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ANALYSIS OF LINKAGE FLUCTUATION IN TIME SERIES DATA OF NICKEL FUTURES PRICE INDEX

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Abstract. This paper explores the variation pattern of nickel futures prices using the daily closing levels of the nickel futures price index of the London Futures Exchange and the Shanghai Futures Exchange. The data coarse-graining method is employed to transform the continuous time series data of price index changes into symbols {P, N, M}, which are slid through continuous windows to form the modalities of price index linkage fluctuations. By treating the modalities as nodes and the transformations between them as edges, a weighted directed complex network is constructed to represent the linked volatility of the LME and SHFE nickel futures indices time series. The complex network is applied to analyse the network characteristics and obtain the inner pattern of the linked fluctuations. The results show that the complex network of time series linked volatility of the LME and SHFE nickel futures indices exhibits a power-law nature, with closely linked subgroups formed within it. And the mode transitions within these subgroups follow certain patterns. This paper also identifies core positioned modes and important intermediate modes that reflect the dynamics of nickel prices in reality. The method presented in this paper may be extended to related fields and has good applicability.

Keywords: nickel futures price index, coarse-graining method, time series data, linkage fluctuation, complex network, positioned modes, intermediate modes.

JEL Classification: F02, F14, F23.

Introduction

Nickel is a metal known for its excellent formability and corrosion resistance. It is widely used in non-ferrous metals smelting, chemical production and other fields, and occupies an important position in the bulk commodity trade (Dubal et al., 2015; Su et al., 2023). In recent years, the widespread use of lithium batteries has led to an increased demand for nickel, one of its key raw materials. As a result, nickel has become a strategic energy raw material with rising prices and is increasingly valued by governments (Murdock et al., 2021). In the

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first half of 2022, international nickel prices experienced sharp fluctuations due to financial turmoil and international political changes (Wang et al., 2023; Zheng et al., 2022). These fluctuations had a significant impact on the global nickel market and deeply affected Chinese enterprises (Guohua et al., 2021). China has relatively limited domestic nickel resources and is largely dependent on imports. As a major manufacturer of nickel-related products, a stable and prosperous nickel market is of great importance to China's industrial development and national security (Sun et al., 2015). Therefore, understanding the links between the Chinese nickel market and the international nickel market, as well as the dynamic characteristics of these links, is of great interest to both administrators and investors.

Long-term studies have shown that commodities are often interconnected in complex ways. These connections often manifest themselves at the economic level as linked volatility between stock options and commodity futures prices (Guo et al., 2019). Such linked volatility may be either an interaction between commodities of the same type, such as the interaction of changes in multiple holdings in the oil and gas chain (Wen et al., 2017), or it may continue to be transmitted over time and across a certain space (Zhao et al., 2020). The effects of such linked volatility may also extend to a wider range of market sectors, such as the interaction of exchange rate markets and commodity markets (Li et al., 2021; An et al., 2020). At the data level, commodity trade data are often presented as time series data. Time series data are sequences of data recorded in a consistent standard and in time order (Fu, 2011), and are an important form of structured data in many fields such as economic management, biomedicine and transport. Time series data contains a wealth of dynamic information, that reflects the changing patterns and dynamic characteristics of things (Mahalakshmi et al., 2016). The further exploration of time series data may greatly enhance people's understanding of the operation mechanism and reveal the essence of these phenomena.

Time series data forecasting is the statistical analysis of historical time series data to predict future trends. Depending on the number of variables involved, time series data forecasting can be divided into two main categories: univariate and multivariate forecasting (Mahalakshmi et al., 2016). Among them, univariate forecasting is the simplest form of time series data forecasting, where the data being analyzed contains only one variable. In this case, there is no need to consider the causes or relationships underlying changes in the data. Common univariate time series forecasting methods include the moving average method (Armstrong, 1985), the exponential smoothing method (Fildes & Lusk, 1984), the Box-Jenkins method (Hill & Fildes, 1984), the ARARMA model (Meade & Smith, 1985), the Pandit-Wu method (Pandit & Wu, 1983), the intervention analysis model (Thury & Anderson, 1980), the state space model and the Bayesian forecasting method (Abraham & Ledolter, 1983). Instead, multivariate forecasting focuses on analyzing causal or correlation relationships between two or more variables. Traditional multivariate time series forecasting methods include the autoregressive model (Pal & Mitra, 2015), the cointegration test and error correction model (Lee et al., 2010), the analysis of variance (Kaufmann & Ullman, 2009), the multivariate statistics (Maslyuk & Smyth, 2009), and the synergistic theory (Dong et al., 2021). The analytical methods in traditional economics are relatively effective in analyzing the correlation effects between multiple relevant factors over time. However, these methods are less capable of revealing the volatile relationships of linkages. Therefore, some scholars have started to explore the use of complex network methods to analyze the evolutionary effects of linkages between things, such as the linkage between commodity prices (An et al., 2015; Dong et al., 2018).

As a traditional commodity, nickel constitutes a typically complex system in international trade, and changes in nickel prices in different regions interact through the transmission of the system (Wang et al., 2022). Complex networks are network systems that demonstrate a high degree of complexity. By abstracting the participants of a real system as nodes in a network and the connections between different participants as links between nodes, and using the direction of the links to represent the active and passive relationships of the participants' connections, complex networks can better simulate real systems (Barabási & Albert, 1999). As two of the world's most representative futures markets, nickel futures prices on the London Metal Exchange (LME) and the Shanghai Futures Exchange (SHFE) could also constitute a non-linear and dynamically changing complex system. The linkages between prices also changing over time. While traditional methods are able to represent this bivariate linkage, they are unable to describe the patterns and evolution of the linkage fluctuations between the two variables.

Therefore, this paper firstly applies the coarse-graining method to transform the linkage fluctuations between the LME and SHFE nickel futures price indices into linkage fluctuation modes. Then, the transmission relationships are determined in a time sequence. Finally, a complex network model is constructed to investigate the inner patterns of variation and evolutionary mechanisms. By exploring these interactions, it is possible to obtain a different perspective on the functioning of the commodity economy, expands the application scope of the complex network method, and provides a useful reference for managers and investors to accurately grasp the market trend.

