057	0.0573	0.0575
0.0595	0.0614	0.0613
0.0652	0.0657	0.0657
0.0667	0.0667	0.0664
0.0708	0.074	0.0738
0.0746	0.0738	0.074
0.0766	0.0799	0.0786
0.0834	0.0826	0.0834
0.0791	0.078	0.0788
0.0781	0.0782	0.0788
0.0778	0.0769	0.0777
0.0779	0.0764	0.0774
entropy E =		
1.3175	1.3173	1.3172
relative weighting lambda =		
0.3335	0.3333	0.3332
Rank = 1 > 2 > 3		

4.2. Changes in Air Pollution

Much of the literature describes the relationship between copper smelting and pollution. For example, Jordanova et al. [45] noted that copper smelting and mining heavily polluted urban areas. Kalinovic et al. [46] noted that copper smelters are a major source of pollution compared with tailings ponds. Scholars have studied the pollution caused by copper smelting to improve smelting strategies [47]. Of course, many other studies on the relationship between copper and pollution exist.

Influenced by COVID-19, the global economy is on the edge of a downturn or recession. China's economic recovery has been rapid due to its effective control of the pandemic. In turn, it has' have increased copper demand, boosted copper prices, and promoted domestic copper smelting, causing air pollution. Table 5 depicts descriptive statistics of air pollutants, including mean, median, standard deviation, skewness value, Kurtosis value, and maximum and minimum values for understanding the trend in air pollutants from 2017 to 2020. The following include changes in China's air pollution over the past few years:

According to the results in Tables 6–8, among the measurement indicators of air pollution, the maximum relative weight value of SO_2 is 0.2615, and $PM_{2.5}$, NO_2, and CO are 0.2477, 0.2457, and 0.2451, respectively. These findings suggest that SO_2 has had the strongest influence on air pollution in recent years.

Table 5. Descriptive statistics of air pollutants.

Variables	$PM_{2.5}$	SO_2	CO	NO_2
Mean	46.403	12.408	0.886	36.362
Median	44.371	11.076	0.884	36.725
Std. Dev.	6.642	3.765	0.076	3.619
Skewness	1.125	1.528	0.105	−0.591
Kurtosis	0.095	2.056	−2.906	1.639
Maximum	55.452	17.803	0.972	40.397
Minimum	41.419	9.679	0.805	31.602

Table 6. Grey relational grade for each year.

Year/Item	Grey Relational Grade	Rank
2017	0.0000	4
2018	0.7596	3
2019	0.7995	2
2020	1.0000	1

Max.Δ = 22.3954, Min.Δ = 18.3217 x_0 = ($PM_{2.5}$, SO_2, CO, NO_2) = (40 μg/m^{-3}, 0.06, 4, and 0.04 ppm).

Table 7. Values of "Attribute D" of four air pollutants.

x_1	x_2	x_3	x_4
47.317	17.803	0.972	40.397
41.419	12.174	0.845	36.528
41.425	9.679	0.805	36.923
55.452	9.977	0.924	31.602
Attribute D =			
185.613	49.633	3.546	145.45

Normalization coefficient k = 0.3859.

Table 8. Weighted values of each factor using grey entropy.

$PM_{2.5}$	SO_2	CO	NO_2
0.1924	0.2312	0.2012	0.2028
0.1761	0.1876	0.1841	0.1905
0.1761	0.16	0.1782	0.1918
0.2114	0.1635	0.195	0.1729
entropy E =			
0.756	0.7424	0.7585	0.758
relative weighting lambda =			
0.2477	0.2615	0.2451	0.2457
Rank = 2 > 1 > 4 > 3			

4.3. Limitations and Future Work

The main limitation of this paper is that the price trend of copper futures in the three futures markets is similar; therefore, the research results could not directly reflect one another's influence. Therefore, we tried to use the daily frequency open interest of the three exchanges for robustness test (We also tried to use the trading volume of the three exchanges. However, due to the lack of some data that could not match the three markets during the study period, grey entropy method could not be used). Our results continue to hold as shown in Tables 9–12.

Table 9. Values of attribute "D" calculated using grey entropy and by importing data from three copper futures markets before the COVID-19 outbreak.

x_1 SHFE	x_2 LME	x_3 COMEX
727,132	178,938	292,480
691,738	179,939	288,577
652,432	177,915	284,300
743,972	173,005	287,352
764,192	175,506	285,964
$\vdots$	$\cdots$	$\vdots$
$\vdots$	$\ddots$	$\vdots$
$\vdots$	$\cdots$	$\vdots$
516,734	33,070.76	212,577
517,688	29,239.44	226,987
612,422	28,863.27	259,207
607,336	26,358.84	263,899
666,656	22,642.57	266,891
Attribute D =		
59,492,038	2,978,871.53	24,476,431

Normalization coefficient k = 0.5146.

