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EVOLUTION OF CO-MOVEMENT PATTERNS BETWEEN CARBON MARKETS: A CASE STUDY IN CHINA

Qi Zhang, Jiuli Yin, Xinghua Fan*

Faculty of Science,Jiangsu University, Zhenjiang, Jiangsu 212013, China.

fan131@ujs.edu.cn(Xinghua Fan)

ABSTRACT

Carbon trading markets play an important role in emissions mitigation through financial tools. China has established seven carbon trading pilots in its major cities and provinces. This paper explores the evolution laws of the co-movement of daily prices between carbon markets using complex network theory. First, we combine the co-movement of prices in five continuous days to co-movement modes. Then, we construct a directed weighted complex network. The nodes are the co-movement modes. Edges are defined as the time adjacent relations of two nodes. The frequency of an edge is taken as its weight. Transaction prices for the pilots in Hubei and Shanghai are selected as the samples. Results show an appearance of 231 modes from the 243 possible patterns, indicating a scattering of co-movement modes. Among all modes, the most frequent one is the fully stable one, showing that the markets are inactive in most time. Compared to the full sample and other periods, the complex networks in the first sample period stands out due to its large nodes and the existence of rings. This finding indicates the exact mirroring of some successive co-movement modes. The method proposed in this paper helps in understanding the evolution of Intermarket co-movement.

Keywords: carbon price, carbon market, co-movement mode, complex network

1. INTRODUCTION

Carbon trading system is an important and potential emission reduction mechanism. In 2005, the European Union(EU) established a European carbon trading system. As the world's largest carbon trading market, the EU has considerable experience in energy conservation and emission reduction. In view of the superiority of the carbon trading system, China issued the “Notice on the Pilot Work on Carbon Emissions Trading” of the National Development and Reform Commission in October 2011. This notice approved the carbon trading pilot projects in seven provinces and cities including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong and Shenzhen [1].

The incomplete co-movement between markets is a complex research issue that is of interest to scholars from all walks of life. There are many ways for scholars at home and abroad to study co-movements. In 1978, by using the linear error correction model to characterize the linear adjustment mechanism between economic variables, Hendry et al. proposed a so-called linear co-integration method [2]. With the development of economic theory, especially the economic analysis of transaction costs and policy response, the traditional linear co-integration analysis method is no longer suitable. In response to this situation, Balk and Fomby proposed a so-called threshold co-integration method in 1997 to characterize the nonlinear adjustment mechanism between economic variables [3]. In view of this method, Huajiao Li et al. analyzed the co-movement relationship of carbon-related markets by constructing a linkage matrix transmission network [4]. Haizhong An et al. designed a complex network method to analyze the transformation characteristics of the co-movement mode between crude oil futures and spot prices by coarsely processing the original data [5]. Abdelkader O. el Alaoui et al. used wavelet techniques (discrete and continuous) attempt to investigate the co-

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movement dynamics at different time scales or horizons of Islamic Dubai Financial Market index returns with their counterpart regional Islamic indices returns, Developing Countries index, Emerging Countries Index, and the Global Sukuk [6].

At present, the co-movement research related to the carbon market is not mature in terms of methods and research content. The content of the research is mainly divided into two parts. The first part is the relationship between the EU carbon market and the Chinese carbon market. The second part is the relationship between the carbon market and the coal market. In analyzing the market structure and common factors of emission reduction tools in Europe and North America, Mizrach found that the spot and futures prices of the European exchange were co-integrated, but the futures curve over the calendar year developed independently [7]. Coal prices, the economy, the temperature of the European market and the price of carbon are all factors influencing the price of carbon trading. Zhao et al. concluded that there is a long-term co-integration relationship between the carbon price and these factors based on the long-term relationship between the carbon price of China's Emissions Trading System pilot and its influencing variables [8].

In complex networks, we usually consider variables as nodes of the network and the relationship between variables and variables as the edges of the network. In recent years, complex networks have not only been applied to general-purpose networks and random networks outside of conventional networks, but also several network models that better simulate real-world systems have been proposed. For example small-world model [9], NW network model [10] and BA scale-free network model [11]. For these networks, researchers have found that they are small-world networks that follow a power-law distribution. Of course, there are also traces of complex network theory in the fields of life sciences [12], social sciences [13], economics [14]and finance [15-16].