The paper is structured as follows. Section 1 shows the data source, the applicability of the method and the calculation formula of the index. Section 2 constructs the theoretical model and the network model of coal trade. Section 3 presents the results. The final section shows the countermeasures and concludes the paper.

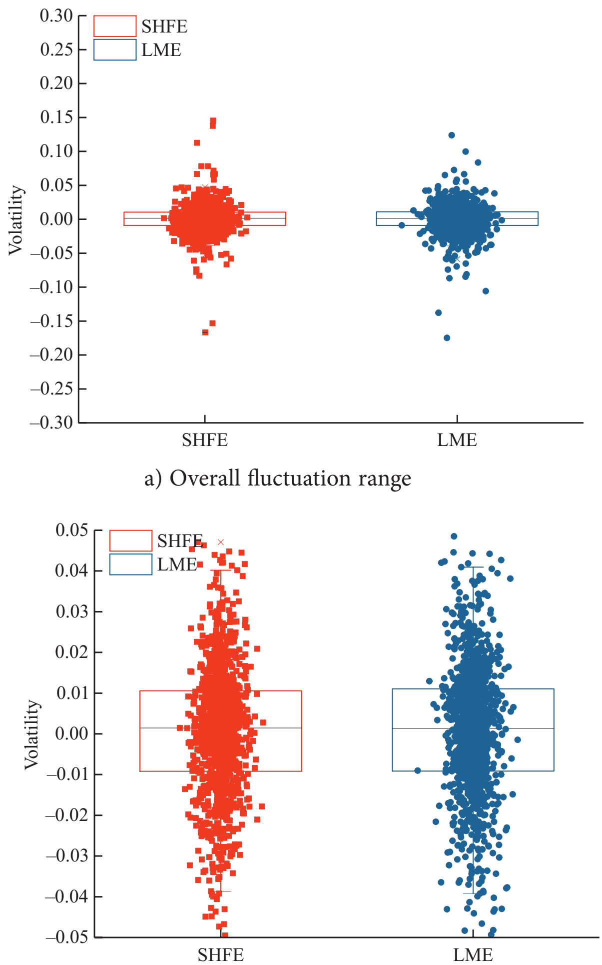
1. Data selection and coarse-grained processing

Commodity price volatility data plays a crucial role in economic data, and this paper examines the daily closing price indices of LME and SHFE nickel futures, which are ranked among the top in the world in terms of annual trading volume and are highly representative of the futures market. LME nickel futures require nickel spot with 99.8% nickel purity, while SHFE also requires nickel products to contain no less than 99.8% nickel or a minimum of 99.96% nickel and cobalt, which is consistent in terms of quality.

The futures price index contains the overall factors of supply and demand in the futures market and implies the overall forecast of futures prices. It can also represent the overall price changes of the relevant products in the industry in a more comprehensive and standard way (Chen, 2013). As this paper focuses on price trends rather than actual prices and has selected nickel futures price index data from the LME and SHFE over the last five years. (May 2017 to May 2022). As trading dates in different markets are influenced by factors such as holidays and uncontrollable events, all data that did not match in time have been removed in order to keep the data consistent. After data pre-processing, a total of 1181 valid matching data have been obtained.

Data coarse graining can divide a huge data set into smaller subsets and extract core data from the noise. In complex systems, the necessary data coarsening work can reduce data size and dimensionality without significantly compromising accuracy, thus improving analysis efficiency. Relevant methods have been widely applied in system science and computer science (Long et al., 2018; Zeng et al., 2019). In this paper, we convert time series data into a collection of change trends.

Suppose the closing price index of LME nickel futures on day t is LNi_t, the closing price index of SHFE nickel futures on day t is SNi_t. Let $\Delta LNi = LNi_t - LNi_{t-1}$ and $\Delta SNi = SNi_t - SNi_{t-1}$. If $\Delta LNi \times \Delta SNi > 0$, it indicates a positive linkage relationship between the two. If $\Delta LNi \times \Delta SNi < 0$, it indicates a negative linkage relationship between the two. And if $\Delta LNi \times \Delta SNi = 0$, it indicates no linkage between the two.



a) Overall fluctuation range

b) Partial enlargement

Figure 1. Change range of index

Choosing a reasonable linkage symbol allows for a more effective analysis of the linkages between nickel futures price indices on different exchanges. As shown in Figure 1, the fluctuations in the nickel futures price indices on both exchanges are relatively concentrated and generally small, with most concentrated in the range of [–0.05,0.05], which suggests that a reasonable level of coarse-graining could simplify the data without filtering out too much information.

Setting the linkage between nickel futures price indices in the two places as CL_i, as shown in formula (1), CL_i is jointly determined by ΔLNi and ΔSNi.

$$CL_i = \begin{cases} \text{P}, & \Delta LNi \times \Delta SNi > 0, \quad \textit{positive linkage} \\ \text{N}, & \Delta LNi \times \Delta SNi < 0, \quad \textit{negative linkage}. \\ \text{M}, & \Delta LNi \times \Delta SNi = 0, \quad \textit{no linkage} \end{cases} \tag{1}$$

As a result, the linkage fluctuations of the nickel futures price indices can be converted into a continuous symbol sequence. The coarse-grained symbol sequence is equivalent to the study of time series data. The converted symbol sequence CL_t is expressed as formula (2).

$$CL_t = \left(CL_1, CL_2, CL_3, \cdots, CL_n\right), CL_i \in \left(P, N, M\right). \tag{2}$$

After symbolizing the linkage fluctuation data of 1181 nickel futures price indices, an abstract symbol sequence $CL_i = \left(CL_1, CL_2, CL_3, CL_4, CL_5, \cdots, CL_n\right)$ with a length of 1181-1 can be obtained. Referring the related research (An et al., 2015; Dong et al., 2018), a symbol sequence set is formed by 5 data symbols of the linkage fluctuation of nickel futures price index, and the data is slid with the step size of 1 day, thus the linkage fluctuation mode of the 1177 price index is obtained. In this paper, the data symbol sequence of nickel futures price index linkage fluctuation data can be expressed as a string in the form of $\{\text{P}, \text{N}, \text{N}, \text{N}, \text{P}, \text{P}, \text{N}, \text{P}, \text{P}, \text{P}, \cdots, \text{P}\}$. The string performs window sliding, and finally forms a modal set of the form $\{(\text{PNNNP}), (\text{PPNNN}), (\text{NPPNN}), (\text{PNPPN}), (\text{PPNPP}), (\text{PPPNP}), \cdots, (\text{PPPNN})\}$. Since the formation of different modes is actually realized by window sliding, the formation of the subsequent mode is based on the previous mode, and the modes are transitive and directional. The specific coarse graining treatment process is shown in Table 1.