Table 10. Values from the processing of each factor after weighted analysis using grey entropy before the COVID-19 outbreak.

SHFE	LME	COMEX
0.0168	0.0782	0.0165
0.016	0.0786	0.0163
0.0151	0.0777	0.016
0.0172	0.0757	0.0162
0.0177	0.0768	0.0161
$\vdots$	$\cdots$	$\vdots$
$\vdots$	$\ddots$	$\vdots$
$\vdots$	$\cdots$	$\vdots$
0.012	0.0153	0.012
0.012	0.0136	0.0128
0.0142	0.0134	0.0146
0.0141	0.0122	0.0149
0.0155	0.0105	0.0151
entropy E =		
1.3809	1.3455	1.3812
relative weighting lambda =		
0.3439	0.312	0.3442
Rank = 3 > 1 > 2		

On the other hand, this paper considers the copper price as the research object and focuses on analysing the pricing power of copper without introducing corresponding factors, such as production and consumption demand. Therefore, this part can be discussed in future research.

Table 11. Values of attribute "D" calculated using grey entropy and importing data from three copper futures markets after the COVID-19 outbreak.

x_1 SHFE	x_2 LME	x_3 COMEX
293,581	27,209.18	270,889
303,893	24,553.8	281,166
270,950	30,197.81	248,958
315,410	28,977.51	264,032
352,386	31,477.11	269,208
$\vdots$	$\cdots$	$\vdots$
$\vdots$	$\ddots$	$\vdots$
$\vdots$	$\cdots$	$\vdots$
295,813	−3871.68	199,899
299,271	−3476.87	208,878
341,976	−2934.5	192,968
316,872	−3591.71	190,030
312,907	−3120.43	190,379
Attribute D =		
20,961,890	549,249.91	14,395,054

Normalization coefficient k = 0.5146.

Table 12. Values from the processing of each factor after weighted analysis using grey entropy after the COVID-19 outbreak.

SHFE	LME	COMEX
0.0193	0.0653	0.0257
0.0199	0.0593	0.0267
0.0178	0.072	0.0237
0.0207	0.0693	0.0251
0.023	0.0748	0.0256
$\vdots$	$\cdots$	$\vdots$
$\vdots$	$\ddots$	$\vdots$
$\vdots$	$\cdots$	$\vdots$
0.0194	−0.0099	0.0191
0.0196	−0.0089	0.0199
0.0224	−0.0075	0.0185
0.0208	−0.0092	0.0182
0.0205	−0.008	0.0182
entropy E =		
1.3732	1.2736	1.3729
relative weighting lambda =		
0.366	0.2683	0.3657
Rank = 1 > 3 > 2		

5. Conclusions

In addition to copper, China is a major importer of iron ore, soybeans, and crude oil. Commodity pricing power has strong and strategic significance for China. The pricing power and influence of China's futures market must improve. Compared to other countries in the postpandemic era, China's economy has recovered rapidly, and its demand determines the trend of most commodity prices. The influence of China's futures market price on commodity pricing power is bound to grow. This paper demonstrates this point by studying the influence of China's copper futures price.

Compared to previous research on commodity pricing power, the grey system provides an efficient research method for analysing small samples. We obtained the change in the weight of copper futures price before and after the epidemic through the grey entropy calculation, which also shows the global influence of the SHFE copper futures price. Since the outbreak of COVID-19, the Chinese government has taken positive and effective measures to effectively control the pandemic in China, stabilise social order, and ensure high-quality economic development. Furthermore, the demand for copper continues to rise. Therefore, the influence of the SHFE copper futures prices has improved significantly, slightly exceeding that of the LME and the COMEX. However, in recent years, SO_2 in air pollutants has had a greater influence than other pollutants. To some extent, copper smelting may be partly responsible for China's air pollution.

Finally, according to our research results, the increased copper demand and the deterioration of the external environment promote the expansion of copper smelting in China, which has caused air pollution. Therefore, the government should consider controlling copper usage and the pollution derived from smelting.

Author Contributions: R.G.: investigation, resources, methodology, and writing—original draft preparation. C.-C.H.: visualization, formal analysis, investigation, and conceptualization. Z.-H.L.: writing—reviewing and editing and conceptualization. W.-T.C.: data curation and writing—original draft preparation. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the First-class Undergraduate Construction Project of Shanghai Business School (SBS-2022-XJJK-17).

