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EDITED BY
Yilun Shang,
Northumbria University, United Kingdom

REVIEWED BY
Saravana Prakash Thirumuruganandham,
SIT Health, Ecuador
Arulprakasam R,
SRM University, India

*CORRESPONDENCE
Qishen Chen,
chenqishen@126.com

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Features of Chinese copper future return: based on a markov network approach

Hongkun Zhao[1], Qishen Chen[1]*, Yanfei Zhang[1], Kun Wang[1], Liuguo Shao[2], Chenghong Shang[1], Hua Zhang[2], Ye Zhang[1] and Dan Song[3]

[1]Institute of Mineral Resources, Chinese Academy of Geological Sciences, Beijing, China, [2]School of Business, Central South University, Changsha, China, [3]China University of Geosciences (Beijing), Beijing, China

Introduction: Copper has the dual attributes of industrial raw materials and financial assets, and its price formation mechanism presents complex non-linear characteristics under the dual role of supply and demand mechanism and financialization. The structural upgrading of industrial demand and the risk contagion effect in the futures market make it difficult to effectively analyze the fluctuation characteristics of copper price in the traditional linear analytical framework. Consequently, it is significant to explore the fluctuation characteristics of copper futures price from the perspective of complex system science.

Methods: This study employed complex network theory and the Markov switching model to develop a Markov network model of copper futures and to explore the evolving characteristics of copper prices.

Results and discussion: This study finds that: (1) There are 243 price switch states in theory, but only 126 types of states actually occur. Among them, 33 high-frequency states account for 90% of the total number of times, indicating that price fluctuations are active and concentrated in a regular manner. (2) The average path length of network state transition is 5.4, and the symmetry coefficient is 0.99, which shows that the transition efficiency is high but the path is highly asymmetric. (3) There are some nodes with low degree centrality and high betweenness centrality in the network, which act as mediators in the network, connecting the transitions between states. (4) The network has a significant association structure, and we find that the state nodes have a relatively obvious "rich club" effect. This study reveals that the nonlinear dynamics and network structures of copper future return.

KEYWORDS

copper, future return, markov network, leiden's algorithm, louvain's algorithm

1 Introduction

As the critical material of the modern industrial system, price fluctuations of copper resources have become a key factor affecting the stability of the global industrial economy and the security of the resource supply chain [1–4]. In recent years, the global copper price has exhibited periodic and volatile, and their price formation mechanism has become very complex. On the one hand, there is a structural contradiction between the surge in demand caused by the accelerated industrialization process of emerging economies and the traditional supply system [5, 6]. On the other hand, copper pricing is not only affected by supply and demand, but also by the coupling of multiple factors such as finance, geopolitics, and climate change under the wave of commodity financialization [7, 8]. Current research focuses on the impact of exogenous variables such as the macroeconomic environment on copper prices [9, 10], but ignores the fact that the copper future time series essentially reflects the evolution of the market's endogenous driving mechanism, especially from the perspective of the auto-correlation characteristics and nonlinear dynamic characteristics of price fluctuations, to analyze the internal operating laws of the copper futures market.

Nonlinear time series analysis and complex network theory are widely regarded as mature fields of complex system science. The thorough combination of these two methods has become an active field of nonlinear time series analysis [11]. The metal market represented by copper is a complex system. Scholars have widely used complex networks to explore the characteristics of its market [7, 12–20], such as trade characteristics [13–15], price characteristics [7, 12, 16] and financial characteristics [17–20]. The copper futures price time series can be regarded as a nonlinear and non-stationary complex system. The fluctuation of copper futures prices can be regarded as a random change between its internal generation mechanism and state. The Markov switching model can be used to describe this process. Markov-switching time-series models were proposed by Hamilton [21, 22], and widely used in the financial research [23–25]. This model is particularly suitable for the division of economic cycles, the transformation of financial market volatility mechanisms (such as the alternation of calm periods and crisis periods), and the analysis of commodity price mutations. It can effectively identify state migration signals before "black swan" events [26]. Taking the copper futures market as an example, the model can reveal the intrinsic dynamic mechanism of prices by quantifying the volatility characteristics and transition probabilities under different regimes (such as steady state, transition state, and chaotic state), and provide a quantitative basis for cross-region risk warning. In order to more fully and reasonably study the characteristics and dynamic characteristics of copper futures price fluctuations, we integrate complex network theory and the Markov conversion model to construct a Markov network model for copper futures prices.

As the world's largest copper consumer and futures trading market, on the demand side, the demand for copper in the new energy industry in 2024 is expected to a year-on-year increase of 17%, accounting for 20% of China's total copper demand [27]. On the supply side, the lagging development of domestic mines has led to a continuous dependence on raw material imports, forming a risk transmission path of "high external dependence + high financial hedging" [28]. In 2024, the annual trading volume of copper futures (CU) of the Shanghai Futures Exchange was 50,864,680 lots, with a transaction amount of 19,398.69 billion yuan, and it has developed into one of the most influential metal derivatives markets in the world [29]. Considering the importance of China's copper market and the complexity of China's copper price changes, it is of practical significance to explore the characteristics of China's copper price changes.

The innovations of this study include the following two points: firstly, unlike many studies on the linkage effects between the copper market and other markets, this study focuses on the copper futures price volatility itself, and then investigates the characteristics and dynamics of the price volatility of copper futures; secondly, this study combines the theory of complex networks and the Markov switching model, and constructs a Markov network model, while considering the complexity and stochastic migration of the price state of the copper futures market.

