A transmission network model for the co-movement between carbon and energy markets

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***Abstract*—Carbon and energy markets react to each other in many respects. This paper proposes directed and weighted transmission network models to indicate the dynamic features of these coupled time series. Trading data of carbon pilots and the coal market in China are selected as the sample. The coarse graining method is used to convert coupled time series into strip sequences. Transmission networks are then constructed by taking the strip as nodes and transformation as edges. Topological characteristics of the networks are employed to disclose the co-movement patterns and state, as well as community transmission capacity. Results of node strength show that more than 60% of co-movement patterns are predictable. The dominant co-movement strips are identified to be two consecutive positive co-movements states intermediated by a negative state. Furthermore, the asymmetric transfer capacity reveals that communities have specific preferences in choosing their transmission targets. Finally, seasonal factors in the co-movements are found with strong positive linkage occurring most often in July and strong negative linkage in August. This study provides an alternative way to predict the co-movement state between the carbon price and energy price.**

Keywords—Carbon market; Coal market; Energy market; Price co-movement; Transmission network

I. Introduction

Emissions Trading Scheme (ETS) is a 'cap-and-trade' system to deal with greenhouse warming caused by energy combustion. Under such a system, allowances for emissions, primarily being carbon dioxide, are traded like ordinary commodities. In 1997, the 'Kyoto Protocol' first proposed the market mechanism as a new path to solve the problem of greenhouse gas emission reduction, then many countries and regions have established carbon trading systems. The European Union Emissions Trading Scheme (EU ETS), set up in 2005, is the first international emissions trading system in the world and the largest installation for reducing greenhouse gas emissions. The Japanese Tokyo ETS covers not only direct emissions from fuel combustion in the industrial sector, which are commonly targeted by other ETSs, but also indirect emissions from energy use (Wakabayashi and Kimura 2018). China is the world's largest energy consumer and carbon emitter which pledged to reduce carbon intensity to hit peak carbon emissions by 2030 (Wen et al. 2021). China started the operation of carbon emission trading in seven pilot regions in 2013 and 2014. In addition, its national carbon market was launched at the end of 2017 and will start in the near future (National Development and Reform Commission of China 2017).

Coal consumption is critically important in China's carbon market. Coal is one of the most important fossil fuels, accounting for 60 % of China's total primary energy consumption in 2017 (Li et al. 2019). In addition, China accounts for about 50% of the world's coal consumption. The dominance of coal consumption is likely to continue. Therefore, the stability of coal price is not only related to the smooth operation of the economy but also has a significant impact on the daily life of the public. However, the coal industry is facing transformation due to serious losses in industries and high leverage since the end of 2012. Considering the current coal market conditions, the direction of coal price fluctuations is particularly important for carbon market.

There are close relationships between the dynamics of energy price and carbon price since the main source of carbon emissions is energy consumption. A large number of studies believe that there is cointegration, equilibrium and causation between carbon price and energy price. However, these relationships can be generalized to the term of co-movement, which is a simple volatility mechanism. Co-movement describes the degree of consistency with which one indicator changes in the same or opposite direction as another indicator. Correlation coefficient is often used to measure bivariate co-movement (de Carvalho and Gupta 2018) but can be biased by heteroscedasticity (Baur 2003). Complex network can not only examine the fluctuation of the co-movement relationship between variables, but also study the evolutionary mechanism behind these fluctuations (An et al. 2014).

The research motivation of this paper includes three aspects. First, studying the co-movement between carbon markets and energy markets is of great importance. Co-movement can reflect the characteristics of fluctuations. We can reveal the dynamic relationship between markets more expressly by capturing co-movement wave strips and co-movement mechanism. The consumption of fossil energies inevitably leads to carbon dioxide emission which makes the supply side of carbon markets. Controlled companies will adjust their energy usage strategies according to varying carbon prices to lower their cost. Second, the relationship between carbon markets and energy markets depends on individual markets. At present, China's national carbon emission market has not yet been operated. If we can find a coupling way to reflect the national carbon price through the pilot price, it will play a positive role in the market research. Third, studying the co-movement during a time period is better than at the daily time instant. The main reason is that the carbon market is not a pure financial system. The carbon market has policy and environmental properties (Yi et al. 2018) which results in a lag effect on the co-movement relationship.