Table 1. Coarse-grained process

Data	LME Ni	Price index changes	SHFE Ni	Price index changes	Linkage direction	Symbolic	Coarse-grained mode
2022/5/9	28 350	–1725	2552.9	–59.55	positive	P	(P,P,P,N,N)
2022/5/6	30 075	–275	2612.45	–112.5	positive	P	(P,P,N,N,P)
2022/5/5	30 350	–2250	2724.95	–108.85	positive	P	(P,N,N,P,P)
2022/4/29	32 600	–700	2833.8	60.4	negative	N	(N,N,P,P,P)
2022/4/28	33 300	245.5	2773.4	–5.25	negative	N	(N,P,P,P,P)
2022/4/27	33 054.5	304.5	2778.65	99.82	positive	P	(P,P,P,P,P)

End of Table 1

Data	LME Ni	Price index changes	SHFE Ni	Price index changes	Linkage direction	Symbolic	Coarse-grained mode
2022/4/26	32 750	100	2678.83	26.73	positive	P	(P,P,P,P,P)
2022/4/25	32 650	–1350	2652.1	–220.99	positive	P	(P,P,P,P,P)
2022/4/22	34 000	150	2873.09	31.48	positive	P	(P,P,P,P,P)
2022/4/21	33 850	50	2841.61	20.38	positive	P	(P,P,P,P,N)
……							
2017/5/9	9145	–	933.37	–	–	–	–

2. Complex networks construction

In this paper, we use the bivariate linked volatility modes of nickel futures index data as nodes, the directed transitions between modes as edges, and the number of transitions between different modes as edge weights to construct a directed weighted network W_{ij}.

$$W_{ij} = \begin{Bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ w_{m1} & w_{m2} & \cdots & w_{nm} \end{Bmatrix}, \ i \le m, \ j \le n. \tag{3}$$

In the formula, w_{ij} represents the edge weight from node i to node j, according to the number of transformations of the i linkage mode to the j linkage mode. And the final construction becomes a complex network of time series linkage fluctuations between LME and SHFE nickel futures indices with weighted direction.

The complex network analysis method provides a variety of effective network analyses and indicators. In this paper, we mainly use indicators such as node strength, cohesive subgroup analysis, clustering coefficients, intermediary centrality and mean path length to analyze the established linkage fluctuation modal networks from three perspectives: statistical pattern, change pattern and evolution pattern.

2.1. The statistical pattern of the linkage fluctuation modes

The statistical pattern of linked fluctuation modes is mainly analyzed using relevant indicators based on the statistical analysis of the complex relationship between them. The complex network of time series linkage volatility between LME and SHFE nickel futures indices constructed in this paper is a typical directional weighted network, and the node strength and node strength distributions are chosen to describe the linkage fluctuation patterns between these two indices and the degree of correlation.

The node strength can be used to measure the importance of the corresponding node (Wasserman & Faust, 1994), and the formula for calculating the node strength is:

$$k_i = \sum_{j \in N_i} w_{ij}. \tag{4}$$

In the formula, N_i represents the set of all neighbouring nodes of node i. The greater the node strength, the more important the mode is in the network species and the more frequently the mode transitions to other modes.

Different nodes have different intensities, and their distribution also varies, which in this paper is defined as:

$$LP(k) = k_i / N. \tag{5}$$

In the formula, N represents the sum of the intensities of all nodes. The intensity distribution of nodes reflects the importance of a mode at a more macro level. The wider the intensity is, the higher the probability of the mode occurring in the network and the more important the mode is.

2.2. The variation pattern of the linkage fluctuation mode

The linkage fluctuation modes are used to analyze the transitions between various important modes in the network, the core modes during mode transitions, the control ability of important nodes over other nodes in the network, and the number of subgroups present within the network.

The n-Cliques method and the k-Plex method are two effective methods for analyzing subgroups in networks (Ronald, 1992). The n-Cliques is a network reachability-based analysis method. In a given network, if there is a subgraph in which the shortest distance $d(i,j)$ between any two nodes i and j does not exceed n and $d(i,j) \leq n,$ then the subgraph consisting of all nodes satisfying this condition is n-Cliques. k-Plex is a node-degree based analysis method. In a given network, assume that there are n nodes in the subgroup and that each node in the subgroup is directly connected to at least $n-k$ nodes, meaning that the degree of each node is not less than $n-k.$ The subgraph consisting of all nodes satisfying this condition is a k-Plex.

The n-Cliques method and the k-Plex method are used to analyze the cohesive subgroups in the network to initially find out which modes have more frequent transformations with each other. The importance of different modes can then be assessed using the clustering coefficient. The weighted clustering coefficient is mainly used to count the clustering characteristics of the nodes in the network and their nearby nodes. The higher the weighted clustering coefficient, the higher the degree of connection between the node and its nearby nodes, which means the more important the position of the mode in the self-circle is, the more frequent the mode transitions with other modes (Barrat et al., 2004).

In a time series linkage fluctuation complex network of LME and SHFE nickel futures price indices, the weights of the edges indicate the closeness of the relationship between connected nodes and the weighted clustering coefficient is calculated as:

$$C^w(i) = \frac{1}{k_i(S_i - 1)} \sum_{j,k} \frac{(w_{ij} + w_{ik})}{2} a_{ij} a_{jk} a_{ki}. \tag{6}$$

In the formula, w_{ij} represents the weight of the edge between nodes $i, j,$ k_i represents the node strength of node $i,$ S_i represents the degree of node $i,$ and a_{ij} represents whether there is a connection between nodes i and $j,$ which takes the value of 0 or 1.

