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Research on the Transmission Mechanism of International Grain Trade Price Volatility

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ABSTRACT

The current international epidemic situation is serious, and countries are more concerned about grain supply issues. This paper selects the US wheat futures price and Chinese high-quality strong-gluten wheat futures price as the sample data, and uses the complex network and statistical physics method to study the impact of international grain prices on domestic grain prices and the law of linkage. The volatility states of two wheat futures prices are transferred to the volatility modes of price linkage by a coarse-grained approach. Then, the modalities are used as nodes and the transitions between the modalities are used as edges to construct a complex network of price linkages. Finally, by analyzing the modal characteristics of the network, the weighted aggregation coefficient of the core modal nodes of the wheat futures price fluctuation, the conduction mode and transition time characteristics of the K-core. The results show that the US wheat futures price significantly affects the Chinese wheat futures price. Modal conduction is a one-way closed loop consisting of 5 main modes. The linkage fluctuation mode has power-law, cluster and periodicity.

1. Introduction

In the context of economic globalization, international grain trade is growing rapidly. More and more countries are involved in grain import and export trade. The abnormal fluctuation of grain prices affects world grain security. As one of the important crops in China, wheat has an important position in the grain security strategy. Its price fluctuations can directly affect the interests of farmers and wheat consumers in the main production areas.

A diverse pattern of research has been developed on domestic and international agricultural price volatility (e.g., Amsler et al., 1997). Among them, important research results were achieved in the areas of wheat price volatility characteristics and influencing factors (e.g., Serra et al., 2013; Sekhar, 2003; Zhang et al., 2020). As the internationalization process accelerates, some domestic scholars have begun to focus on the impact of international factors on the prices and futures markets of grain commodities (e.g., Trostle, 2008; Lu, 2017). Examples include the integrated relationship between domestic and foreign rice prices (e.g., Zhou, 2017), the asymmetric response of agricultural prices (e.g., Alexander et al., 1994; Peng et al., 2016; Han, 2018), and the linkage (e.g., Zhang et al., 2020) and power-law (e.g., Lu, 2015) among agricultural prices. Luo Feng analyzed the transfer effect of international agricultural price fluctuations on domestic agricultural prices using cointegration tests and vector autoregressive models (e.g., Luo et al., 2009). A transmission effect between international and domestic commodity prices was found, and changes in international agricultural prices significantly impacted the pricing of agricultural products in China.

Currently, there is relatively little literature on scholars who analyze prices from an informatics perspective. Yao Hongxin et al. analyzed the price time series by the data information separation method and derived the basic characteristics of the economic cycle in China (e.g., Yao et al., 2002). Hu Anqi combined an autoregressive conditional heteroskedasticity model with international wheat price fluctuations to study the volatility patterns of different agricultural commodity prices (e.g., Hu, 2012). Several economic physicists have used the complex network approach to analyze time series (e.g., Lacasa et al., 2008; Fang et al., 2018; Long, 2013) and the volatility characteristics of international oil prices (e.g., Chen et al., 2010; Ji et al., 2012). A directed weighted network of prices at different moments was constructed and the evolution of new nodes in the price network was analyzed (e.g., Wang et al., 2016). In recent years a part of scholars has combined coarse-grained methods and complex networks to construct temperature fluctuation modes (e.g., Zhou et al., 2009), trade networks (e.g., Duan et al., 2021; Li et al., 2021), study the volatility relationship between crude oil futures and spot prices (e.g., Gao et al., 2012), and analyze the correlation between futures indices (e.g., Zhang et al., 2014). The above study is based on the theory of

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complex network propagation dynamics and provides an in-depth analysis of the relationship between the two variables and the non-stationary fluctuation law. Related research also includes least squares and maximum spanning tree problems (e.g., Li et al., 2019; Wang et al., 2019), and optimization of network models(e.g., Wang et al., 2018). Thus, the statistical physics approach provides a new way to study the price fluctuations of domestic and foreign agricultural products. The existing literature is of great theoretical value in explaining the causes of domestic and international wheat price changes. It is of great practical importance to grasp the volatility characteristics and dynamic correlation of domestic and international wheat prices. However, there is still room for in-depth exploration. The existing literature does not provide an in-depth study of the patterns of grain futures price volatility and the cycles of its fluctuations. Secondly, the accelerated internationalization process and more frequent grain trade exchanges have led to changes in the pattern of domestic and international grain price linkages. Its previous findings no longer reflect the new pattern of current wheat price volatility. Finally, changes in world trade patterns will directly affect imports and exports between countries, which in turn will affect agricultural prices and linkages.