II. Literature Review

A. *The co-movement between markets*

Over the past decades, many studies have examined the interconnection between different variables in carbon and energy markets. The literature confirms that there is a strong relationship between futures prices and fundamental factors such as German electricity prices, natural gas, and coal prices (Aatola et al. 2013). The carbon market and the fossil energy markets have a significant positive correlation in time (Zhang and Sun 2016). Smale et al. (2006) believed that EU ETS can significantly induce power price increases by studying the impact of EU ETS on corporate profits and market prices. Furthermore, Chevallier (2012) claimed that energy prices are the main driver of the EU's carbon emission allocation spot price.

As well known, coal prices significantly affect carbon prices (Chevallier 2011). Batten et al. (2021) examined the negative correlation between the coal price and the carbon price. The increases in the coal price will cause utilities to switch from coal to gas, emitting less carbon in the process so that fewer carbon allowances are required, and this will put downwards pressure on the carbon price in Europe. Zhao et al. (2017) showed that coal prices played a leading role in carbon prices setting by studying the long-term cointegration relationship between China's carbon pilot market prices and coal prices, economy, and temperature.

Previous studies on the co-movement between the carbon market and coal market were mainly based on the price fluctuation of the two markets. A small number of scholars have studied the transmission mechanism of co-movement between the carbon market and energy market, but no scholars have considered the relationship between short-term co-movement wave strips and seasons. In the past, econometric methods are common analytical methods used by researchers. Sousa et al. (2014) used multivariate wavelet analysis to describe the relationship between carbon prices, energy prices (electricity, natural gas, and coal), and economic activity. Hammoudeh et al. (2015) employed the nonlinear autoregressive distribution lag model to analyze the asymmetric and non-linear effects of crude oil price, natural gas price, coal price, and electricity price changes on CO_2 emission limit price.

Complex networks are powerful methods to model real-life systems in various fields such as life sciences, social sciences, economics (Souma et al. 2003), and finance. In recent years, complex networks have been applied in researching the co-movement transmission mechanism between markets. Chen et al. (2020) studied the interdependence between stocks to understand the common movement of the Chinese stock market and its temporal and spatial pattern. They found that the stability of the stock index is closely related to time. The provincial index grows sharply during bull and bear markets while moves in the opposite direction of the Shanghai Composite Index during normal market oscillation. Jia et al. (2018) investigated the transmission law of price fluctuations in five carbon pilot cities of Beijing, Shanghai, Tianjin, Shenzhen, and Guangdong based on complex network theory. To explore whether there is a certain linkage between China's coal stock market, carbon market, and coal price, Li and An (2017) focused on the relationship between markets from a new perspective by constructing a matrix transmission network. They pointed out that when a linkage mode occurs, a corresponding linkage pattern will follow.

B. *Literature gap and contributions*

We note some research gaps in the present literature. First, few studies have been carried out taking China as an integrated market. The majority of researches focus on the relationship between EU carbon markets and energy markets. The analysis of the situation in China is mainly limited to some of China's seven carbon pilots. Second, there lacks a general model of co-movement transmission mechanism about two markets. Most researches present merely the co-movement mechanism in specific markets. Third, the effects of seasonality have not been considered by scholars when applying transmission networks. Although this effect is significant to the reliability of the co-movement mechanism, almost all researches only analyze transmission mechanisms by the network structure. Fourth, using the coal market to replace the entire energy market to study the connection with carbon markets has potential application value. The reason lies in the prominent position of the coal market in energy markets.