2.3. The evolutionary pattern of the linkage fluctuation mode

The evolution pattern of the linkage fluctuation modes focuses on the evolution of different modes over time, such as the transformation relationship between modes, the transformation cycles and so on. This can be analyzed using betweenness centrality and mean path length.

The average path of the network is the average of the distance between any two nodes in the network and is calculated as:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}. \tag{7}$$

In the formula, d_{ij} represents the distance between nodes i, j and N represents the number of nodes in the network.

Betweenness centrality refers to the number of times a node acts as a "bridge" between two other nodes, and the higher the betweenness centrality, the stronger the control of the node over its neighboring nodes (Zhou et al., 2011). The formula for betweenness centrality is:

$$w_k = \sum_{(i,j)} w_k(i,j) = \sum_{(i,j)} \frac{c_k(i,j)}{c(i,j)}. \tag{8}$$

In the formula, $c(i,j)$ represents the total number of all shortest paths between nodes $i, j.$ In these paths, the number of paths through node k is c_k.

3. Analysis and results

3.1. Study of the statistical patterns of the linkage fluctuation mode

This paper analyzes the node strength and intensity distributions of the LME and SHFE nickel futures daily closing price linkage fluctuation modes. The sign sequence of the fluctuation modes is obtained by coarse-graining the modes. According to the results of the analysis, a total of 85 modes occurred in practice, compared to a theoretical total of 243(3^5) for all modes, indicating that some of the modes did not occur in practice. As shown in Figure 2, the statistics on the frequency of occurrence of different symbols show that the symbol P, representing positive linkage fluctuations, appeared 818 times, accounting for 69.32%. The symbol N, representing negative linkage fluctuations, appeared 342 times, accounting for 28.98%. And the symbol M, representing no linkage fluctuations, appeared 20 times, accounting for 1.69%. This suggests that LME and SHFE nickel futures prices are strongly linked over the five-year period from May 2017 to May 2022.

The node strength and node strength distributions of the nodes of the linkage fluctuations mode of the LME and SHFE nickel futures price indices have been calculated and the results are shown in Table 2.

As shown in Table 2, the node strength of the symbol (P,P,P,P,P) representing five consecutive positive linkages between LME and SHFE nickel futures daily closing prices is 194, while the node strength of the symbol (N,N,N,N,N) representing five consecutive negative linkages is 4. This indicates that the positive linkage between LME and SHFE nickel futures daily closing prices was strong in the last 5 years, with five consecutive positive changes

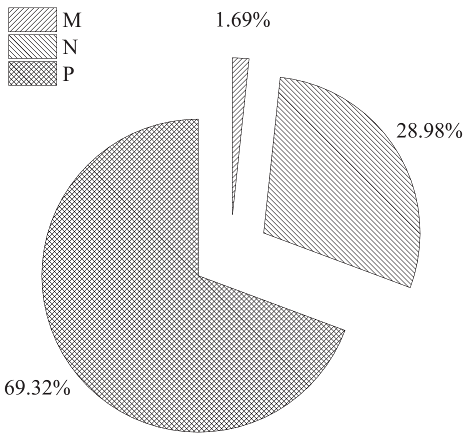


Figure 2. Percentage of occurrences of the linkage fluctuation symbol

Table 2. Node strength and strength distributions in the network

No.	Node	Node strength	Distribution of node strength/%
1	(P,P,P,P,P)	194	16.50
2	(N,P,P,P,P)	87	7.40
3	(P,P,P,P,N)	87	7.40
4	(P,P,P,N,P)	76	6.46
5	(P,P,N,P,P)	74	6.29
6	(P,N,P,P,P)	71	6.04
7	(N,N,P,P,P)	41	3.49
8	(P,N,N,P,P)	40	3.40
9	(P,P,N,N,P)	39	3.32
10	(P,P,P,N,N)	37	3.15
11	(P,N,P,N,P)	35	2.98
12	(P,N,P,P,N)	34	2.89
13	(P,P,N,P,N)	34	2.89
14	(N,P,P,N,P)	32	2.72
⋮	⋮	⋮	⋮
85	(P,P,P,M,N)	1	0.09

having occurred a total of 194 times, while five consecutive negative changes occurred just four times. Among the top 29 nodes with the highest node strength, the symbol "M" appears zero times, indicating that price fluctuations in the nickel futures market were more intense over the last five years.

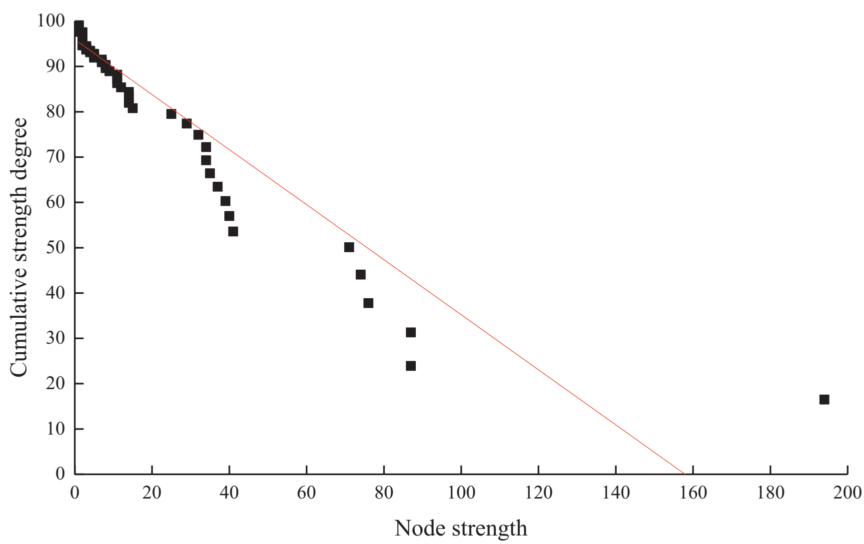
The directionality of the linkage between the LME and SHFE nickel futures price indices can be expressed by the weighted number of index volatility symbols, Q, defined as the product of the number of occurrences of the index fluctuation symbols and the node strength distribution of that node. The weighted counts of index fluctuation symbols for the top 29 nodes with the highest node degree are shown in Table 3. From Table 3, it can be seen that as the number of positive and negative symbols increases, the ratio of their weighted counts increases. This indicates that the ratio of simultaneous linkage appearing in the network is increasing over time, with nickel futures prices simultaneous growing or decreasing more frequently.