2 Markov network theory

2.1 Construction of markov network

The first step is to convert the copper futures price time series into several discrete states. At present, the method to discretize time series into several states is relatively mature [11]. This study adopts the idea of coarse-graining to transform the copper futures price series into several modes. In order to clearly represent the change law of copper futures prices, we use I to represent an increase in copper futures prices, O to represent no change in prices, and D to represent a decrease in prices, as shown in Formula 1.

$$l_i = \begin{Bmatrix} = I, \Delta P_i > 0 \\ = O, \Delta P_i = 0 \\ = D, \Delta P_i < 0 \end{Bmatrix} \tag{1}$$

where l_i represents the mode of the copper price on the ith day, $\Delta P_i = P_i - P_{i-1}$, and P_i represents the copper futures price on the ith day.

Through coarse-graining, the original copper futures price is transformed into a series of continuous symbols that can indicate the rise and fall of copper prices. Generally, the copper futures trading day is 5 days, so we regard the symbol string composed of the modalities of five consecutive trading days as a state of the copper futures price π_i. Each state reflects a specific price fluctuation law. For example, π_i = IIIII means that the copper futures price continues to rise, and π_i = IIIID means that the copper price continues to rise, but there is a trend of falling back. Theoretically, there are 243 discrete states of copper futures prices in this study, and all discrete states $\Pi = \{\pi_1, \pi_2 \ldots \pi_i \ldots \pi_{243}\}$ constitute all state spaces of historical copper futures prices.

The second step is to calculate the Markov network parameters. First, we use the state space obtained in the first step Π as the node of the Markov network. Next, we use the following steps to construct the edges of the Markov network.

1. Calculate the number of transitions between each two states n_{ij}, and n_{ij} indicates the number of times the state π_i changes into another state π_j. All the transition times n_{ij} constitute the transition matrix N.
2. Calculate the total number of times each state transforms into other states within the time period $N_i = \sum_j n_{ij}$.
3. Calculate the state transition probability between every two states $p_{ij} = \frac{n_{ij}}{N_i}$, p_{ij} represents the transition probability of a state π_i changing into a state π_j. All state transition probabilities p_{ij} constitute the state transition probability matrix P.

The third step is to build a Markov network. The parameters calculated in the first and second steps are used to construct a Markov network G (, P) with states as nodes and state transition probability as edges. It is obvious that the Markov network is a directed network that can reflect the state transition of copper futures prices, and it has the properties of both complex networks and Markov processes.

2.2 Markov network topology characteristics

Since the Markov network has significant complex network characteristics, the general indicators of complex networks are still applicable in the Markov network. Based on the principle of being able to reflect the state transition law of copper futures prices in this study, we selected the following indicators for specific description.

1. Average path length [30]. The average path length of the network is defined as the average distance between any two points. In this study, the network distance and average path length can directly reflect the speed of transition between different copper price fluctuation states and the speed of state transition in the entire network. The Formula 2 is as follows:

$$\mathbf{L} = \frac{\mathbf{1}}{\mathbf{C}_{\mathbf{N}}^{\mathbf{2}}} \sum\nolimits_{\mathbf{I} \le \mathbf{i} \le \mathbf{j} \le \mathbf{N}} \mathbf{d}_{\mathrm{ij}} \tag{2}$$

Where N represents the number of nodes, $\mathbf{d}_{\mathrm{ij}}$ represents the distance from state node i to state node j.

2. Symmetry coefficient. Masoller et. al. proposed the symmetry coefficient [31], which reflects whether the transitions between different nodes in a directed network are symmetrical. The Formula 3 is as follows:

$$\boldsymbol{\alpha} = \frac{\sum_{\mathbf{i}} \sum_{\mathbf{i} \ne \mathbf{j}} \left| \mathbf{p}_{\mathrm{ij}} - \mathbf{p}_{\mathrm{ji}} \right|}{\sum_{\mathbf{i}} \sum_{\mathbf{i} \ne \mathbf{j}} \left| \mathbf{p}_{\mathrm{ij}} + \mathbf{p}_{\mathrm{ji}} \right|} \tag{3}$$

Where $\mathbf{p}_{\mathrm{ij}}$ is the weight of the edge from node π_{i} to node π_{j}, and $\mathbf{p}_{\mathrm{ji}}$ is the weight of the edge from node π_{j} to node π_{i}. When $\boldsymbol{\alpha} = \mathbf{0}$, it means that the network is completely symmetrical, and when $\boldsymbol{\alpha} = \mathbf{1}$, it means that the network is completely asymmetrical. In the copper futures Markov network of this article, $\boldsymbol{\alpha}$ represents the degree of symmetry of the transition between different states of copper futures price fluctuations.

3. Centrality. Node centrality reflects the relative importance of a network node in the network. Compared with other state nodes, state nodes with high node centrality can better reflect the fluctuation state of copper prices. Here we simply give the calculation formulas for degree centrality and betweenness centrality.

Degree centrality [32] is the most basic and simplest measure of centrality, reflecting the centrality of a node among several nodes directly connected to it. The Formula 4 is as follows:

$$C_D(v_i) = \frac{k_i}{N - 1} \tag{4}$$

Among them, k_i represents the degree of node i, and N represents the total number of network points.

Betweenness centrality [33, 34] is an extremely important indicator for measuring network centrality. It reflects how much of a "bridge" role the node plays in the network. Removing nodes with high betweenness may cause the entire network to be disconnected. The Formula 5 is as follows:

$$C_B(v_i) = \frac{2}{(N-1)(N-2)} \sum\nolimits_{s \ne i \ne t} \frac{n_{st}^i}{g_{st}} \tag{5}$$

Where n_{st}^i represents the number of paths passing through node i and constituting the shortest path. g_{st} represents the count of shortest paths connecting nodes s and t. N represents the total number of nodes in the network.