Based on the current research status, the contribution of this study to the literature is mainly reflected in three aspects. First, we analyze the co-movement between carbon markets and energy markets, taking China as a whole research object. We integrate China's seven pilot carbon markets into one market by averaging the pilot's prices. We regard the average price as the situation of the national carbon market in China to discuss the relationship between carbon markets and energy markets. Second, this paper constructs a directed and weighted transmission network model to analyze the transmission laws of co-movement wave strips. Based on such a virtual integrated market, we analyze co-movement mechanisms between China's carbon and energy markets. Third, we suggest an auxiliary aspect to study transmission mechanism. In addition to the common methods of analyzing network characteristics, this paper takes seasons as an example to reveal factors that affect the co-movement mechanisms between the carbon market and energy market.

III. Methodology

A. Co-movement wave strip

We symbolize the time series and then coarse grain them to obtain the co-movement wave strips (Wackerbauer et al. 1994). For two connected markets, here we take a carbon market and a coal market as the example. Let $\{X_1(t)\} = \{X_1(1), X_1(2), \cdots, X_1(M)\}$ and $\{X_2(t)\} = \{X_2(1), X_2(2), \cdots, X_2(M)\}$ denote the price series of the carbon market and the coal market, respectively.

The co-movement state is defined as the direction of daily returns of the two price series. The value of the state takes 'P' when two prices change in the same direction; 'N' when reverse directions; 'O' when either of the two prices is stable. Mathematically, letting $\triangle X_1(t) = X_1(t+1) - X_1(t)$ and $\triangle X_2(t) = X_2(t+1) - X_2(t)$, the co-movement state series $\{y_t\}$ is then written as

$$y_t = \begin{cases} N, & \triangle X_1(t) * \triangle X_2(t) < 0 \\ O, & \triangle X_1(t) * \triangle X_2(t) = 0 \\ P, & \triangle X_1(t) * \triangle X_2(t) > 0. \end{cases} \quad (1)$$

A co-movement wave strip is a string of co-movement states. The first strip starts from the initial co-movement state. Any other strip is obtained by sliding the previous one forward. Let L be the length of the string and s be the sliding step. Then, the r-th co-movement wave strip is $\{y_{(r-1)s+1}, y_{(r-1)s+2}, \cdots, y_{(r-1)s+L}\}$, $r = 1,2,\cdots,\lfloor\frac{(M-L)}{s}+1\rfloor$, where $\lfloor x \rfloor$ represents the maximum integer not exceeding x.

B. Transmission network model

We define the transmission network to be the set $G = (V, E)$, where V is the set of nodes and E is the set of edges. We take co-movement wave strips as nodes and the transformation between strips as edges in this transmission network. There are at most 3^L nodes in the network. The transformation among nodes generates an edge, that is, two consecutive strips lead to an edge between their corresponding nodes v_i and v_j. Then a_{ij}, the element of the adjacent matrix of G, is evaluated to be 1. Obviously, there are rings when the two consecutive strips are identical. The weight of an edge, w_{ij}, is defined as the frequency of transformation from v_i to v_j.

C. Topological characteristics

We introduce some topological characteristics of networks to study the transmission mechanism of the co-movement wave strips. Node strength measures the strength of nodes in terms of the total weight of their connections (Barrat et al. 2004). Let N_i^{in} (N_i^{out}) be the set of nodes directing to (from) v_i. Then $s_i^{in} = \sum_{j \in N_i^{in}} w_{ji}$ is the sum of weights of edges pointing to node v_i. Similarity, $s_i^{out} = \sum_{j \in N_i^{out}} w_{ij}$. By adding them, then we have

$$s_i = \sum_{j \in N_i} w_{ij} = s_i^{in} + s_i^{out}, \quad (2)$$

where N_i represents the set of adjacent nodes of node v_i.