Table 3. Weighted counts of linkage fluctuation combination symbols of former 29 nodes

Symbol combination	Weighted times	Symbol combination	Weighted times
P	3.28	N	1.30
P,P	1.88	N,N	0.30
P,P,P	1.00	N,N,N	0.06
P,P,P,P	0.31	N,N,N,N	0.01

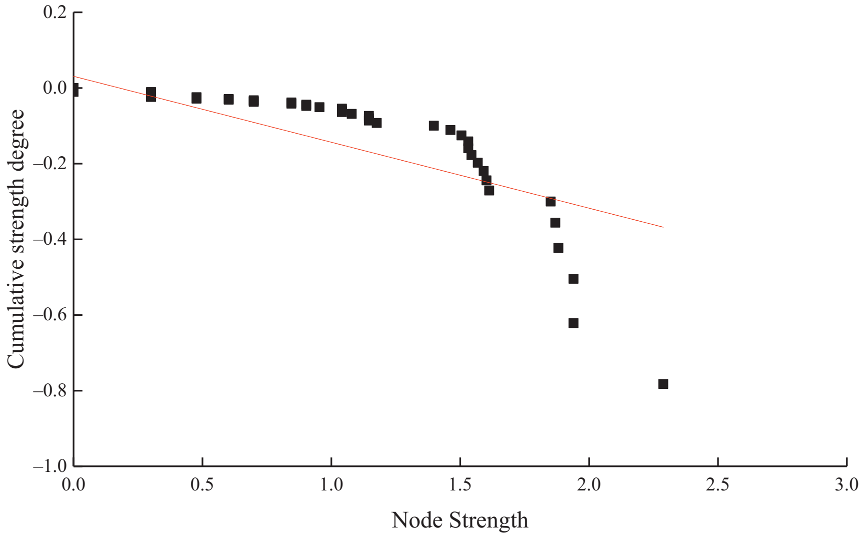
Among all 85 nodes, the top 29 nodes in node strength have an intensity distribution of 91.97%, indicating that these nodes represent modes that are more likely to transform to or from other modes. The node strength distribution of the bottom 48 nodes in node strength are all below 0.2%, indicating that these nodes have a limited number of occurrences and transitions in the network.

The relationship between the distributions of node strength k and cumulative node strength LP(k) for the complex network of time series linkage fluctuations of the LME and SHFE nickel futures price indices is shown in Figure 3, both of which follow a power-law distribution overall.



a) Ordinary scale

Figure 3. *To be continued*

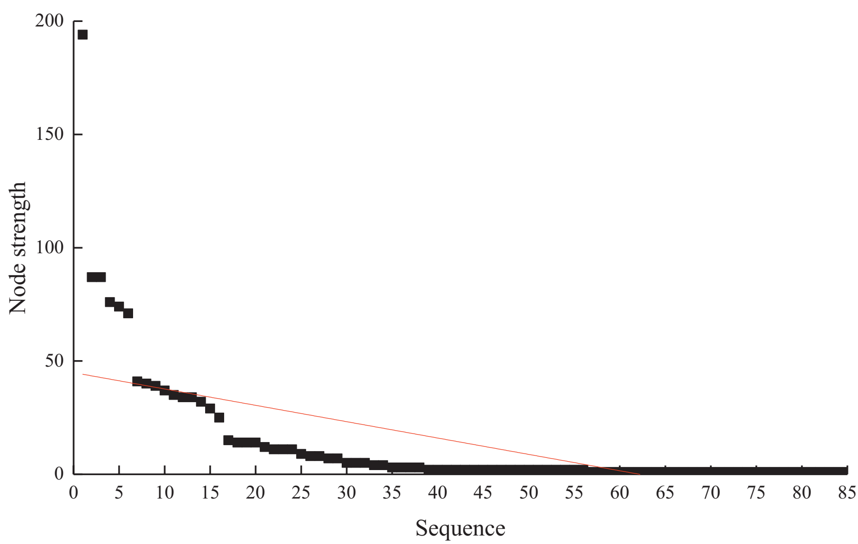


b) Log-log scale

Figure 3. Distribution of node strength and cumulative strength degree

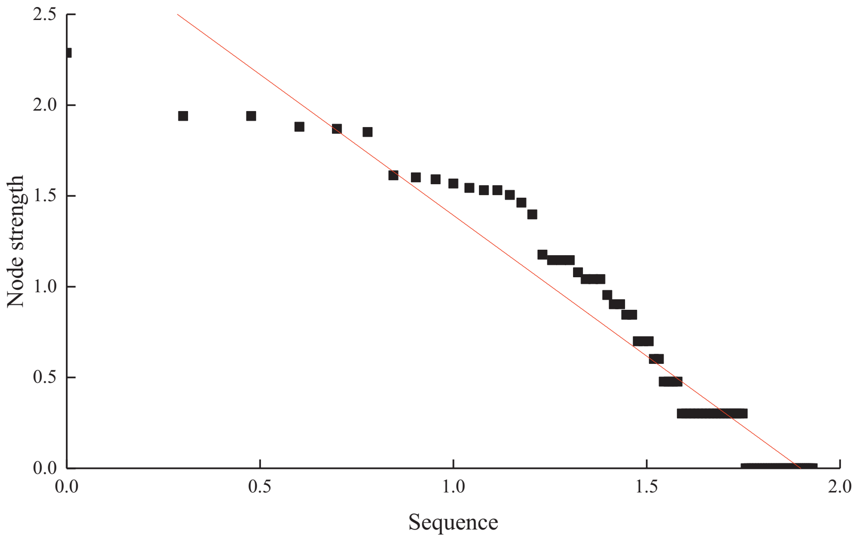
As shown in Figure 4, after ranking the nodes in the network by node strength, the logarithm of node strength and ranking position was calculated and fitted to obtain the linear regression equation $Y = -0.72X + 44.88$, and they follow a power-law distribution overall.