4. Network uncertainty. Since the Markov network has the characteristics of state transition, we introduce the concept of information entropy to describe the uncertainty of the state transition of the copper futures Markov network. Based on the application of information entropy [35], we give the local node out-of-link entropy of the copper futures Markov network to reflect the uncertainty of each state node. The Formula 6 is as follows:

$$S_i^l = -\sum p_{ij} \log(p_{ij}) \tag{6}$$

Where p_{ij} represents the probability of a node transitioning from state π_{i} to state π_{j}. The smaller S_i^l is, the lower the uncertainty of the corresponding node and the entire network. When $S_i^l = 0$, we can say that the price change of copper futures prices in the period after state i is certain.

3 Data and empirical results

3.1 Data sources and basic analysis

This paper uses the continuous daily price of copper futures of the Shanghai Futures Exchange as the research object, and selects 4,859 copper futures price data from 2000 to 2020. This range covers all situations of the world economy's ups and downs, and also includes many major events such as the 2008 economic crisis, and studies all possibilities of copper futures price fluctuations as comprehensively as possible. The data comes from the Wind database.

According to the construction steps of the Markov network, the relevant parameters of the Markov network for copper futures prices, N and P, are calculated. According to the calculation results, we found that there are only 126 fluctuation states of copper futures prices, which is 117 less than the theoretical value of 243. The number of transitions between states is shown in Table 1. Combining Table 1 and Figure 1, we found that the number of occurrences of the 33 states with the largest number accounted for 91.57% of the total number of states. The 15 states with the highest proportion are mostly "3 + 2"patterns, that is, in five consecutive trading days, the copper price rose for 3 days and fell for 2 days, or rose for 2 days and fell for 3 days. The state containing "O" only accounted for 8.43%, and the state containing "OO" only appeared for 1.6%, indicating that the futures price volatility of China's copper market is relatively large.

TABLE 1 Number of changes in copper futures price volatility.

State π_i	IDIDI	DIDII	IIDID	DIDID	IDIII	IIIDI	IDIDD	IDIID	DIDDI	DIIDI
Status times	198	181	180	174	166	164	160	159	158	157
Ratio to total transfer times/%	4.08	3.73	3.71	3.59	3.42	3.38	3.30	3.28	3.26	3.24
State π_i	**DDIDI**	**IDDID**	**DIIID**	**IIDII**	**IDDII**	**DIIII**	**IIIID**	**DDDID**	**……**	**ODDDI**
Status times	155	148	147	145	138	135	135	135		1
Ratio to total transfer times/%	3.19	3.05	3.03	2.99	2.84	2.78	2.78	2.78	……	0.02

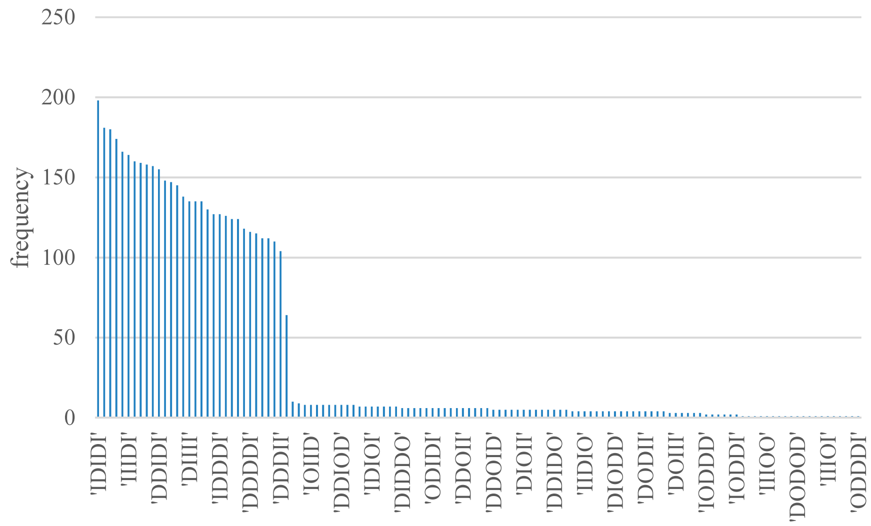

FIGURE 1
Copper futures price volatility state change times histogram.

TABLE 2 Copper futures price fluctuation symbol combination frequency.

Combination	Frequency	Combination	Frequency
I	98.2 7%	D	97.44%
II	57.88%	DD	52.92%
III	23.18%	DDD	19.25%
IIII	7.87%	DDDD	6.14%
IIIII	2.2 7%	DDDDD	1.32%

Since the frequency of "O" is relatively low, we pay more attention to the rise and fall of copper futures prices. We combined the symbols "I" and "D". These combinations and the frequency of occurrence are shown in Table 2. We found that at the corresponding level, the probability of copper price rise is always higher than the probability of fall. That is to say, within five trading days, copper prices are more inclined to rise, indicating that the overall trend of China's copper futures prices is rising. The frequency of IIII and IIIII is about 10%, and the frequency of DDDD and DDDDD is about 7.4%, indicating that in the copper futures market, continuous rises and falls often occur.