From the above research review, it is found that international wheat prices are correlated with domestic wheat prices. The volatile relationship between the two variables can be expressed traditionally, but the linkage between them has been less studied. Therefore, the study of wheat price fluctuation patterns and the analysis of network characteristics using complex networks can help to better explain the fluctuation characteristics of its changes. In this paper, we draw on the methods of statistical physics and complex network theory to abstract the correlated fluctuation relationship between these two variables as a relational model. Then the complex network of modal transitions is established by analyzing the relationship between related modalities using complex networks. By analyzing the correlation degree and fluctuation pattern between them, to provide a basis for the linkage between domestic and international grain prices. The method can be used not only as a research method of domestic and foreign grain price linkage to provide theoretical support for grain trading, but also provides ideas for the research of linkage of other agricultural products at home and abroad.

2. Research methods and data sources

2.1 Data source

Grain futures prices have developed into an important signal of pre-trade supply and demand in grain markets and their price fluctuations. With the changes and development of grain futures markets, the joint effect between national grain futures markets has increased significantly. The futures market has developed into an important bridge linking international grain prices. International grain futures prices accelerate changes in domestic grain prices by constantly influencing domestic grain futures prices. China and the United States are currently the two countries with the highest GDP rankings in the world. The trade between the two countries is close and the amount of trade is huge. This data has a high analytical value. Meanwhile, the futures prices of the Chicago Board of Trade are the authoritative prices in the international futures market. In terms of agricultural price transmission, the data from this exchange have a significant impact on agricultural prices in various countries (e.g., Tes et al., 1997; Holder et al., 2002; Hernandez et al., 2014). Therefore, based on the availability and recognition of the sample, the daily closing price of wheat futures on the Chicago Mercantile Futures Exchange in the U.S. is used for international wheat futures prices, and the daily closing price of high-quality durum wheat futures on the Zhengzhou Commodity Futures Exchange is used for domestic wheat futures prices. The selected period is January 4, 2011 - December 31, 2020. Differences in holidays or weekends between the United States and China will produce data with different time dates. In order to more accurately study the fluctuations between the two, a total of 2,408 sets of data were obtained after removing these discrepant data. The futures price trends for the two wheat species are shown in Fig. 1. and Fig. 2.

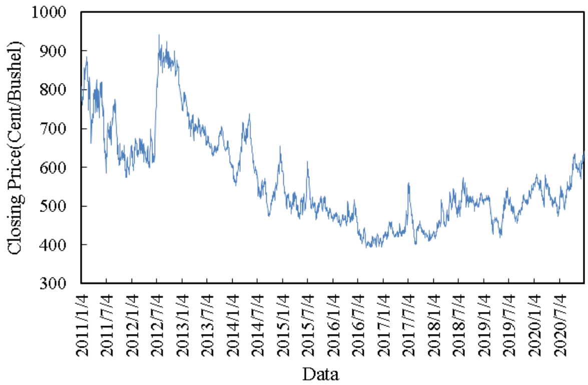

Fig. 1. U.S. Chicago Mercantile Futures Exchange wheat futures closing price chart

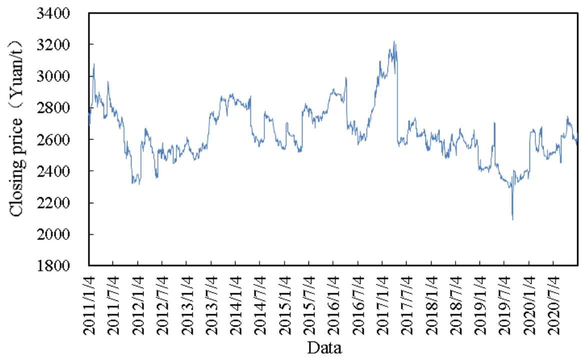

Fig. 2. Zhengzhou Commodity Futures Exchange premium durum wheat futures closing price chart

As seen in Fig. 1. and 2, the two wheat futures price trends alternate between same-way linkage and inverse linkage during January 2011-June 2017. During June 2017-December 2020, the futures price charts for both products show a high degree of same-directional linkage. This indicates that the U.S. wheat futures prices have had a strong influence on Chinese wheat futures prices since June 2017, related to the accelerated economic globalization and increased wheat import and export volumes. Chinese and U.S. wheat futures prices are constantly fluctuating, and this volatile relationship constitutes a complex network system.

