Interaction among the China carbon markets and the coal market: Nonlinear granger causality

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***Abstract*—As the global warming problem becomes more and more serious, the establishment of a carbon market is an effective tool to deal with it. Energy prices and carbon prices affect each other in a complex ways, so it is particularly important to study this essential causal relationship which can provide valuable information for market participants in both markets. Sample Entropy (SampEn) is used to study the complexity of the China carbon market and coal market. Furthermore, the Nonlinear Granger Causality method is applied to analyze the causality relationship based on the perspective of complexity. The empirical results show that the China's carbon markets have a low-level complexity inferring that the markets are immature. Guangdong, Hubei and Shenzhen market are more complex than other carbon markets. Meanwhile, the Granger causality index indicate that there is bidirectional causality between the carbon market and the coal market. China's coal mar ket affects the carbon markets. Shanghai, Hubei and Shenzhen market affect the coal market when time scales at a month's perspective. The coal market affect the carbon market between the small time scales and the large time scales. All these results demonstrate that a mature carbon market is required for the full function of emission trading.**

Keywords—Carbon Market; Coal Market;Granger Causality;Entropy

I. INTRODUCTION

In recent years, climate issues caused by greenhouse gas have received attention [1]. It not only affects the quality of our life, but also threatens the environment in which human beings live. Carbon trading is a key to solve this problem. The carbon emission trading market is a financial tool to relieve the increasing pressure of global greenhouse gas emissions [2].

Carbon markets have been heavily promoted around the world, especially in the European Union. EU Emissions Trading System (EU ETS), established in 2005, reached the transaction peak in 2013. The experience of the EU carbon market shows that in addition to restricting carbon emissions, a mature carbon market can also bring many economic benefits. As an emerging carbon market, China has launched eight piloting projects since 2013. For developing countries, a unified carbon trading market can realize the reduction of carbon emissions and the sustainable development. At present, the lack of the development history lead to the slow construction of the carbon trading market [3]. Moreover, the imperfection of the laws and regulations of China's carbon market has brought a lot of challenges in terms of environmental pollution [4].

It is meaningful to study the causality of the China's carbon market and coal market, whose carbon emissions mainly come from fossil fuels. According to BP's data on China in 2018, coal accounts for 58% of China's fossil fules, the lowest level in history, but coal still dominates China's energy market [5]. On account of the dominates of coal in carbon dioxide emission, the carbon market is closely relevant to the coal market. There exists a huge interaction between the carbon market and the coal market. In practice, the study of the causal relationship between the carbon market and the coal market makes valuable contributions to market participation and policymaker. Indepth studies on relationship between the carbon market and coal market will bring about friendly promotions, which is of great significance in their future developments.

This research is motivated from the following three aspects. Firstly, it is valuable to study the causality of carbon and energy markets under complexity view. From the perspective of complexity, we can get the information behind the market. Secondly, considering that both the coal and carbon markets are complex systems, we study the causal relationship between the markets from a nonlinear perspective. It is more valuable to study by using nonlinear Granger causality method. Thirdly, the time scale is an important parameter in financial markets. Time scale is a method to study the relationship of market from short-term and long-term. We can get changes through different time scale study the causality relationship. In general, Chinas carbon market is still in its infancy. It will be a very interesting topic to explore the causality relationship between its carbon and coal markets. This study focuses on the complexity and causality of carbon and energy markets in China.

Our paper is organized as follows: Section 2 is the Literature review. Section 3 introduces the methodology about Sample Entropy, Nonlinear Granger Causality of kernel method and multi-scale. It also presents the data used in this paper. Section 4 reports the findings and shows the results. Section 5 devotes to the conclusions of our works.

II. LITERATURE REVIEV

With the development of ETSs, the carbon market plays a more and more significant role in the carbon emission trading system. The carbon emissions produced by coal are the most important part, so a lot of research pay attention to the evaluation and comparison between the carbon market and the coal market. This research has attracted more and more scholars' enthusiasm and attention. For example, some scholars try to analyze the dynamic linkages [6], volatility spillover [5] and the correlation between the two markets [7]. Wu et.al [5] use the recurrence plot method and recurrence quantification analysis method to find that the volatility spillover between the coal market and carbon emission market is strongest. The carbon market affected the coal market and when one comovement pattern occurred, a certain comove ment pattern would appear subsequently [8]. Zhang [6] indicates that the coal market to the carbon market has a significant unidirectional volatility spillover. The carbon market and fossil energy markets have significantly positive correlation across time. At the same time, there is a significant time-varying correlation between the Beijing CET market, the coal market and the NEC stock market [9]. Yin et.al [10] study the correlation between China's carbon market. The results show that the Beijing market is the core of China's carbon market.