The weighted clustering coefficient of the node v_i (Barrat et al. 2004) is

$$C^w(i) = \frac{1}{s_i(k_i-1)} \sum_{j,t} \frac{(w_{ij}+w_{it})}{2} a_{ij} a_{jt} a_{ti}, \quad (3)$$

where k_i represents the number of edges associated with node v_i.

The definition of betweenness centrality f_k (Zhou et al. 2008) is as follows:

$$f_i = \sum_{(j,t)} \frac{\sigma_i(j,t)}{\sigma(j,t)}, \quad (4)$$

where f_i represents the betweenness centrality of node v_i; $\sigma(j,t)$ represents the total number of the shortest paths between a pair of nodes (v_j, v_t). $\sigma_i(j,t)$ represents the number of the shortest paths through the node v_i. The length of a path is the total weights of the edges which the path passes.

Transfer capacity measures the degree of preference for nodes moving to others on the whole community level. Supposing there are n communities, then the transfer capacity (Gao et al. 2014) from community C_s to C_t is

$$T_{C_s \to C_t} = \sum_{v_i \in C_s, v_j \in C_t} w_{ij} (s,t = 1,2,\cdots,n). \quad (5)$$

IV. Data and Results

A. Data

We take China as the study case. For the carbon variable, we average all the carbon pilot prices to be the carbon prices. The comprehensive carbon price situation of each pilot can well reflect the price changes in China's carbon market since China's national carbon market has not yet started trading. For energy variable, we use China Coal Price Index, which is the first coal price index in the country. Sample period covers from June 19, 2013, the initial day of carbon trading in China, to August 23, 2019. Data are obtained from the China Carbon Trading Network (http://k.tanjiaoyi.com/) and China Energy Network (https://www.china5e.com/energy-index/). We recover the missing data by the method of 5-day moving average since there are 5 trading days per week. Finally, we obtain a sample of 1,500 pairs of variables: average carbon prices (ACP) and coal index (CI).

B. Co-movement transmission network

This paper builds the directed and weighted network model to obtain the topological characteristics of the network. We first identify the co-movement wave strips to be the nodes. We specify the sliding step to be 1 and the strip length to be 5 considering that there are 5 trading days in one week. Tab. 1 shows the process of identifying. Each node represents a segment of co-movement state between two markets. The node indexes are named by the chronological order of its corresponding strip. However, we only get 85 wave strip patterns compared with the 243 possible patterns in theory. This phenomenon means that the co-movement strips appear in a certain sub-domain. Then, we use the methods in Section 3 to construct the co-movement transmission network.

TABLE I. ILLUSTRATION OF CO-MOVEMENT STRIPS AND THE NODE INDEXES

Day	$ACP(t)$	$CI(t)$	$\Delta ACP(t) * \Delta CI(t)$	y_t	Wave strip (Sliding window)	Node index
1	29	907.74	0	O	OOOOO	1
2	29	880.39	0	O	OOOOO	1
3	29	871.79	0	O	OOOOO	1
4	29	827.87	0	O	OOOOO	1
5	29	774.36	0	O	OOOOO	1
6	29	800.55	0	O	OOOOO	1
7	29	791.23	0	O	OOOOO	1
8	29	799.76	0	O	OOOOO	1
9	29	796.24	0	O	OOOOO	1
10	29	794.21	0	O	OOOOO	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮
1491	32.60	808.47	—	N	NNPNN	72
1492	32.93	802.35	—	N	NPNNP	65
1493	32.01	807.19	+	P	PNNPN	74
1494	32.10	810.44	—	N	NNPNN	72
1495	31.65	813.60	—	N	NPNNP	65
1496	31.49	832.97	+	P		
1497	31.878	833.30	—	N		
1498	31.884	831.76	—	N		
1499	31.74	832.07	+	P		
1500	31.87	834.92				

C. High predictable nodes

We use strength distribution to locate the set of predictable nodes. Fig. 1 shows the strength distribution with a high head and a long thin tail. The head is located on the most left corner of the graph, and the corresponding strengths are 2 and 4. The smaller strength of nodes are easier to be predicted since the fewer types of co-movement modes may appear in the next stage. Therefore, those wave strips with smaller strength are higher predictable. Furthermore, those two nodes take more than 60% of the probability, which means that 60% co-movement patters almost are predictable accurately between the two markets.