2.2 Data correlation coarse granularity processing

The data correlation modalities were established using a coarse-grained approach. Setting x and y as wheat prices of corresponding varieties in the U.S. and China, the correlation between the two variables is first quantified using the correlation coefficient R_{xy}. R_{xy} is defined as:

$$R_{xy}=\frac{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)\left(y_i-\overline{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\overline{x}\right)^2}\sqrt{\sum_{i=1}^{n}\left(y_i-\overline{y}\right)^2}} \tag{1}$$

Where R_{xy} is the correlation coefficient; x_i is the value corresponding to the time series of the variable x; $\overline{x}$ is the mean of the variable x; y_i is the value corresponding to the time series of the variable y; $\overline{y}$ is the mean of the variable y; n is the sum of the terms of the series of all variables.

Fig. 3. presents the results of the analysis of the correlation coefficients for the 2,408 data sets. The range interval of correlation coefficients is [-1,1] and the two variables are non-stationary fluctuations.

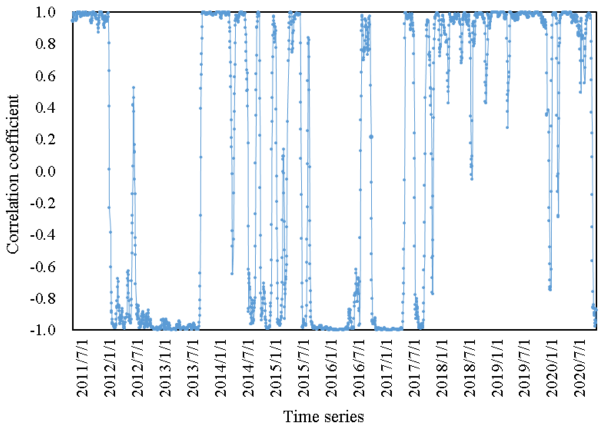

Fig. 3. Correlation volatility series between U.S. wheat futures prices and Chinese wheat futures prices

Based on the value of the correlation coefficient the degree of bivariate correlation can be abstracted into the sign DS_i and classified into five categories:

$$DS_i=\begin{cases} P & 0.8\le R_{xy}\le 1 \\ Q & 0.3\le R_{xy}<0.8 \\ M & -0.3<R_{xy}<0.3 \\ N & -0.8<R_{xy}\le -0.3 \\ T & -1<R_{xy}\le -0.8 \end{cases} \tag{2}$$

where DS_i is the degree of correlation; P、Q、M、N and T are strong positive correlation, weak positive correlation, no correlation, weak negative correlation, and strong negative correlation, respectively.

Modal series of correlation characters are obtained by calculating the correlation degree of daily futures prices. The "data sliding window 1" is made in steps of 1 day for every 10 days of price data. A correlation coefficient was obtained for every 10 days of price data. The final 2390 correlation modes are obtained as follows:

$$DS_i=\left(DS_1,DS_2,DS_3,DS_4,\ldots,DS_n\right) \tag{3}$$

These 2,390 correlation modalities are abstracted into 2,399 correlation characters, and a sequence of correlation characters is obtained. This eliminates the time lag effect compared to linkage where only one day of data is acquired to establish a fluctuating state. In order to obtain better analysis results, it is not advisable to have too many symbols for the coarse-grained model. In this paper, we use every 5 relevant symbols in steps of 1 as the "data sliding window2". Every 5 correlation symbols constitute a correlation fluctuation mode, and the final 2395 modes were obtained as shown in Table. 1. :

Tab. 1. Correlation fluctuation modal coarse-graining process.