3.2 Analysis of markov network topology

According to the calculated Π,P value, we constructed the Markov network G = G (Π,P), as shown in Figure 2. The topological structure of the Markov network G reflects the transformation between different fluctuation states of copper futures prices. The diameter of the network G is 12, and the average path length is 5.4, which means that the number of transitions between the two states of copper futures price fluctuations is as high as 12 times, and the average number of transitions between the copper futures price fluctuation states is 5.4 times, indicating that the conversion efficiency between the copper futures price fluctuation

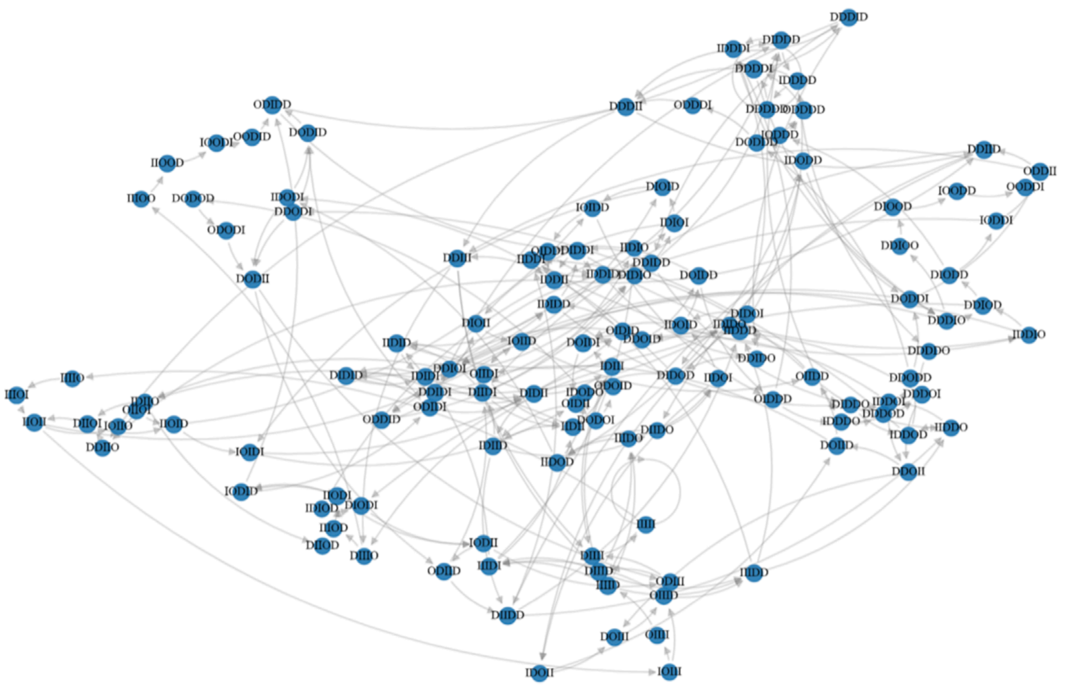

FIGURE 2
Markov network diagram.

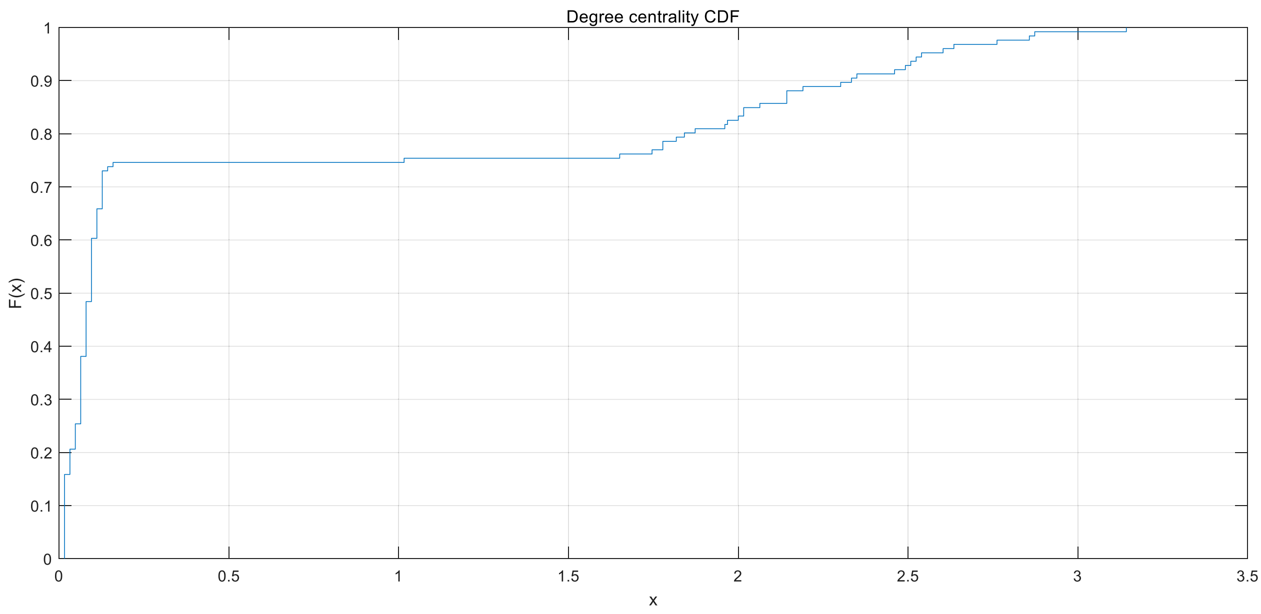

FIGURE 3
Cumulative distribution of degree centrality.

states is relatively high. The symmetry coefficient of the network G nodes is 0.99, indicating that the transition between states in the copper futures price network is highly asymmetric, which provides a reference for predicting the trend of copper price fluctuations in the next period.