Complex networks have been applied in many fields. However, there are few studies on the evolution of co-movement between different carbon markets by using complex networks. Mapping carbon data to networks is a new method for analyzing data information. The network structure diagram makes the important data nodes clear at a glance. The structure of the network can reflect some implicit evolutionary relationships among data nodes.

Therefore, in this paper, we define the "interaction matrix" and introduce a co-movement method to study the evolution of the co-movement of carbon market and the carbon market transaction prices. If we consider the object we are studying as a system, it is obviously a complex system that is nonlinear and unstable [17-19].

2. DATA AND METHODOLOGY

2.1 Data

Carbon prices in Hubei and Shanghai pilots are selected as the sample data of this study. Such selection is based on that the two pilots respectively took the lead in building China's national carbon emission registration system and trading system. As Hubei was set up later, the sample period covers from its initial transaction date April 2, 2014, to January 11, 2019. Data are obtained from China Carbon Trading Network (http://www.tanjiaoyi.com/). For the missing data, the 5-day moving average method is used for filling. Finally, a total of 1167 sets of sample data are obtained.

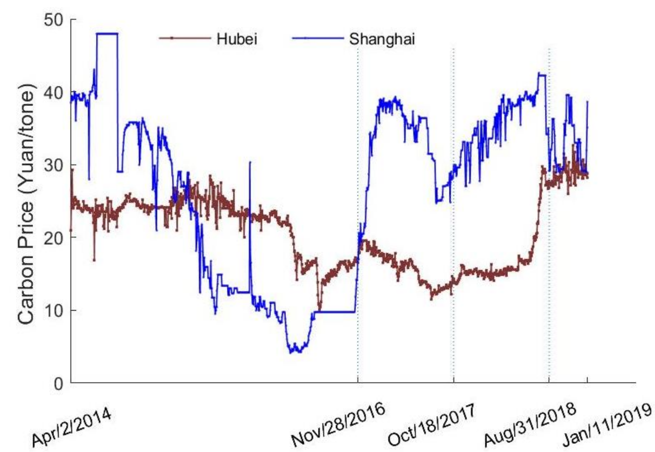

Fig 1 Carbon prices in Hubei and Shanghai pilots from April 2, 2014, to January 11, 2019

Figure 1 visualizes the prices. We see a clear decreasing and increasing trends for both prices in certain time periods. Therefore, we divided the entire sample period into four stages as shown in figure 1. The corresponding critical points are November 28, 2016, October 18, 2017, and August 31, 2018.

2.2 Type of co-movement

We define the types of co-movement from the original price series. Let $HBCP(t)$ $(SHCP(t))$ be the price series of Hubei (Shanghai) pilot. And we use the simple

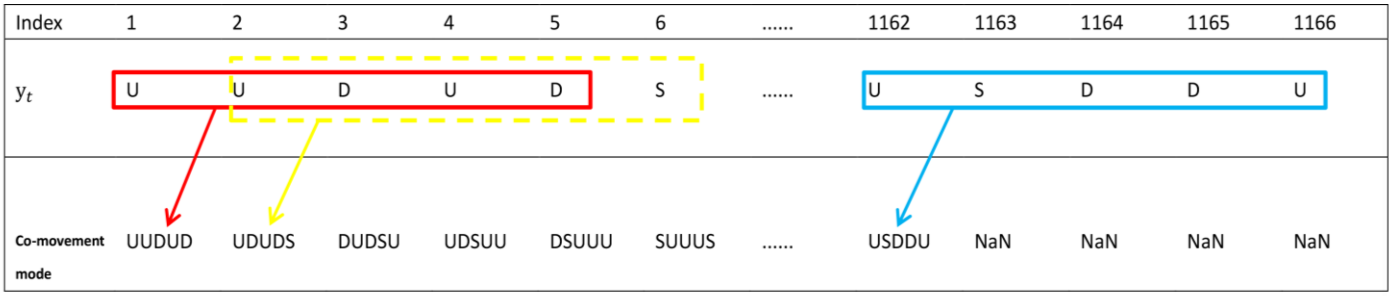

Fig 2 Co-movement mode construction.