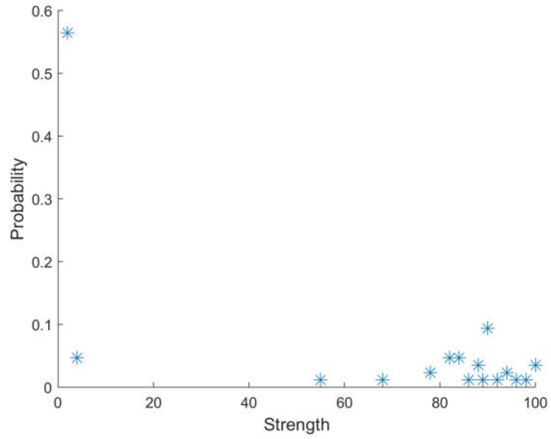

Fig. 1. *Probability distribution of node strength*

We just sort the weighted out-degree of nodes since the aim of prediction is to find the subsequent wave strip. Then Tab. 2 shows the results of nodes ranking. Considering the length of this paper, only some nodes are listed. The nodes with weighted out-degree 1 or 2 are on lines 34 to 85. This means that these nodes have merely one or two possibilities among the types of wave strip in history. When those nodes with 1 or 2 weighted out-degree appear, we can find the co-movement state most likely to occur in the next stage in Tab. 1 through the index in Tab. 2.

TABLE II. RANKING OF CO-MOVEMENT WAVE STRIPS ACCORDING TO WEIGHTED OUT-DEGREE

Ranking	Node index	Node	Weighted out-degree
1	45	PNPPN	50
2	46	NPPNN	50
3	62	NNNPN	50
4	72	NNPNN	49
5	29	PPPNP	48
6	30	PPNPP	47
7	48	PNNPP	47
8	42	PPNPN	46
⋮	⋮	⋮	⋮
31	37	NNNNN	39
32	59	PPPPP	34
33	1	OOOOO	28
34	2	OOOOP	2
35	6	POOPP	2
36	52	OOPPP	2
37	53	OPPPP	2
38	13	NOOOO	1
⋮	⋮	⋮	⋮
85	85	OPNNP	1

D. The dominant strips during transfer process

The authors find the dominant nodes based on the measures of clustering coefficient and node strength. In complex networks, a node is called the dominant node if its clustering coefficient and strength are relatively high (An 2014). Fig. 2 shows the dependence of clustering coefficient and strength on nodes index. The left vertical axis is the node clustering coefficient and the right one is the node strength. We notice that there are 12 nodes with nonzero weighted clustering coefficients. This means that the dominant node should be selected from those nodes. Therefore, these 12 nodes have certain importance in the transmission process. Among the dominant candidate nodes, the clustering coefficient of node 37 is 0.5 while the others are concentrated around 0.1. However, node 37 is not the most dominant node when considering other criteria of node strength. We plot the strength of the dominant node candidates in the same figure. We find the strength of nodes distribute almost randomly. The strength peaks at nodes other than node 37, indicating that the strength and coefficient have not reached the maximum value at the same node.