Serial number	American wheat	High-quality strong gluten wheat	Correlation coefficient	Correlation symbol	Coarse-grained state
1	699.00	2787.00			
2	675.50	2818.00			
3	679.50	2841.00			
4	682.75	2850.00			
5	696.50	2857.00			
6	708.25	2865.00			
7	708.50	2876.00			
8	716.50	2683.00			
9	721.50	2688.00			
10	729.00	2686.00	0.86	P	
11	739.00	2687.00	0.81	P	
12	737.75	2652.00	0.75	Q	
13	735.00	2649.00	0.69	Q	
14	722.50	2633.00	0.64	Q	PPQQQ
15	715.50	2636.00	0.58	Q	PQQQQ
16	709.25	2627.00	0.50	Q	QQQQQ
17	690.25	2629.00	0.61	Q	QQQQQ
18	678.00	2628.00	0.51	Q	QQQQQ
19	674.25	2639.00	0.41	Q	QQQQQ
20	674.50	2624.00	0.17	M	QQQQM
...	...	...	...	...	...
2408	641.75	2592.00	-0.88	T	TTTTT

Data sliding window 1

Data sliding window 2

Since each set of modes is realized by a sliding window of data, the former set of modes lays the foundation for the formation of the latter set of modes. Each mode has directedness and transferability between them. After coarse granulation, there should be 3,125 different mode combinations in theory. However, only 51 modal combinations are actually formed, as shown in Table. 2. :

Tab. 2. Modal set of complex network subgroups.

Serial number	Subgroup modal set
1	PPPPP,NNNNN,PPPPQ,QQQQQ,MMMMM,NMMMM QPPPP,QQQPP
2	PPQQT,QQPPP,MNNNN,MMNNN,MMMMT,TTQQQ PPPQQ,QQQQP
3	QTTMM,MMMNN,QQQTT,TTTMM,PPQQQ,MMMTT TTTTT,TQPPP
4	NNMMM,MTTQQ,TTTQQ,NMMTT,QQTTT,QTMMN MMTTQ,TMMMN
5	NNNMM,MMTQQ,TTMMM,TTMMN,PQQTM,MMMMN NNNNM,QQPQQ,MMTPP
6	PQQTT,TMMNN,QQTTM,QPQPP,PQQQQ,TTQPP,QTQQQ TMMMM,QTTTT,NNNNN

As can be seen in Table. 2. , some patterns do not appear, indicating the power-law nature of the distribution of the associated fluctuation modes. To verify its power-law property, the strengths of the nodes in the complex network of correlated fluctuations were calculated and ranked. The power-law distribution is obtained by making a double logarithm of the node strength p and the ranking order R (Fig. 4.).

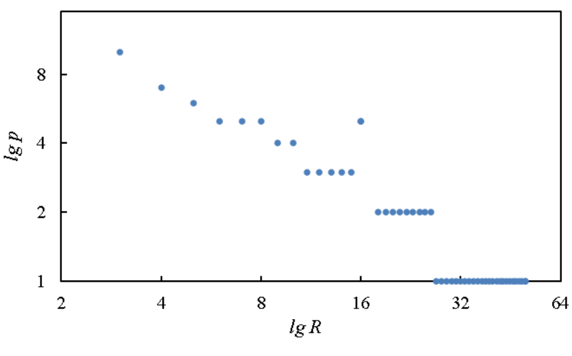

Fig. 4. Node strength and sequence number double logarithm

2.3 Construction of a complex network of price-dependent modalities

In order to effectively analyze the volatility relationship between the two variables, this paper makes a "data sliding window" for the relevant volatility string PPQQQPQQQQQQ…of wheat futures prices. A directional weighted complex network for wheat futures price linkage was developed using the correlation modal matrix. The directed connections of strings in the modal matrix of wheat price correlation fluctuations are of the form PPQQQ→PQQQQ→PQQQQQQ→QQQQQ→QQQQQ→QQQQ M→... In this network, the network nodes are the string modalities; the network connected edges are the transitions of the modalities; the number of transitions are used as the weights of the edges.