price return series $\Delta HBCP(t) = HBCP(t+1) - HBCP(t)$ to indicate price fluctuation sequence. We convert two price fluctuation sequences $\Delta HBCP(t)$ and $\Delta SHCP(t)$ into a co-movement symbolic sequence y_t according to the sign of their product

$$y_t = \begin{cases} D, & \Delta HBCP(t) * \Delta SHCP(t) < 0 \\ S, & \Delta HBCP(t) * \Delta SHCP(t) = 0 \\ U, & \Delta HBCP(t) * \Delta SHCP(t) > 0 \end{cases} \tag{1}$$

In Equation. (1), the symbol "U" represents the same growth direction, "S" represents the steady-state and "D" represents the opposite growth direction. Therefore, totally three types of co-movement are defined and we got a symbolic time series.

2.3 Co-movement modes

The authors use the coarse-graining method to define the co-movement modes of two markets. The coarse-graining method refers to placing a set of points in a roughly defined state [20]. In order to study the fluctuations of the price co-movement between the two markets rather than the co-movement itself, the author uses the coarse-graining method to divide the co-movement sequence into multiple windows on average [Fig 2]. Coarse-graining ignores some details but makes the conclusions more conducive to reveal the evolution laws of co-movement. A specific step is as follows: use the sliding window to cut the symbol sequence into the same length segments in order(co-movement modes) to find the evolution mechanism of co-movement mode fluctuations. The length of the sliding window is closely related to the validity of the conclusion. It is necessary to ensure that each window represents a relatively independent mode.

2.4 Co-movement network model

We construct a co-movement network model to study the evolution laws of co-movement modes. The nodes are the co-movement modes. Duplicate modes are ignored. Edges are defined as the time adjacent relations of two nodes. Therefore the edge is directed. The frequency of an edge is taken as its weight.

Some topological measure is used to analyse the hidden features of the network. The degree of a node M is the number of connections of node M. The degree is common indicators for analyzing complex networks. The strength of a node takes into account two elements of the number of adjacent nodes and the weight of each edge. The interaction matrix is used to map the index

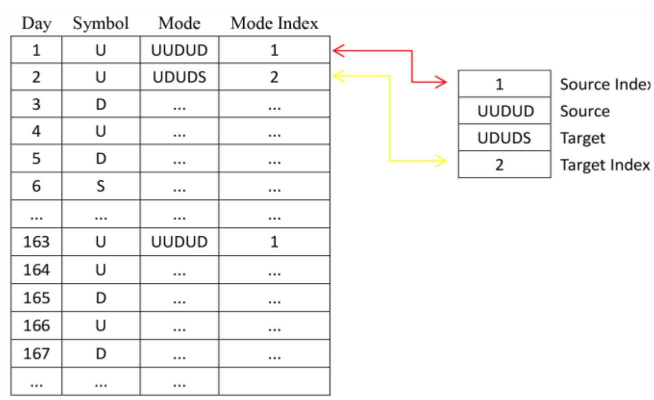

Fig 3 Interaction Matrix.

number to the only mode [Fig 3]. Although the same mode will appear multiple times, the mode index value is determined by the first appearance order of the mode.

3. EXPERIMENTAL RESULTS

We first mapped the return series to a co-movement mode sequence. The price series of two carbon markets are mapped to a co-movement symbolic sequence with 1166 elements. When using coarse-graining, the values of τ and window size are taken as 5 because the carbon trading market only trades for 5 days a week. Consequently, we get the co-movement mode sequence with 1162 elements including duplicate modes.

3.1 Importance of modes

A complex network is then built based on the co-movement mode sequence. There are 231 nodes in the network. Theoretically, there should be 243 modes. As only 12 modes are missing, a result of the number of nodes in the complex network indicates that the co-movement modes scatter in the sample space. It also infers that the two pilots are connected in a certain manner.