Figures 3–5 show the cumulative distribution of degree centrality and betweenness centrality of Markov network G. Intuitively, the distribution of degree centrality and betweenness centrality of network G is different. From the perspective of node degree centrality, 73% of the nodes in the network have low degree

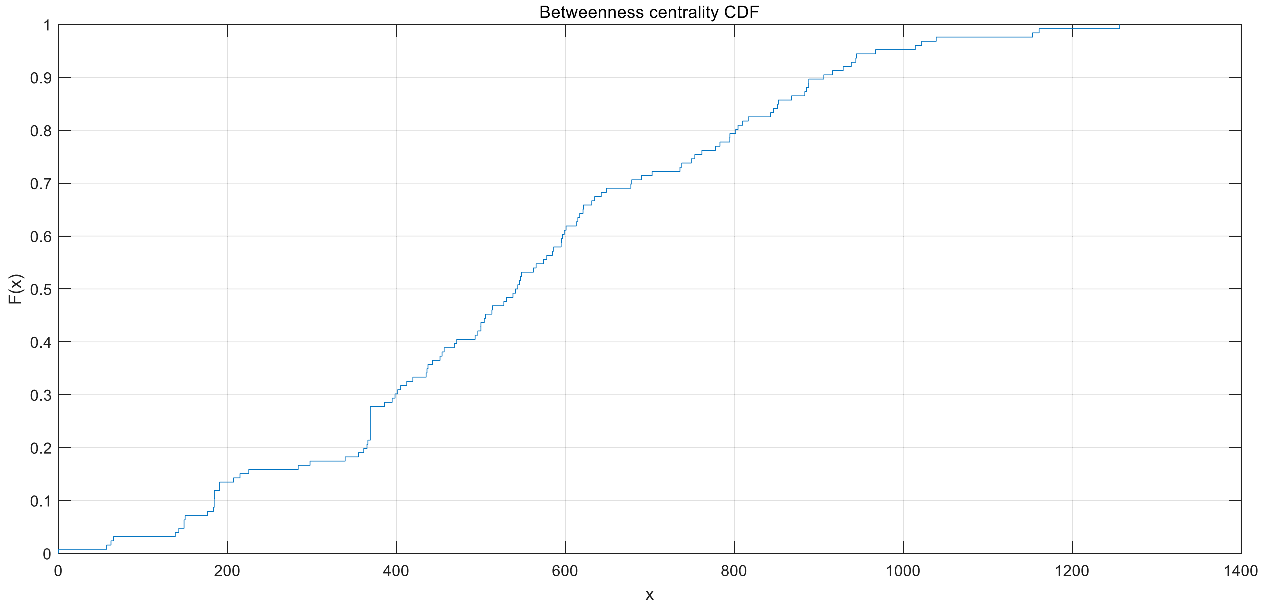

FIGURE 4
Cumulative distribution of betweenness centrality.

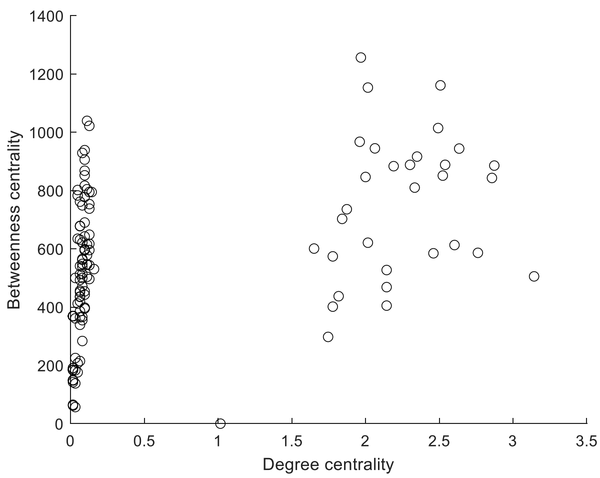

FIGURE 5
The relationship between degree centrality and betweenness centrality.

centrality, and 25% of the nodes have high degree centrality, which means that there are a large number of state nodes that have little impact on other nodes during the copper price fluctuation process, and the nodes that have a more drastic impact on the copper price fluctuation process only account for 25% of all state nodes. From the perspective of betweenness centrality, the distribution of betweenness centrality of network G is relatively uniform overall, but there are still some nodes with very high betweenness in the network, indicating that there are some nodes that act as transmission intermediaries during the copper price fluctuation process, and play an important role in the formation of the copper price time series.

Considering degree centrality and betweenness centrality comprehensively, we plotted the relationship between degree centrality and betweenness centrality, as shown in Figure 5. When degree centrality is less than 0.5, betweenness centrality and degree centrality are positively correlated. When degree centrality is greater than 0.5, betweenness centrality and degree centrality have no significant correlation. In general, nodes with higher degree centrality generally do not have very low betweenness centrality, but some nodes with very low degree centrality have higher betweenness centrality. This indicates that some states that do not occur often may play an important transmission role in the 126 state changes of copper price fluctuations. When these high-betweenness centrality but low-degree centrality states appear during copper price fluctuations, this is likely to be a transitional period in copper futures price fluctuations, which can provide an early warning for copper price fluctuations in the next period.