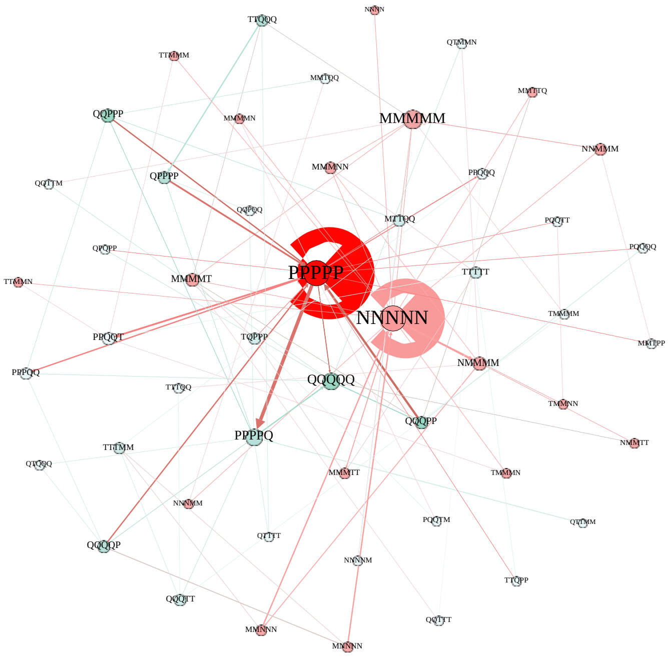

Fig. 5. Complex network chart of linkage fluctuation of wheat futures prices between China and the United States

As shown in Fig. 5. for a complex network, the transitions between modes are represented by connecting lines. The thickness of the linkage reflects the weight of the edges. The thicker the line, the more transitions between modes. From the fig. 5. , it can be seen that wheat price linkage is mostly concentrated on the transitions of PPPPP, PPPPQ, QQQPP, QQPPP, QPPPP, and PPPQQ modalities, with PPPPP as the core. Through an empirical analysis of a complex network of linkage changes between the U.S. and Chinese wheat prices, we aim to propose a new method to forecast wheat futures prices and thus hedge the risk of agricultural price volatility.

3. Analysis of wheat price correlation fluctuation and transmission mechanism

3.1 Node strength and node strength distribution

The node strength is the number of edges connected by two nodes in the network. The higher the node strength, the more the number of transitions from this mode to other modes. Modal interaction High degree of interaction, immediate giving, and other modal relationships. Node strength definition (e.g., Garlaschelli et al., 2005):

$$p_i = \sum_{j \in N_i} X_{ij} \tag{4}$$

where p_i is the node strength; N_i is the set of all the nearest neighbor nodes connected to node i nodded by node i; X_{ij} is the weight of node i to j.

The node strength distribution a of wheat price fluctuation network is defined as (e.g., Garlaschelli et al., 2005):

$$W_p = \frac{p_i}{N} \tag{5}$$

where W_p is the node strength distribution; p_i represents the node strength of node i, N and is the sum of the strength values of all nodes.

The node strength and node strength distribution in the complex network of wheat price linkages reflect the importance of the modalities of each node. It reflects the degree of correlation between the two wheat futures prices. Therefore, the larger the node strength distribution of the node, the more frequently this node mode appears. The more often this modality is converted to other modalities. The node strength and node strength distribution of the China-US wheat futures price linkage network are shown in Table. 3.

Tab. 3. Node strength and strength distribution.

Serial number	Node	Node strength	Node strength distribution/%
1	PPPPP	204	42.5
2	NNNNN	166	34.5
3	PPPPQ	10	2.08
4	QQQQQ	8	1.67
5	MMMMM	6	1.25
6	NMMMM	5	1.04
7	QPPPP	5	1.04
8	QQQPP	5	1.04
9	PPQQT	4	0.83
10	QQPPP	4	0.83
11	MNNNN	3	0.63
12	MMNNN	3	0.63
13	MMMMT	3	0.63
⋮	⋮	⋮	⋮
50	QTTTT	1	0.21
51	NNNN	1	0.21

From Table. 3. , it can be seen that in the correlation volatility series of wheat prices, the modal PPPPP has the highest node strength with an intensity value of 204. It indicates that during the correlation fluctuations of wheat prices, the highest number of simultaneous linkages between the price of U.S. wheat futures and the price of high-quality durum wheat futures for 5 consecutive days is observed. The strength of the character TTTTT node, which represents the reverse correlation between the prices of U.S. and Chinese wheat futures for 5 consecutive days, is relatively low. Thus, it can be seen that there is mainly an isotropic linkage between the U.S. and Chinese wheat futures prices.