Table 1 The most important dozen modes

ID	mode	Weighted In-Degree	Weighted Out-Degree	Weighted Degree
51	SSSSS	230	230	460
39	SSSSU	21	21	42
38	USSSS	19	19	38
124	DSSSS	17	17	34
52	SSSUS	17	17	34
83	UDUDU	16	16	32
55	SSSSD	15	15	30
136	SDSSS	14	14	28
135	SSDSS	14	14	28
84	DUDUD	14	14	28
53	SSUSS	14	14	28
1	UUDUD	13	14	27

We then identify the most important co-movement modes using node degrees. The greater the degree, the more important the node. We calculated both weighted in-degree and weighted out-degree. The weighted in (out)-degree is the sum of the weight on the edge to (from) a node. The weighted degree is their sum. Table 1 shows the most important dozen nodes according to the weighted degree. The column ID stands for the index of modes used in this paper. We see almost equal in-degree and out-degree of these nodes, implying an equivalent chance to transfer from and to other modes. Furthermore, the weighted degree of the node ‘’SSSSS” is almost the ten times of that of the second large node. Therefore, the frequency of mode 51 is especially prominent compared with other modes. This result indicates that the co-movement between the two markets has been in a stable state for a long time in the whole sample period.

The absence of the mode ‘’UUUUU” or ‘’DDDDD’’ in Table 1 indicates the weak co-movement relationship between two carbon pilots. According to the definition of the symbolic co-movement sequence, those modes represent the positive or negative correlation between two signals.

3.2 Co-movement evolution network in the entire period

Based on the constructed network in the previous subsection, we find the anomalous nodes and reveal the evolutionary relationships between the nodes.

Figure 4 shows the topology of the network. The coloured circles represent the nodes of the network. The number inside a circle is the index of a co-movement mode (see Table 1 for some examples). The area of a circle is proportionable the strength of the node. The greater the strength of the node, the larger the area of the circle. The thickness of the edge between nodes is determined by the weight value of

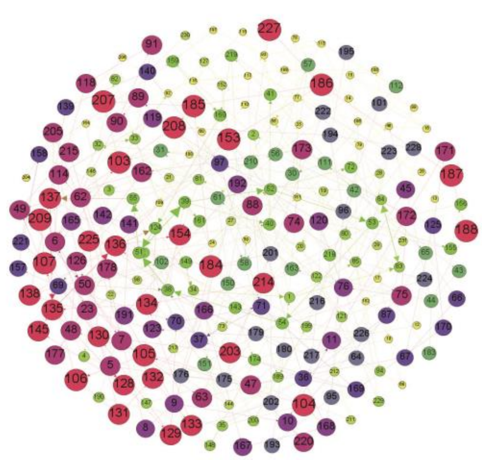

Fig 4 Co-movement evolution network in the entire sample period.

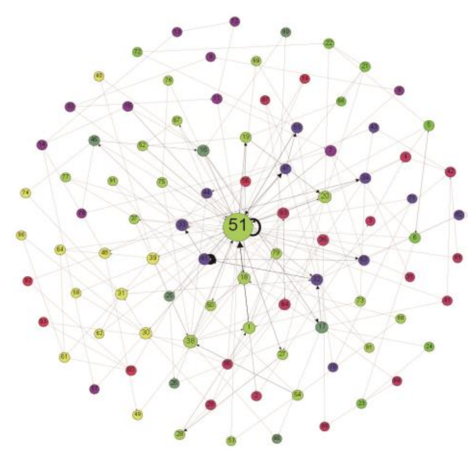

Fig 5 Co-movement evolution network of the first sub-period. The number 51 refers to the mode ”SSSSS”.

the edge. When the thickness of one edge is large, it indicates that the conversion probability between the two modes connected by this edge is larger.

Figure 4 is a long-term co-movement evolutionary relationship network based on complete data. There are no extraordinary large circles, indicating that no significant differences exist in the degree of the nodes. The network looks like random. In fact, we failed to verify the power law of the degree distribution. This scattering pattern indicates that there is no abnormality in the transition between the modes.