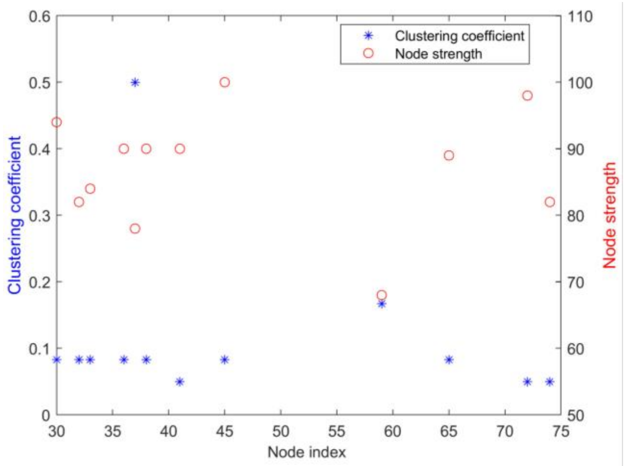

Fig. 2. *Clustering coefficient and strength of nodes*

We constructed a comprehensive evaluation factor through the strength and clustering coefficient to find the dominant nodes. We assume that the clustering coefficient and strength of nodes have the same effect on the node's dominance since no prior information has been given. First, we rank the clustering coefficients and strength of nodes respectively in descending order. The comprehensive evaluation factor is defined as the sum of the ranks of clustering coefficients and the strength of nodes. Dominant nodes are determined by smaller comprehensive evaluation factors. Tab. 3 shows the comprehensive evaluation factor. The average order of node 30 ('PPNPP') is 3, which can be regarded as the dominant node. Pattern 'PPNPP' is almost strongest positive linkage, which indicates that positive linkage is nearly the theme of co-movement between the two markets.

TABLE III. THE MOST DOMINANT CO-MOVEMENT WAVE STRIPS

Order	Node (Node index)	Clustering coefficient ranking	Strength ranking	Comprehensive evaluation factor
1	PPNPP(30)	3	3	6
2	PNPPN(45)	8	1	9
3	PNNNN(36)	6	5	11
4	NNNNN(37)	1	11	12
5	PPPPN(33)	5	8	13
6	NNNNP(38)	7	6	13
7	NNPNN(72)	11	2	13
8	NPPPP(32)	4	10	14
9	NPPNP(41)	10	4	14
10	PPPPP(59)	2	12	14
11	NPNNP(65)	9	7	16
12	PNNPN(74)	12	9	21

E. *Analysis of the transmission hub*

We choose the transport hub of transmission network using betweenness centrality. The higher the betweenness centrality, the greater the role of hub in the transmission network. When the most important hub node changes, the entire transmission network will be severely affected. The authors calculate the betweenness centrality using the equation (4). We find that the wave strip 'POOPP' has the highest betweenness centrality. There are shortest paths passing near the strip 'POOPP', which may indicate that the wave strip 'POOPP' plays a crucial role in maintaining the co-movement mechanism between markets. Furthermore, we note that the betweenness centrality of two wave strips is 0, namely 'OOOOO' and 'NNNNN'. It means that there is no betweenness effect in the co-movement mechanism of markets.

F. *The community transmission capacity*

The authors analyze the transmission capacity between communities by the method of optimizing modularity (Blondel et al 2008). Modularity is a standard to measure whether the partitioning is effective (Newman 2004). Then we divide the co-movement wave strips into 10 communities. We measure the transmission capacity between the 10 communities by the equation (5). Fig. 3 shows the transmission capacity between communities. The highest energy value in Fig. 3 represents the strongest transmission between communities. This result is consistent with the notion that nodes in the same community have a higher connectivity relative to nodes that are not classified into the same community. In addition, most areas in Fig. 3 are dark blue indicating that there is no transmission relationship between most of these 10 communities. However, there is a one-way transmission relationship between communities (for example, between communities 8 and 1) since Fig. 3 does not constitute a symmetrical graph about diagonals. This phenomenon means that there exists a preference for the transmission direction.