Data Availability Statement: Publicly available datasets were analyzed in this study. This data can be found here: https://www.gtadata.com/ (accessed on 3 November 2022).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Xue, Y. On the Reasons and Countermeasures of the Loss of China's Pricing Rightin Bulk Commodity. *Reform. Strategy* **2016**, *2*, 142–145.
2. Wang, J.Q. Analysis of Dollar Hegemony in Commodity Pricing. *Soc. Sci.* **2019**, *9*, 12–26.
3. Xu, B. An economic analysis of international pricing power for bulk commodities. *China Price* **2007**, *5*, 32–35.
4. Zhang, Q.S.; Fang, Y.; Huang, K. An empirical study on the function and international influence of Chinese futures market. *J. Manag. World* **2006**, *4*, 28–34.
5. Liu, L.; Zhang, X.; Wang, H.Q. Research on the mechanism of commodity price influence from the perspective of financial speculation, real demand and international commodity price—Information friction. *J. Financ. Res.* **2018**, *4*, 35–51.
6. Tian, H.Z.; Yao, F.; Li, H. Does China have the international pricing power for crude oil? *Chin. J. Manag. Sci.* **2020**, *11*, 90–99.
7. Krugman, P. The Increasing Returns Revolution in Trade and Geography. *Am. Econ. Rev.* **2009**, *3*, 561–571. [CrossRef]
8. Kilian, L. Not all Oil Price Shocks are alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *Am. Econ. Rev.* **2009**, *3*, 1053–1069. [CrossRef]
9. Lu, F.; Li, Y.F. The Fluctuation of international commodity price and China's Factor: China's open economy is facing new problems. *J. Financ. Res.* **2009**, *10*, 38–56.
10. Gulley, A.; Tilton, J.E. The relationship between spot and futures prices: An empirical analysis. *Resour. Policy* **2014**, *41*, 109–112. [CrossRef]
11. Yu, H.; Ding, Y.H. Multi-scale comovement of the dynamic correlations between copper futures and spot prices. *Resour. Policy* **2021**, *70*, 101913. [CrossRef]
12. Fung, H.G. The information flow and market efficiency between the U.S. and Chinese Aluminum and copper futures markets. *J. Futures Mark.* **2010**, *12*, 1192–1209.
13. Kenourgios, D.; Samitas, A. Testing efficiency of the copper futures market: New evidence from London Metal Exchange. In *Global Business and Economics Review*; SSRN: Rochester, NY, USA, 2004; pp. 261–271.
14. Park, J.; Lim, B. Testing efficiency of the London metal exchange: New evidence. *Int. J. Financ. Stud.* **2018**, *6*, 32. [CrossRef]
15. Guo, Y.Q.; Yao, S.S. China's copper futures market efficiency analysis: Based on nonlinear Granger causality and multifractal methods. *Resour. Policy* **2020**, *68*, 101716. [CrossRef]
16. Cortazar, G.; Millard, C.; Ortega, H.; Schwartz, E.S. Commodity price forecasts, futures prices, and pricing models. *Manag. Sci.* **2019**, *65*, 4141–4155. [CrossRef]
17. Tian, L.H.; Tan, D.K. Financialization and Americanization of Bulk commodities' pricing: A study of the relation between stock indices and spot commodities. *China Ind. Econ.* **2014**, *10*, 72–84.
18. Liu, H. The Study on Futures Market Promoting Commodity International Pricing Power. *Price Theory Pract.* **2017**, *6*, 111–114.