As to the edges, we notice that they are almost the same and quite thin. Recalling that the mode “SSSSS” has the predominate degree, the thin edges indicate the modes are equally connected to or from any other modes.

3.3 Co-movement evolution network in sub-periods

We see a clear decreasing and increasing trends for both prices in certain time periods. Therefore, we divided the entire sample period into four stages as shown in Fig. 1. The corresponding critical points are November 28, 2016, October 18, 2017, and August 31, 2018.

In order to reveal the co-movement evolution laws, the author constructed sub-network for each sub-period. Their network structure was then analyzed and compared. In general, only the network in the first period present some special characteristics.

Figure 5 is a network structure diagram of the co-movement evolution relationship of carbon trading prices in the first period, that is, from April 2, 2014, to November 28, 2016.

Figure 5 differs from Figure 4 in the existence of an extraordinary large node and an apparent ring. We can find that the nodes corresponding to mode 51 are abnormally larger than the other modes. Through the " interaction matrix", we can know that the node 51 points to the mode "SSSSS". The corresponding source data has the following characteristics: the two markets have one market carbon price unchanged at least for six consecutive days. Observing the scale of each side of the network, we can find that the edge scale from the 51 modality points to itself is the largest. The self-loop of the 51st mode reveals the evolution law of a co-movement mode: the last possible mode when the mode "SSSSS" occurs is also "SSSSS". In addition, this ring is not unique. There are other rings, taking the ring from "SUDDD" (mode 45) to "SUDDD" as an example.

Networks in the remaining sub-periods have similar properties and are close to that of the network in the whole sample time. Comparing Figure 6 with Figure 5, mode 51 in the second sub-period, which represents market inactivity, is not prominent. The same study was conducted in the third and fourth periods. The results

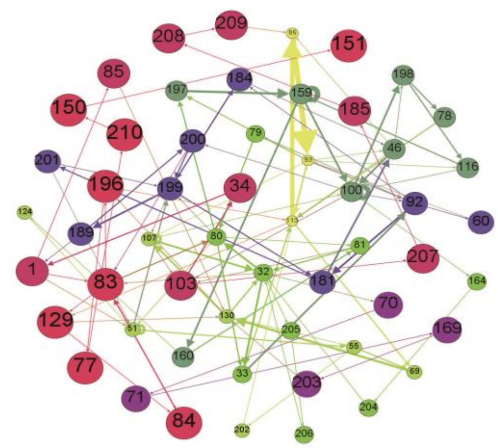

Fig 6 Co-movement evolution network of the second sub-period.

are similar to Figure 6. We believe that the abnormal performance of node 51 in the first period is inseparable from the initial establishment of the market. In the initial sub-period of market establishment, the number of controlled companies is small and the allocation quota is large. In this case, the high frequency of stable mode can be regarded as an almost normal phenomenon. After the establishment of the market, with the passage of time, the number of controlled companies has gradually increased, and relevant policies have been continuously improved. Therefore, the proportion of the second to fourth sub-period stable modes is reduced.

4. DISCUSSION AND CONCLUSIONS

Taking the Hubei pilot and Shanghai pilot as the research objectives, this paper studies the co-movement pattern between carbon markets using complex network method. First, the symbolic co-movement sequence was constructed from daily trading prices. Then the co-movement modes were obtained using the coarse-grain method. Next, directed weighted co-movement evolution networks were built and analyzed. The co-movement modes are found to be scattered due to the occurrence of 95% potential modes. Node degree indicates that the fully stable mode is the essential one, indicating the weak co-movement between the pilots. The network topology in the initial period of the carbon pilot differs significantly from others.

Results of this study have potential applications. Firstly, the weak co-movement between the pilots is consistent with the aim of pilots. China's seven carbon pilots were designed and operated independently in order to gain experience for the national carbon market. Thus, the market performance of each pilot, especially the Hubei and Shanghai pilots should be concerned. Furthermore, the similarity among network topology in the recent time shows the silence in the development of carbon markets. As ``high-quality development" has been promoted as a strategy in China, policy measures should be taken to promote carbon trading so that potential for emission reduction is stimulated to the greatest extent.

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