Furthermore, we analyze the characteristics of each community itself. The future wave strips are more likely appearing in highly transmitted capacity communities. We regard capacity as the ability from one community to itself, scale as the number of one community members, and unit ability as the ratio of ability to scale of a same community in Tab. 4. The table shows that community 4 has the strongest transmission capacity, while communities 6 and 7 have the smallest transmission capacity. Community 4 having the strongest transmission capacity can be also observed from Fig. 3, while community 4 has relatively few members. This means that the community 4 has a greater impact on the co-movement evolution of the entire network. We underline that community 4 plays an active role in maintaining the stability of the co-movement rule between the two markets. On the other hand, for the community that transmission capacity equal to scale, community transmission ways are simpler and better predictive. The transmission capacity of the community 1, 2, 6 and 7 are almost respectively equal to the scale of communities themselves. Therefore, when the community is one of 1, 2, 6, and 7, we can predict the co-movement trend of the two markets in the next stage better. For enterprises, they can understand the price trend of the two markets so that saving costs and increasing profits.

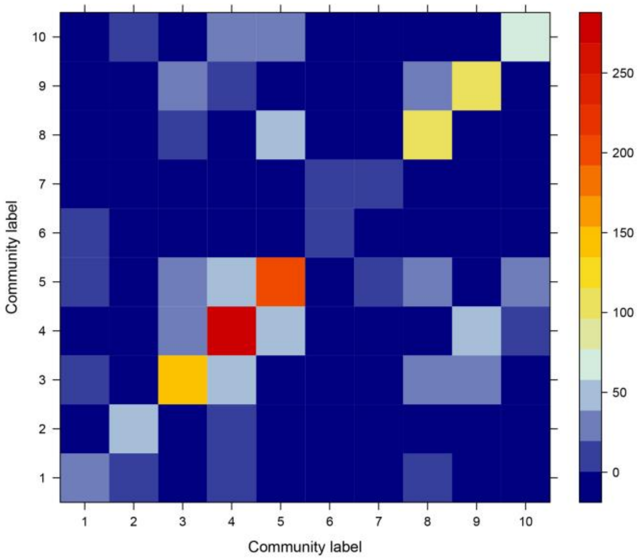

Fig. 3. *Transmission capacity between communities*

TABLE IV. SELF TRANSMISSION CAPACITY

Community	Capacity	Scale	Unit capacity
1	24	24	1.00
2	47	16	2.94
3	231	10	23.10
4	398	9	44.22
5	321	7	45.86
6	4	4	1.00
7	4	4	1.00
8	174	4	43.50
9	174	4	43.52
10	117	3	39.00

G. *Effect of seasonality on transmission*

Considering that both the coal market and the carbon market are affected by seasons, the relationship between market linkages and seasonal changes is then analyzed. This paper finds seasons has a prominent influence on the appearance of strong linkage wave strips. The strong linkage wave strips include a positive strong linkage wave strip 'PPPPP' and a negative strong linkage wave strip 'NNNNN'. It represents a stable co-movement between two markets over a trading week and facilitates discovering long-term stable co-movement rule between the markets. First, we consider the effect of seasonality on the appearance of 'PPPPP'. The result shows that 'PPPPP' appears 34 times in the whole period in Fig. 4. A red circle indicates the strip 'PPPPP' appearance on a certain day. Due to the limited width of the figure, the adjacent circles maybe overlap. We find the distribution of 'PPPPP' is concentrated in February, March, July and November every year. In China, the main power generation mode is still based on coal. March is the end of winter and November is the beginning of winter. People need coal for electricity and heat in winter. In July, the weather is very hot so there is a great demand for air conditioners. Therefore, these three months are the peak period of electricity consumption of the year. Then, we consider the effect of seasonality on the appearance of 'NNNNN'. The result shows that 'NNNNN' appears 39 times in the whole period in Fig. 5. We find the distribution of 'NNNNN' is scatter than 'PPPPP'. However, August is the month with the highest frequency. This finding means that different strong wave strips appear in two adjacent months. The direction from 'PPPPP' to 'NNNNN' is caused by the reverse change in coal demand from an increase to a decrease after the peak of electricity consumption.