Among the top 8 modal linkage sign strength rankings, the probability of the P sign appearing is higher than the probability of the N and M signs. It indicates that in the long-term wheat futures market, there is a significant long-term linkage between the U.S. and Chinese wheat prices, and the direction of the linkage is mainly in the same direction. The maximum weighted number of occurrences of P and N symbols in all modes is shown in Table. 4. As the number of combinations of the two symbols increases, the weighted number of simultaneous linkages in the U.S.-China wheat futures prices significantly exceeds the weighted number of reverse linkages. This suggests that there is an increased likelihood that wheat futures prices in China and the U.S. will be linked in the same direction. This reflects the fact that domestic wheat prices have been subject to factors such as the volume of imported commodities since the implementation of China's open-door policy. The transmission mechanism of its volatility is also changing dramatically.

Tab. 4. Weighted times of linkage symbol combination.

Symbol combination	Weighted times	Symbol combination	Weighted times
P	28.09	N	3.24
PP	13.52	NN	1.62
PPP	7.76	NNN	1.09
PPPP	5.76	NNNN	0.64

As can be seen from Table. 4. , the modalities with high node intensities have a higher probability of occurrence, and the price correlations between the U.S. and Chinese wheat futures are mainly realized as isotropic linkages. The cumulative and nodal strengths of the complex network composed of the two linkages conform to a power-law distribution. The PPPPP model plays a key role in wheat price volatility, with a strong positive correlation forming a key node for many consecutive days. The corresponding correlation modes are obtained from the correlation coefficient values and the number of occurrences of each mode is counted. It represents the importance of the model in the complex network and reflects the fluctuating trend of wheat price correlation (Fig. 6.).

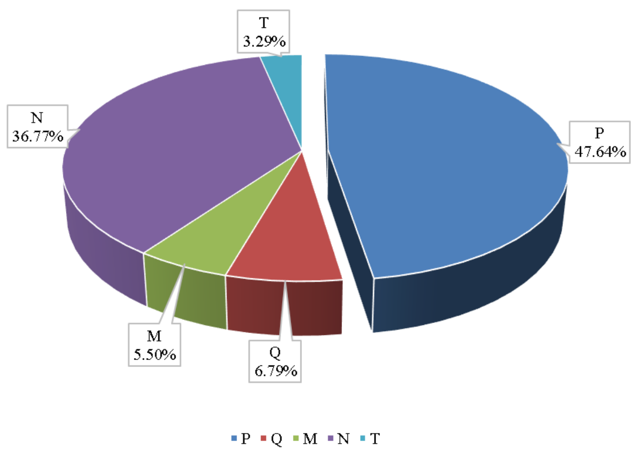

Fig. 6. Correlation modal character proportion chart

P and N are the two symbols with a higher share in the whole series, reaching 47.64% and 36.77%, respectively. As shown in Fig. 1 and 2, the two wheat futures prices are strongly linked in June 2017-December 2020 and weakly linked in January 2011-June 2017. It indicates that wheat price correlation mainly showed a weak negative correlation before June 2017. With the accelerated economic globalization, greater wheat import and export volume, and higher degree of openness to the outside world, U.S. wheat and Chinese wheat prices continued to show a strong positive correlation after June 2017.

3.2 Weighted aggregation factor analysis

The weighted aggregation coefficient is an important statistical parameter in directed complex networks, representing the clustering properties between individual neighboring nodes in the network. It is used to measure the degree of interconnection between a node and another neighboring node. A higher value of the weighted aggregation coefficient represents a higher number of transitions between that mode and other modes. The shorter the period of price fluctuations, the more important the position in the subgroup. This indicator allows studying the cyclical pattern of wheat futures price fluctuations. The weighted aggregation coefficient is defined as (e.g., Barrat et al., 2004) :

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

where C^w is the weighted aggregation coefficient; W_{ij} represents the weights from node i to node j; K_i represents the node strength of nodes i; S_i represents the degree of nodes i; $a_{ij} a_{jk} a_{ki}$ indicates whether the three nodes i, j, k are correlated with each other.