In summary, in the complex network of time series linkage fluctuations between LME and SHFE nickel futures indices, the node strength and cumulative intensity distributions, node



a) Ordinary scale

Figure 4. *To be continued*



b) Log-log scale

Figure 4. Distribution of node strength and its ranking

strength and ranking order all follow a power-law distribution, with a relatively strong trend of simultaneous linkage. This suggests that the prices of Chinese nickel futures products are influenced by the prices of London nickel futures products, and generally remain synchronized. However, China does not simply follow international prices when setting prices for nickel futures products, but adjusts them to the current political and economic environment in China, with a certain degree of independence.

3.2. Study of the variation pattern of the linkage fluctuation mode

This paper presents a statistical analysis of the complex network of time series linkage fluctuations between LME and SHFE nickel futures indices based on n-Cliques. n = 2 is set, where there are six subgroups in the network, four of which contain seven nodes and two of which contain eight nodes.

As shown in Table 4, the transformation between the six subgroup modes does not exceed two steps, and the modes within a subgroup have a higher probability of transforming into other modes within the same subgroup. Further observations show that the distribution of the six subgroups tends to be consistent, with the symbol P having a clear quantitative advantage, indicating that there are more positive price index linkage transitions in all of the modes. Additionally, the symbol N appears in a significantly higher proportion in subgroups 2 and 4, indicating a greater chance of negative linkage fluctuation transitions in these two subgroups compared to the other subgroups.

Using the k-Plex method to statistically analyze the complex network of time series linkage fluctuation between LME and SHFE nickel futures price indices, a total of 24 subgroups were found when setting k = 2 and the subgroup size was 4. When setting k = 2 and the subgroup size was 5, no aggregated subgroups were found.

As shown in Table 5, most of the subgroups have no more than 2 steps of transition between modes, but some of the subgroups have longer shortest paths from one node to another, and some nodes belong to more than one subgroup at the same time. The 24 subgroups can be divided into three categories according to their modes: 11 of them have significantly more symbols P than

Table 4. Clusters of a linkage fluctuation complex network based on n-Cliques

No.	Node scale	Subgroup modal set
1	7	(M,P,P,P,N) (N,P,P,P,N) (P,P,N,P,M) (P,P,N,P,N) (P,P,N,P,P) (P,P,P,N,P) (P,P,P,P,N)
2	7	(M,P,P,N,P) (N,P,P,N,P) (P,N,P,N,M) (P,N,P,N,N) (P,N,P,N,P) (P,P,N,P,N) (P,P,P,N,P)
3	7	(M,P,N,P,P) (N,P,N,P,P) (N,P,P,P,M) (N,P,P,P,N) (N,P,P,P,P) (P,N,P,P,P) (P,P,N,P,P)
4	7	(M,P,P,P,N) (N,P,P,P,N) (P,P,N,N,M) (P,P,N,N,N) (P,P,N,N,P) (P,P,P,N,N) (P,P,P,P,N)
5	8	(N,N,P,P,P) (N,P,P,P,N) (N,P,P,P,P) (P,N,P,P,P) (P,P,P,N,M) (P,P,P,N,N) (P,P,P,N,P) (P,P,P,P,N)
6	8	(N,N,P,P,P) (N,P,P,P,P) (P,N,P,P,P) (P,P,P,N,M) (P,P,P,N,N) (P,P,P,N,P) (P,P,P,P,N) (P,P,P,P,P)

Table 5. Clusters of a linkage fluctuation complex network based on k-Plex

No.	Node scale	Subgroup modal set
1	4	(M,P,P,N,P) (N,P,P,N,P) (P,P,N,P,N) (P,P,N,P,P)
2	4	(M,P,P,N,P) (P,P,N,P,N) (P,P,N,P,P) (P,P,P,N,P)
3	4	(M,P,P,P,N) (N,P,P,P,N) (P,P,P,N,N) (P,P,P,N,P)
4	4	(M,P,P,P,N) (P,P,P,N,N) (P,P,P,N,P) (P,P,P,P,N)
5	4	(N,N,N,P,N) (N,N,P,N,N) (N,N,P,N,P) (P,N,N,P,N)
6	4	(N,N,N,P,P) (N,N,P,P,N) (N,N,P,P,P) (P,N,N,P,P)
7	4	(N,N,P,N,N) (N,P,N,N,N) (N,P,N,N,P) (P,N,P,N,N)
8	4	(N,N,P,N,P) (N,P,N,P,N) (N,P,N,P,P) (P,N,P,N,P)
9	4	(N,N,P,P,N) (N,P,P,N,N) (N,P,P,N,P) (P,N,P,P,N)
10	4	(N,N,P,P,N) (N,P,P,N,N) (P,N,N,P,P) (P,P,N,N,P)
11	4	(N,N,P,P,P) (N,P,P,P,N) (N,P,P,P,P) (P,N,P,P,P)
12	4	(N,P,N,M,N) (P,N,M,N,M) (P,N,M,N,N) (P,P,N,M,N)
13	4	(N,P,N,N,N) (P,N,N,N,M) (P,N,N,N,N) (P,P,N,N,N)
14	4	(N,P,N,N,N) (P,N,N,N,M) (P,N,N,N,P) (P,P,N,N,N)
15	4	(N,P,N,N,N) (P,N,N,N,N) (P,N,N,N,P) (P,P,N,N,N)
16	4	(N,P,N,N,P) (P,N,N,P,N) (P,N,N,P,P) (P,P,N,N,P)
17	4	(N,P,N,P,N) (P,N,P,N,N) (P,N,P,N,P) (P,P,N,P,N)
18	4	(N,P,N,P,P) (P,N,P,P,N) (P,N,P,P,P) (P,P,N,P,P)
19	4	(N,P,P,N,N) (P,P,N,N,N) (P,P,N,N,P) (P,P,P,N,N)
20	4	(N,P,P,N,P) (P,P,N,P,N) (P,P,N,P,P) (P,P,P,N,P)
21	4	(N,P,P,P,N) (P,N,P,P,P) (P,P,N,P,P) (P,P,P,N,P)
22	4	(N,P,P,P,N) (P,P,P,N,M) (P,P,P,N,N) (P,P,P,P,N)
23	4	(N,P,P,P,N) (P,P,P,N,M) (P,P,P,N,P) (P,P,P,P,N)
24	4	(N,P,P,P,N) (P,P,P,N,N) (P,P,P,N,P) (P,P,P,P,N)