Next, we examine the uncertainty of each state from the perspective of information entropy. Figure 6 shows the value of the local out-of-link entropy of each state node. The horizontal axis represents each state, and the frequency of states from left to right is getting lower and lower. Generally speaking, the uncertainty of states with low frequency is also relatively low. The higher the frequency of states, the higher the out-of-link entropy value they contain. This means that when the copper futures price fluctuations are in a high-frequency state, it is difficult to predict the copper futures price. This difficulty is largely because the copper futures price fluctuation state at this time has high uncertainty in changing to other states. Of course, not all high-frequency states are characterized by high uncertainty. For example, the uncertainty of high-frequency states such as IIIII and DDDDD is relatively low, and the same is true for actual copper price fluctuations. When copper futures prices

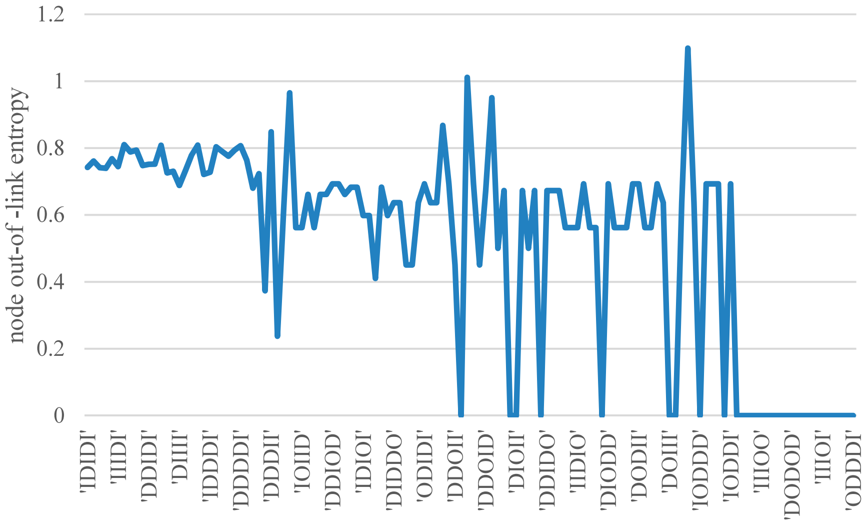

FIGURE 6
Outbound entropy of each node in the Markov network.

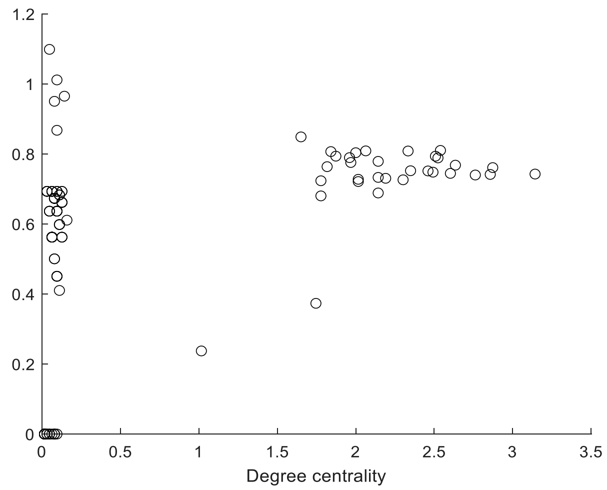

FIGURE 7
Relationship between node degree centrality and node out-link entropy.

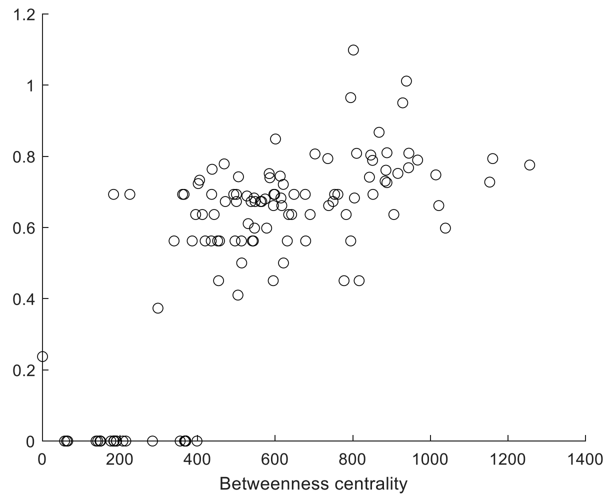

FIGURE 8
The relationship between node betweenness centrality and node out-link entropy.

continue to rise or fall, the probability of stopping rising and falling is very high.

In order to further explore the uncertainty of the state nodes of copper futures price fluctuations, we study the relationship between the out-link entropy of each node and the node degree centrality and betweenness centrality. The results are shown in Figures 7, 8. In general, degree centrality and betweenness centrality are positively correlated with node out-link entropy, which means that it is more difficult to predict the state transition of nodes with high frequency of state nodes and important status in the network structure. It is worth noting that for points with low centrality, the characteristics reflected by degree centrality and betweenness centrality are different. The uncertainty of state nodes with low betweenness centrality is very low, while most of the state nodes with low degree centrality are in a low uncertainty state, but some nodes are in a high uncertainty state. When the copper futures price is at a low centrality point, the price fluctuations in the copper futures market are traceable, and the uncertainty of predicting the price state is relatively small at this time.