19. Dehghani, H.; Bogdanovic, D. Copper price estimation using bat algorithm. *Resour. Policy* **2018**, *55*, 55–61. [CrossRef]
20. Lasheras, F.S.; de Cos Juez, F.J.; Sánchez, A.S.; Krzemién, A.; Fernández, P.R. Forecasting the COMEX copper spot price by means of neural networks and ARIMA models. *Resour. Policy* **2015**, *45*, 37–43. [CrossRef]
21. Rossen, A. What are metal prices like? Co-movement, price cycles and long-run trends. *Resour. Policy* **2015**, *45*, 255–276.
22. Sebastián, C.; Gonzalo, C.; Hector, O.; Eduardo, S.S. Expected prices, futures prices and time-varying risk premiums: The case of copper. *Resour. Policy* **2020**, *69*, 101825.
23. Antonio, G.G.; Rodrigo, M.G. Cointegration between the structure of copper futures prices and Brexit. *Resour. Policy* **2021**, *71*, 101998.
24. Herbert, J.H. The relation of monthly spot to futures prices for natural gas. *Energy* **1993**, *11*, 1119–1124. [CrossRef]
25. Haritika, C.; Himanshu, P. Relationship between Indian Spot and Future Crude Oil Prices: A Phasewise Empirical Analysis. *Asia-Pac. J. Manag. Res. Innov.* **2013**, *3*, 305–313.
26. Frank, A.; Bárd, M.; Atlen, O. The spot-forward relationship in the Atlantic salmon market. *Aquac. Econ. Manag.* **2016**, *2*, 222–234.
27. Lai, K.S.; Lai, M. A Cointegration Test for Market Efficiency. *J. Futures Mark.* **1991**, *11*, 567–575. [CrossRef]
28. Schroeder, T.C.; Goodwin, B.K. Price Discovery and Cointegration for Live Hogs. *J. Futures Mark.* **1991**, *11*, 685–696. [CrossRef]
29. Watkins, C.; McAleer, M. Cointegration analysis of metals futures. *Math. Comput. Simul.* **2002**, *59*, 207–221. [CrossRef]
30. Breitung, J.; Candelon, B. Testing for short and long-run causality: A frequency-domain approach. *J. Econom.* **2006**, *132*, 363–378. [CrossRef]
31. Croux, C.; Reusens, P. Do stock prices contain predictive power for the future economic activity? A Granger causality analysis in the frequency domain. *J. Macroecon.* **2013**, *34*, 93–103.
32. Gradojecvic, N.; Lento, C. Multiscale analysis of foreign exchange order flows and technical trading profitability. *Econ. Model.* **2015**, *47*, 156–165. [CrossRef]
33. Mi, J.S.; Zhang, W.X. An axiomatic characterization of a fuzzy generalization of rough sets. *Inf. Sci.* **2004**, *160*, 235–249. [CrossRef]
34. Bohl, M.T.; Salm, C.A.; Schuppli, M. Price discovery and investor structure in stock index futures. *J. Futures Mark.* **2011**, *31*, 282–306. [CrossRef]
35. Rittler, D. Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. *J. Bank. Financ.* **2012**, *36*, 774–785. [CrossRef]
36. Liu, B.J.; Wang, Y.; Wang, J.; Wu, X.; Zhang, S. Is China the price taker in soybean futures? *China Agric. Econ. Rev.* **2015**, *7*, 389–404. [CrossRef]
37. Miao, H.; Ramchander, S.; Wang, T.; Yang, D. Role of index futures on China's stock markets: Evidence from price discovery and volatility spillover. *Pac.-Basin Financ. J.* **2017**, *44*, 13–26. [CrossRef]
38. Wu, W.Z.; Zhang, W.X. Constructive and axiomatic approaches of fuzzy approximation operators. *Inf. Sci.* **2004**, *159*, 233–254. [CrossRef]
39. Chen, D.G.; Wang, X.Z.; Yeung, D.S.; Tsang, E.C.C. Rough approximations on a complete completely distributive lattice with applications to generalized rough sets. *Inf. Sci.* **2006**, *176*, 1829–1848.
40. Hasani, H.; Tabatabaei, S.A.; Amiri, G. Grey relational analysis to determine the optimum process parameters for open-end spinning yarns. *J. Eng. Fibers Fabr.* **2012**, *7*, 81–86. [CrossRef]
41. You, M.L.; Shu, C.M.; Chen, W.T.; Shyu, M.L. Analysis of cardinal grey relational grade and grey entropy on achievement of air pollution reduction by evaluating air quality trend in Japan. *J. Clean. Prod.* **2017**, *142*, 3883–3889. [CrossRef]
42. Kung, C.Y.; Wen, K.L. Applying grey relational analysis and grey decision-making to evaluate the relationship between company attributes and its financial performance: A case study of venture capital enterprises in Taiwan. *Decis. Support Syst.* **2007**, *43*, 842–852. [CrossRef]
43. Xie, Y.H.; Yang, Y.F.; Wu, L.F. Power Consumption Forecast of Three Major Industries in China Based on Fractional Grey Model. *Axioms* **2022**, *11*, 407. [CrossRef]
44. You, M.L.; Hsieh, W.F.; Chen, P.J.; Wen, K.L. The Development of GSM Toolbox and Its Application in Outstanding Teacher Assessment&300m Man's Race. *J. Grey Syst.* **2012**, *3*, 151–157.
45. Jordanova, N.; Jordanova, D.; Tcherkezova, E.; Georgieva, B.; Ishlyamski, D. Advanced mineral magnetic and geochemical investigations of road dusts for assessment of pollution in urban areas near the largest copper smelter in SE Europe. *Sci. Total Environ.* **2021**, *10*, 792. [CrossRef] [PubMed]
46. Kalinovic, T.S.; Serbula, S.M.; Radojevic, A.A.; Kalinovic, J.V.; Steharnik, M.M.; Petrovic, J.V. Elder, linden and pine biomonitoring ability of pollution emitted from the copper smelter and the tailings ponds. *Geoderma* **2016**, *1*, 266–275. [CrossRef]
47. Zhou, H.H.; Liu, G.J.; Zhang, L.; Zhou, C.; Mian, M.; Cheema, A.I. Strategies for arsenic pollution control from copper pyrometallurgy based on the study of arsenic sources, emission pathways and speciation characterization in copper flash smelting systems. *Environ. Pollut.* **2021**, *1*, 270. [CrossRef] [PubMed]