others, and in these subgroups the price index has more frequent positive linkage fluctuations. 6 of them have more symbols N, and in these subgroups the price index has more frequent negative linkage fluctuations. The remaining 8 subgroups have the same number of symbols P and N.

The results of both analyses show that, the nodes in the network form relatively obvious clusters. When modes are in a subgroup of modes, they have a greater tendency to transform with other modes within the subgroup. In reality, this reflects the fact that changes in the nickel futures price index follow a certain pattern, with a high probability of transformation within a limited number of changing modes, which could provide some reference for investment, trade and risk management.

By analyzing the clustering coefficients of the network, the core modes of the network and the importance of the different modes in the transition process can be further explored. As shown in Table 6, the analysis shows that there are 12 nodes in the network with non-zero weighted clustering coefficients, and 12 small clusters are formed around these 12 nodes in the network. However, by observing the node strength-weighted clustering coefficient plot shown in Figure 5, it can be found that nodes with higher node strength do not generally

Table 6. All modes and its weighted clustering coefficients

No.	Mode	Weighted clustering coefficients	No.	Mode	Weighted clustering coefficients
1	(N,P,P,P,P)	3.10	7	(P,P,N,P,P)	1.30
2	(P,P,P,P,N)	3.10	8	(N,N,P,N,N)	0.33
3	(N,P,P,N,P)	2.25	9	(N,P,N,N,P)	0.33
4	(P,P,P,P,P)	2.08	10	(P,N,N,N,N)	0.25
5	(N,N,N,N,N)	2.00	11	(P,N,N,P,N)	0.20
6	(P,N,P,P,N)	1.67	12	(N,N,N,N,P)	0.15

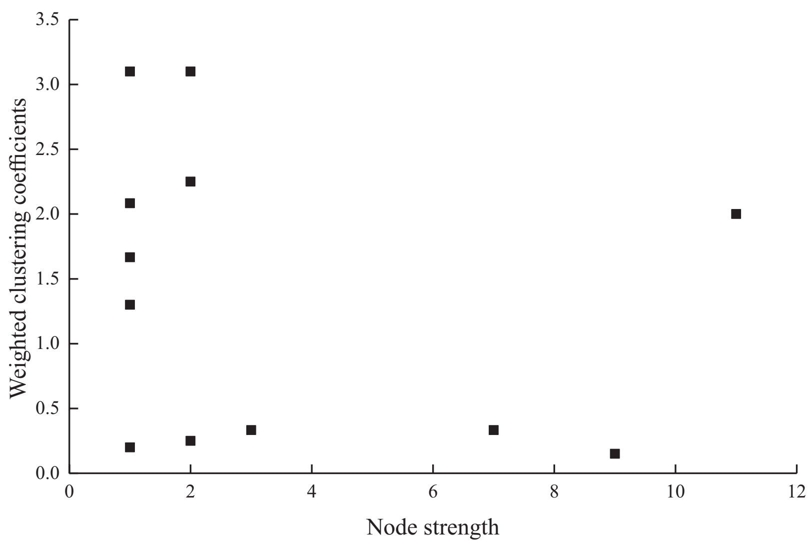


Figure 5. Distribution of node strength and weighted clustering coefficients

have higher weighted clustering coefficients, which indicates that these nodes do not have sufficient control over the other nodes in the network and do not have a dominant position. Thus, the complex network of time series linkage fluctuations between LME and SHFE nickel futures indices has a high degree of complexity. Although small clusters with their own cores have been formed in the network, the linkages between the clusters are relatively weak.

3.3. Study of the evolutionary pattern of the linkage fluctuation modes

The complex network of time series linkage fluctuations between LME and SHFE nickel futures price indices is a directed weighted network with an average path length of 6.550, a network degree of clustering of 0.194 and a weighted distance of 0.806. Combining the results of the subgroup and clustering coefficient analysis, shows that although there is some node aggregation in the network, the number of nodes contained within each subgroup is small and inside the subgroup, the transitions between different modes only require passing through a small number of intermediate modes. Since the different subgroups are weakly correlated, while part of the nodes of the different subgroups can be converted directly, such as nodes (N,P,P,P,P) and (P,P,P,P,N), most of them require passing through more than one node before transformation, such as nodes (P,P,P,P,P) and (N,N,N,N,N). A visual graph of two pairs of typical nodes and associated nodes based on the gravitational layout (Jacomy et al., 2014) is shown in Figure 6, which shows that the nodes that can be directly transformed are closer together and the nodes that are difficult to directly transform are further away, providing an intuitive understanding of the difficulty of mode change.