3.3 Community structure

The community structure of a complex network refers to small groups with similar structures and close connections in the network. The internal nodes of each community structure tend to

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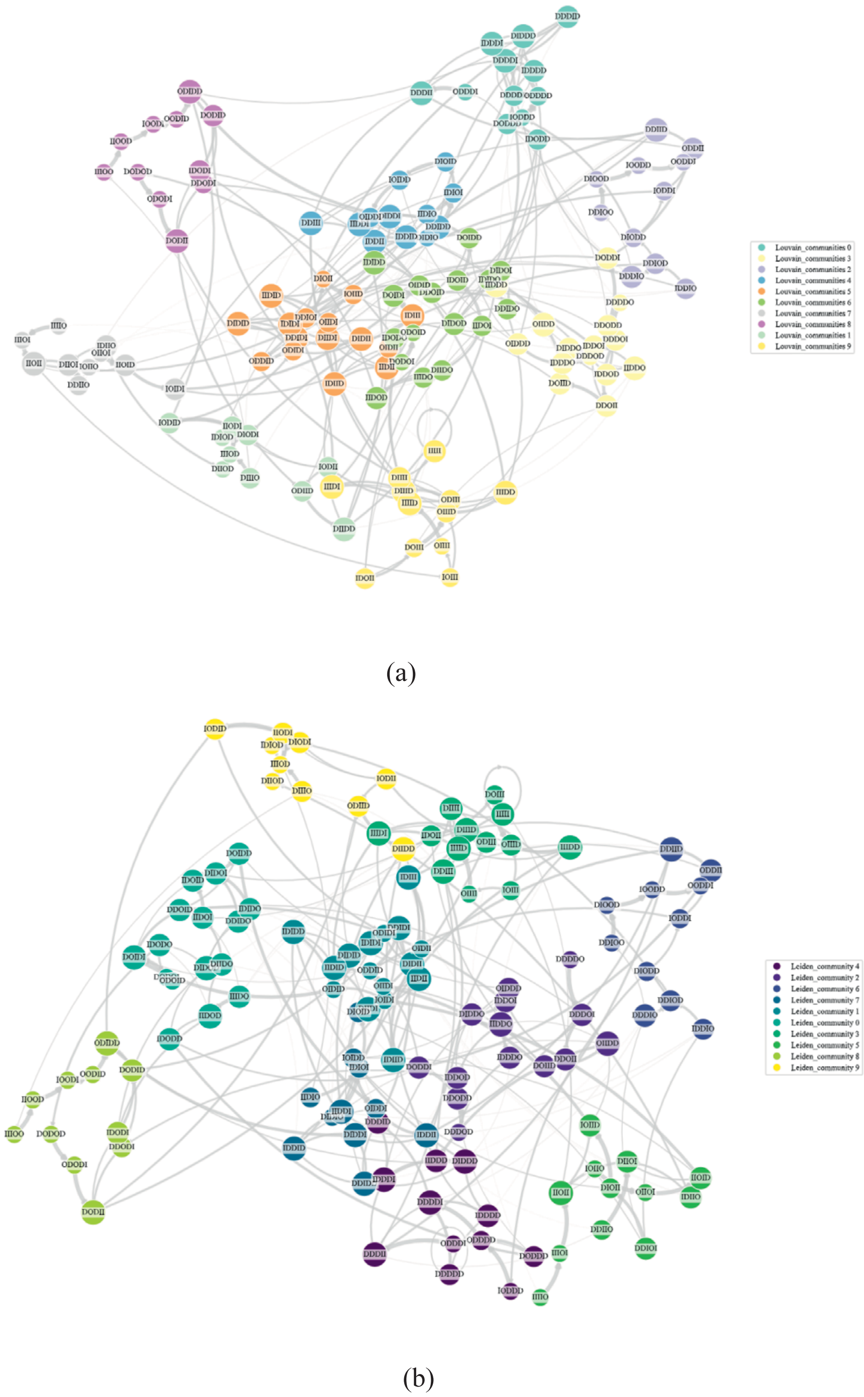

FIGURE 9
Markov network graph based on community structure distribution. **(a)** Louvain algorithm. **(b)** Leiden Algorithm.

transmit information within the community. Community analysis can divide the 126 nodes in the entire Markov network into several substructures, and then study the characteristics of the state changes of these substructures, which is very meaningful for studying the fluctuations of copper futures prices. We use Louvain's algorithm and Leiden's algorithm [36, 37] to analyze the association structure of the copper futures price Markov network. Both algorithms divides the network into 10 communities, with modularities Q (0.64) and Q (0.65) respectively. The modularity Q function value is an indicator that can reflect the quality of clustering effect, ranging from 0 to 1. The larger the Q value is, the more significant the community structure in the network is. We can say that the Markov network for copper futures prices in this study has a significant community effect. Furthermore, we find that the Normalized Mutual Information (NMI) and Normalized Mutual Information (ARI) between the two distinct community partitioning methods are 0.91