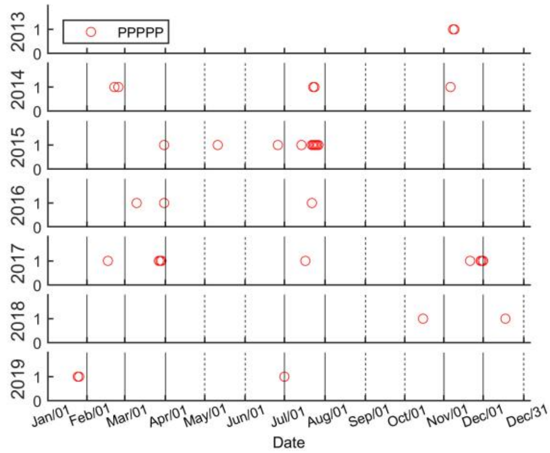

Figure 4: Distribution of positive strong linkage wave strip in each year.

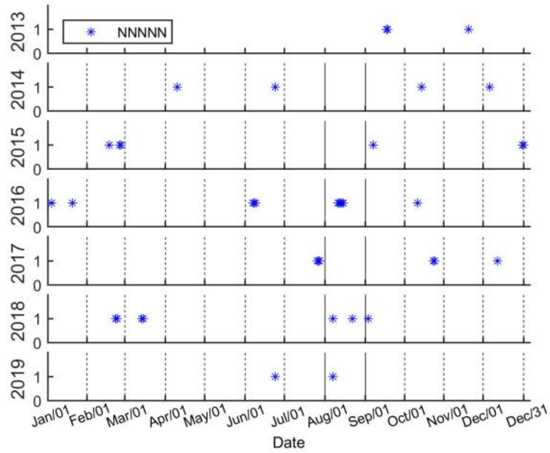

Figure 5: Distribution of negative strong linkage wave strip in each year.

V. CONCLUSIONS

This paper takes China as a research example to study the co-movement mechanism between carbon markets and energy markets. A general method to construct directed and weighted transmission networks for co-movement mechanism analysis is proposed. In this method, the co-movement wave strips are regarded as nodes, the transformation between wave strips as edges, and the frequency of transformation as the weight of edges in the transmission network. Moreover, a comprehensive carbon market for China is built by averaging transaction prices of seven pilot carbon markets. Experimental results show that there are 243 types in theory, but only 85 types of nodes actually appear in the network. Then we analyze the transmission mechanisms from the view of topological characteristics. We identify the nodes with high predictability and find the dominant strips. Considering the transmission hub node, the community transmission capacity is investigated by calculating the node strength, strength distribution, clustering coefficient and betweenness centrality. Finally, we consider the annual distribution of positive and negative strong linkage wave strips.

This study has important theoretical and practical significance. First, market participants can make specific investment decisions on the co-movement results. The number of predictable wave strips exceed 60 %, which means that there are observable laws about the co-movement evolution of the markets. Second, this study confirms the common sense that there is a positive connection between carbon markets and energy markets. We find that positive co-movement is the main theme between the carbon market and coal market by the dominant wave strip ‘PPNPP’. Third, this paper suggests that marketing managers should pay close attention to certain types of wave strips. The shortest paths passing through the node ‘POOPP’, and the community 4 has the strongest transmission capacity. This result means that community 4 and hub node ‘POOPP’ contribute to stabilize the existing co-movement mechanisms of markets. Finally, seasonal factors are important parts that market participants should consider. The Co-movement affected by seasonal factors provides the basis for controlled enterprises to allocate and trade carbon emission credits rationally. In addition, positive co-movements between the two markets are more likely to occur continuously during peak electricity consumption periods. This characteristic will help market managers and enterprises understand the dynamic markets better and adjust the corresponding policies timely.

However, this study is far from perfect. Due to the data limitations, the co-movement mechanism between carbon markets and energy markets still needs to be further explored. In addition, this study only considers the effect of seasonal factors on co-movement transmission. This perspective obviously is unsatisfactory for a deep understanding of the internal mechanism between markets. How to analyze the effects of co-movement mechanism between markets from multiple influencing factors will be our next research work.

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