A value of 1 for the weighted aggregation coefficient indicates that the 3 nodes are correlated with each other and can form triangles; a value of 0 means that there is no edge correlation between them and they cannot form a triangle. It is calculated that there are 20 modalities in this network with weighted aggregation coefficients greater than 0, as shown in Table. 5.

Tab. 5. Node weighted aggregation coefficient.

Modality	Weighted aggregation times	Modality	Weighted aggregation times
QPQPP	1.13	MMMNN	0.30
PQQQQ	0.86	NMMMM	0.26
MMNNN	0.78	QQQQQ	0.24
PPPQQ	0.70	PPPPQ	0.21
NNNNM	0.50	MTTQQ	0.20
QQPQQ	0.50	NNMMM	0.20
QPPPP	0.34	PPPPP	0.13
QQPPP	0.33	TTQQQ	0.08
QQQPP	0.33	MMMMM	0.07
QQQQP	0.32	MMMMT	0.07

As can be seen from Table. 5. , the cumulative share of the weighted aggregation coefficients of the top 11 of these modalities is 80%. This shows that these 11 patterns are closely connected, forming 11 small clusters with these patterns as the core. It indicates that these modes occupy an important position in the complex network. In order to test whether the weighted aggregation coefficients are correlated with the node strength, a node diagram was produced as shown in Fig. 7.

As can be seen from Fig. 7. , the weighted aggregation coefficients do not show significant correlation properties with the node strength, indicating that the price linkage network is complex.

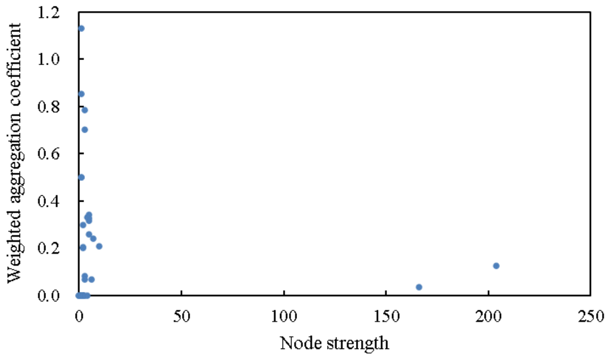

Fig. 7. Plot of node strength and weighted aggregation coefficient

3.3 Modal transformation of wheat price network

In order to analyze the conduction characteristics between various modes in the wheat price network, the concept of k-core is introduced. Nodes with degree less than k and the corresponding edges are deleted, and all vertices in the remaining subgraph are defined as high kernels. The nodes within the high kernel have strong connectivity and conductivity. The k-core nodes (k=5) of the complex network of two wheat futures price fluctuations were analyzed, and the results of the k-core resolution are shown in Fig. 8.