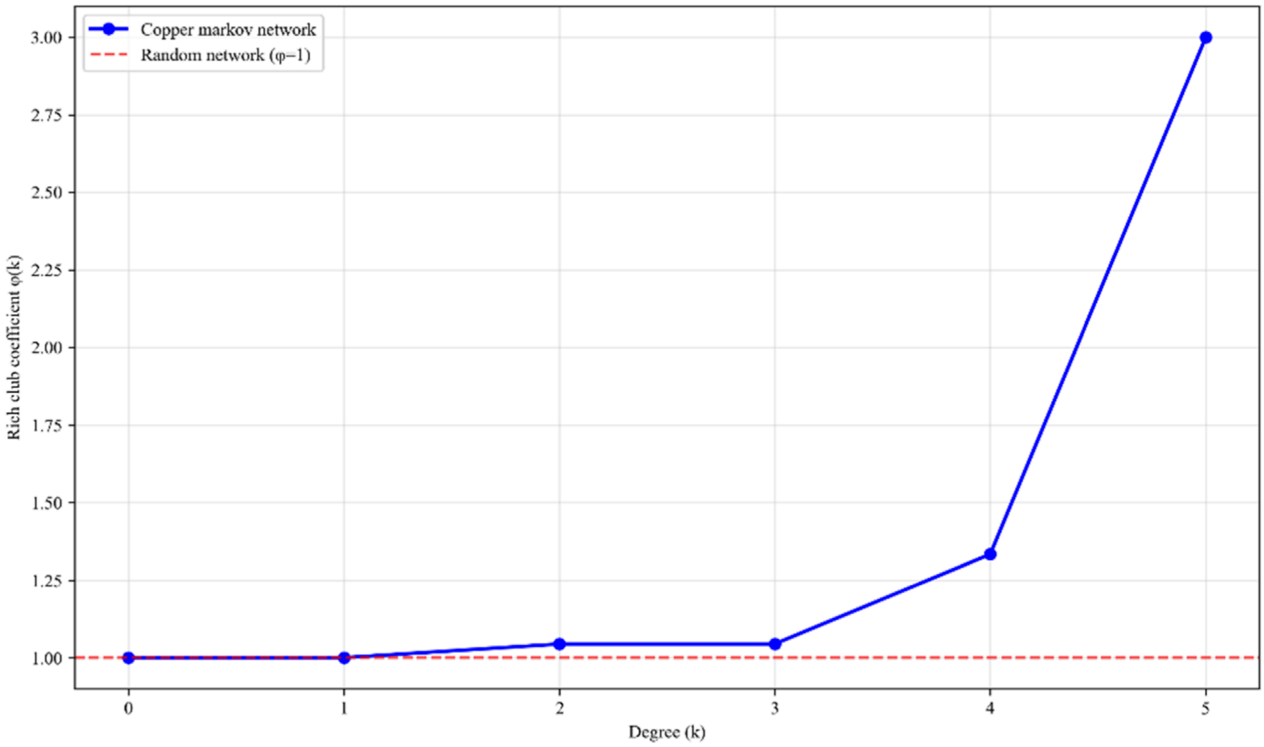

FIGURE 10
Markov network's rich club coefficients.

and 0.84, respectively, indicating consistent results. The Markov network of copper futures prices based on community structure is shown in Figure 9.

3.4 Rich club effect

To investigate whether the Markov network of copper futures prices exhibits a "rich club effect", this study calculated the rich club coefficient $\varphi(k)$ [38–40]. The results in Figure 10 showed that nodes with degrees 0, 1, 2, 3, 4, and 5 had $\varphi(k)$ values of 1.00,1.04,1.04,1.33, and 3.00, respectively. This indicates a pronounced rich club effect in the copper futures price Markov network, where the coefficient increases significantly with node degree. Notably, the coefficient peaks at 3.0 for nodes with degree 5, suggesting that connections between core nodes are three times denser than in a random network. This structural feature reveals tightly connected core groups within the network, where high-degree nodes act as critical information hubs. While this configuration facilitates efficient interactions among core groups, it may also exacerbate network inequality and increase dependence on core nodes, potentially compromising the network's robustness and the equilibrium of information dissemination.

4 Conclusion

This study constructs a Markov network based on complex network theory and Markov transition mechanism, and analyzes the fluctuation law of time series between China's copper futures prices and the dynamic characteristics of different state transitions. The main research conclusions are as follows.

1. Theoretically, there are 243 states that reflect the fluctuation of copper futures prices. However, according to the daily data, only 126 of these states appeared, and the 33 states with the highest frequency accounted for 90% of the total number of states. These 33 states do not include the "O" state, indicating that the fluctuation of China's copper futures prices is very active, and the main fluctuation pattern is among these 33 states.
2. The average path length of the state nodes in the network is 5.4, indicating that the efficiency of the state transition in reflecting the fluctuation of copper prices is relatively high. The symmetry coefficient is 0.99, indicating that the transition between state nodes is highly asymmetric.
3. By analyzing the centrality of the network, we found that there are a large number of nodes with low degree centrality in the network, but some of these nodes have high betweenness centrality. These nodes with low degree centrality and high betweenness centrality act as intermediaries in the network, connecting the transitions between states. Paying close attention to these nodes is conducive to accurately predicting the fluctuations in copper futures prices.
4. From the perspective of node uncertainty indicators, generally speaking, nodes with high frequency have higher out-of-link entropy, which means that their uncertainty is high. From the relationship between out-of-link entropy and centrality,

we can clearly see that for degree centrality, the higher the out-of-link entropy of nodes with high degree centrality, the higher the uncertainty of these states changing to other states. Nodes with low degree centrality show a polarized status, with some having high out-of-link entropy and others having low out-of-link entropy, which means that when these states change to other states, some have high uncertainty and others have low uncertainty. For betweenness centrality, nodes with low betweenness centrality have relatively small out-of-link entropy, which means that the uncertainty of these states changing to other states is relatively small. When price fluctuations appear in this state, the accuracy of network prediction is relatively high. Nodes with relatively high betweenness centrality have relatively high out-of-link entropy, which means that the uncertainty of these states changing to other states is relatively high.

5. This network has a significant community structure, and there is a relatively obvious "rich club" effect. When the degree of a node reaches 4, the "rich club"effect begins to appear. When the degree of a node is 5, the "rich club" effect is very obvious.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HZ: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review and editing. QC: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review and editing. YaZ: Formal Analysis, Funding acquisition, Methodology, Project administration, Writing – original draft, Writing – review and editing. KW: Methodology, Writing – review and editing. LS: Formal Analysis, Writing – review and editing. CS: Formal Analysis, Software, Visualization, Writing – original draft, Writing – review and editing. HZ: Formal Analysis, Software, Visualization, Writing – original draft, Writing – review and editing. YeZ: Formal Analysis, Writing – review and editing. DS: Formal Analysis, Writing – review and editing.

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