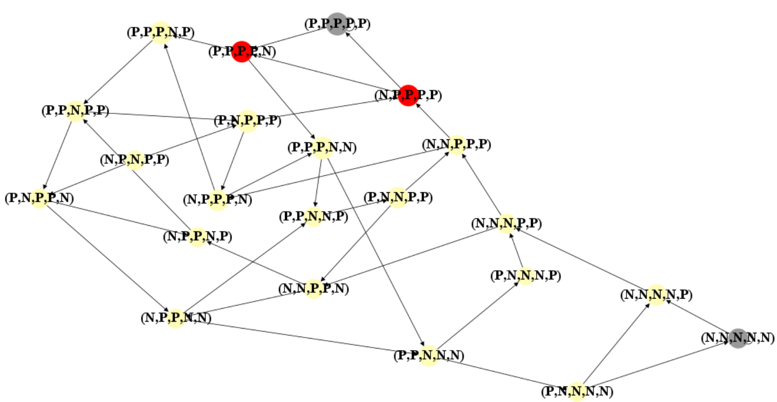


Figure 6. Example of transformation processing

As shown in Figure 7, the analysis of the betweenness centrality of the complex network of time series linkage fluctuations between LME and SHFE nickel futures indices indicates that there are a number of nodes with high betweenness centrality in the network, and these nodes play an important bridging role in some groups. Some of these nodes have both high betweenness centrality and node strength. Such nodes are surrounded by more nodes and are intermediate states in the transformation process of many modes to other forms. They play a role in a larger scale and are the core of the network, which represents the overall change pattern of nickel futures prices, such as nodes (P,P,N,P,N), (P,P,P,N,N), (P,N,P,P,P) and (P,P,P,N,P). Some of the nodes have lower node strength and limited influence, but have high betweenness centrality, such as nodes (M,P,P,P,N), (N,P,N,M,N) and (M,P,P,N,P), which indicate fluctuations in nickel futures prices during a certain period, but similar situations are not common in reality.

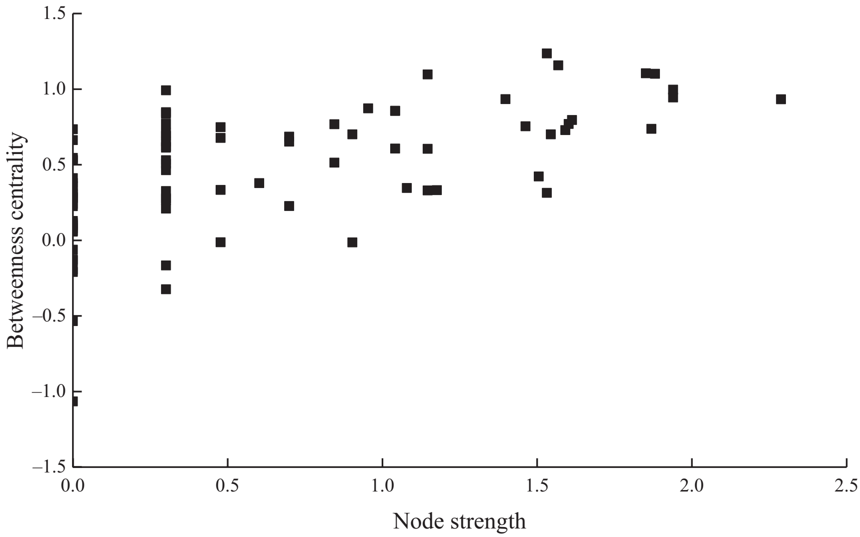


Figure 7. Double logarithm distribution of betweenness centrality and ranking

In the complex network of time series linkage fluctuations between LME and SHFE nickel futures indices, nodes with specific characteristics often signal the beginning of a shift in reality, implying a long-standing market pattern, and they can, to some extent, act as precursors for transitions between linkage fluctuation modes. The study of these nodes with specific properties could help to understand the pattern of price changes in nickel futures, thus supporting market risk avoidance and more efficient business decisions.

Conclusions

The fluctuations of the LME and SHFE nickel futures price indices form a typically complex system that is non-linear and unstable, making it difficult for traditional methods to identify the mechanism of price fluctuations. In this paper, the fluctuation status of the nickel futures price indices is transformed into specific symbols by the coarse-grained method. A suitable sliding window length is selected to form continuous fluctuation modes, different modes are regarded as nodes, and the nodes are directed according to the sequence of mode formation, and finally a complex network of time-series linkage fluctuations is constructed.

Based on the complex network theory, the nodes reflect the linkage change modes of nickel futures prices over a period of time in reality, the connecting lines of the nodes foretell the possible ways of transformation from one mode to another, and the changing modes contain the precursors of price changes. From the perspective of methodological, this paper incorporates the ideas of physical economy, which provides a feasible way to study multivariate linkage fluctuations and allows for a better understanding of the complexity of multivariate systems. From the perspective of practical application, this paper studies the modal distribution patterns, change patterns and evolutionary mechanisms of nickel futures prices in different countries, providing a scientific basis for grasping the nickel futures market, using futures prices to predict spot price fluctuations, setting spot prices, and avoiding market risks.

Over the past five years, the LME and SHFE nickel futures price indices have been mostly linked in the same direction, demonstrating the relatively strong linkage between the two nickel spot trades. Despite the sparse network, this paper identifies a number of core linked fluctuation modes, which occur frequently and represent realistic price fluctuation patterns. Additionally, the transition paths of the modes have been explored and a number of important intermediary nodes have been identified. Based on the strength of the intermediary nodes, the nodes are divided into core intermediary nodes and regionally important nodes, both of which play a bridging role in the inter-transition of different modes. The occurrence of core intermediary nodes can predict the beginning of different mode transitions and may provide a guiding significance for the trend of nickel futures prices.

It is worth nothing that the data in this study is limited by the sample size and the difference in trading dates between the two futures exchanges. This restricts the size of the network and reduces the applicability of the study. However, the careful selection and analysis of the data in this study have enabled the results to provide as comprehensive a picture as possible of the patterns of interest under the conditions set. Future research should not only cover a longer time horizon, but also include products in the chain of a particular type of commodity or its important complementary/alternative products, beyond a single commodity.

The methodology used in this paper could also be extended to other complex systems. By exploring these interactions, this study could provide a unique perspective on the economic functioning of commodities, which may extend the application of the complex network approach and provide a valuable reference for managers and investors to accurately grasp market trends.

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Author contributions

Both authors initiated this research and a manuscript. Chen Xiaoci proposed the study goal. Chen Xiaoci, Huo Guanyu and Cao Gaojie was responsible for data analysis and conducted literature search.

Disclosure statement

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