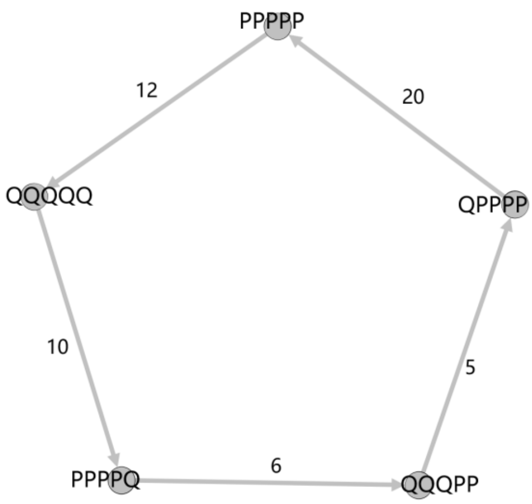

Fig. 8. k-core analysis of price-complex networks

After k-core resolution of the complex network of wheat price fluctuations and filtering out irrelevant nodes outside the closed loop, a total of five high-core in-nodes remain. The final subgraph forms a one-way closed loop: PPPPPP>QQQQQ>PPPPPPQ>QQQPP>QPPPPPP. When the price fluctuation of Chinese wheat futures is in any nodal mode in this loop, there is a high probability that the price fluctuation will return to the original starting point after 5 sliding cycles. For example, the modality represented by the node PPPPPP as a start includes 5 sliding cycles afterward. Chinese wheat futures prices fluctuate from “weak positive correlation - weak positive correlation - weak positive correlation - weak positive correlation - weak positive correlation” to “strong positive correlation - strong positive correlation - strong positive correlation - strong positive correlation - weak positive correlation” to “weak positive correlation - weak positive correlation - weak positive correlation - strong positive correlation - strong positive correlation” to “weak positive correlation - strong positive correlation - strong positive correlation - strong positive correlation” and then back to “strong positive correlation - strong positive correlation - strong positive correlation - strong positive correlation - strong positive correlation”. From these modal processes of transmission, it can be concluded that Chinese wheat futures prices are highly correlated with U.S. wheat futures prices.

3.4 Average shortest path length

In a directed weighted network, the average shortest path length refers to the average of the distances of all node pairs. The Chinese wheat futures prices and the U.S. wheat futures prices are linked, and their associated linkage networks are directed networks. The average path length of the average pair is calculated by the statistics module in Gephi for this directed network and the value is 4.012. Due to the data sliding window step of 1, it takes 4-5 days to convert the 21 core models to each other. It indicates that the Central American wheat futures prices move around a cluster of modalities with a long time (4-5 days) and are cyclical.

4. Conclusion and discussion

4.1 Conclusion

In this paper, we analyze the price volatility of Chinese and U.S. wheat futures from the perspective of complex networks. The two wheat price volatility states are first abstracted into character modes. Then, these modalities are used as network nodes; the modal transformation relationships are edges; and a complex network of futures prices is established. The weighted out-degree of futures price network nodes, core modes, and wheat futures price volatility transmission are analyzed to clarify the dynamics of wheat futures price volatility and transmission. The specific findings are as follows:

(1) There is a correlation between the U.S. wheat futures price and the domestic high-quality durum wheat futures price, which is dominated by strong positive correlation fluctuations for five consecutive days. During the last three years, the price of high-quality durum wheat futures has been influenced to some extent by the price of U.S. wheat futures, producing a trend of positive correlation fluctuations. However, this trend does not persist all the time, indicating that the linkage between the two wheat futures prices has complex network characteristics.

(2) The weighted number of linkage symbols is as high as 28.09 times for the P symbol and 5.76 times for the PPPP symbol. It is significantly higher than the N with 3.24 times and NNNN symbols with 0.64 times. The aggregation coefficients of modalities QPQPP, PQQQQ, and MMNNN are 1.13, 0.86, and 0.78. It reflects that after 10 consecutive days of strong and weak correlation of Chinese wheat futures prices by U.S. wheat futures prices, the volatility state of the prices has changed after the moderation effect of the domestic market.

(3) The k-core analysis reveals that the main transmission path of wheat futures price volatility is a unidirectional closed loop formed by six modes. Wheat futures price volatility has strong network

characteristics, and the transmission between modes is persistent and cyclical.

4.2 Discussion

With the acceleration of internationalization, the correlation between both China's total grain prices and the prices of different varieties of grain and international grain prices will be further strengthened. The correlation coefficients will increase accordingly, and domestic and international grain markets will further integrate. Therefore, deepening the integration of agricultural markets between the two countries and maintaining the healthy development of agricultural trade between the two countries is crucial to ensuring the security of China's grain industry. At the same time, it is necessary to strengthen the agricultural trade cooperation between the two countries and deepen the integration to stabilize the grain market. Due to the limited access to data and the wide variety of agricultural products, we have not been able to study the price linkage of other products, and we will discuss the price linkage fluctuations of other agricultural futures at home and abroad in the future. Meanwhile, other external factors such as weather, environment, and national policies are combined with price linkage analysis. Further research on the characteristics of dynamical behavior in price transmission will provide a better guarantee for domestic grain security.

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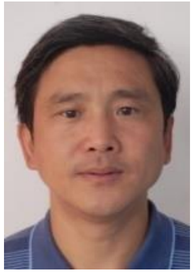

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