As a financial tool for emission reduction, the carbon market has an important impact on the energy market. There is a causal relationship between carbon market and energy market, and its dominant position is constantly changing. Xu et al. [11] study the information connection between carbon and energy by using multilayer recursive network, and measured the mutual dominant relationship between carbon and energy market. The mutual dominant relationship between energy and carbon price changes in differen-t stages, and the carbon price plays a dominant role at the present stage. Keppler et al. [12] use the Granger causality test and confirme that the coal price in the first stage of the EU ETS would affect the price and change in the second stage from the price sequence. Yu et al. [13] use the linear Granger method study the causal relationship between the carbon market and the crude oil market. The results show that the causal relationship between the carbon market and the crude oil market is not obvious on a short time scale but in the long-term is linear. Zhao et al. [14] use nonlinear Granger causality to verify the internal causality of China's carbon market. The results showed that Guangdong, Hubei, and Shenzhen CET markets have significant interactions.

Entropy is generally applied to measure the complexity of the market. Carbon market and coal market are a sort of financial markets, thus they are all complexity systems. Yin et al.[15] employ sample entropy measure the complexity of China's carbon market and study the correlation and synchronization from the complexity. Their results show that the carbon markets not mature. As a method of judging causality, Granger causality is usually used to assess the causality between carbon and energy markets. The linear Granger causality is the major research method in the early period. However, the original Granger causality test has the limitation that it can only be applied to the linear models, and many economic sequences exhibit nonlinear characteristics [11]. Many studies show that the existence of nonlinear dynamics in the prices of commodities is an endemic feature and one of the most basic stylized [16]. The increasing number of research [17] shows that studying nonlinear relationships can obtain more powerful results. They can detect hidden nonlinear relationships, which may not be captured using linear methods. Nevertheless, in carbon and coal markets, causality analysis using nonlinear Granger causality from the perspective of complexity has never been reported to the best of authors' knowledge.

There are still some gaps in the literature on the relationship between the carbon markets and the coal market. First, few scholars study the re lationship between markets from the perspective of complexity. From the perspective of complexity, they only investigate the correlation of market not the causality between markets. Second, the nonlinear of causality between markets is not fully taken into account. The existing only consider the linear Granger causality between the market. However, the markets exhibit nonlinear characteristics. Third, there are few studies have researched the relationship between markets from the time scale. From different perspectives by using different time scales, the relationship between markets may show different phenomena. More information would be obtained if we consider their relationship in time scales.

In this backdrop, this study fills those gaps by examining the complexity and causality of the carbon and coal markets. The contribution of the research is divided into the following points. First, sample entropy is used to measure market complexity. The sliding window technology is used to obtain the complexity sequence, and the relationship between markets is s-tudied by the complexity sequence. Secondly, we pay attention to the causal relationship between the coal market and the energy market. The Nonlinear Granger Causality is used as an indicator to measure the causality between two markets. Therefore, the direction of mutual influence between the two markets can be found. We consider multiple nonlinear orders to make the results more comprehensive. Finally, we study Granger Causality relationship with time scales, and the results show that the coal market affects the carbon market at small time and large time scales.

Which is related to the fact that coal is the dominant energy source in China.

III. METHOD AND DATA

A. Sample entropy

We use Sample Entropy to measure the market complexity [18]. The advantage of sample entropy is that its calculation does not depend on the length of data and has good consistency.

Sample Entropy [19] is defined as follow. Given A time series $x(i), i = 1,2,\cdots,N$ we construct a vector on m-dimension space.

$$X_i = \{x(i),\ldots,x(i+m)\}, i = 1,2,\cdots,N-m. \quad (1)$$

The distance between two vectors X_i and X_j is calculated as the largest absolute difference between their corresponding elements:

$$d_m[X_i,X_j] = \max_{0\le k\le m-1} |x(i+k) - x(j+k)|. \quad (2)$$

Where $1 \le i,j \le N-m, i \ne j$. For each $i\ (1 \le i \le N-m)$, given the tolerance factor r and dimension m, we denoted $C_m(r)$ as the number of pairs of vectors having distance smaller than r. Then we also can calculate the $C_{m+1}(r)$of the length $m+1$ follow the same r.

The sample entropy then calculated as

$$Sampen(m,r,N) = -ln\frac{C_{m+1}(r)}{C_m(r)} \quad (3)$$

A smaller sample entropy represents higher self-similarity of the sequence while a larger value means more complexity.

In this paper, we use the embedding dimension $m = 2$ and tolerance $r = 0.15\delta$, where δ is the standard deviation of the data points. Empirically, the specific values of m and r have little effect on the entropy value [20].

B. Nonlinear Granger Causality Index

We use the Nonlinear Granger Causality index to measure the causality between the markets.

Given two time serie $\{x(i)\}_{i=1,2,\ldots,N}$ and $\{y(i)\}_{i=1,2,\ldots,N}$ the Nonlinear Granger Causality index is calculate by the following steps [21].

Step 1: Construct the dynamics using embedding dimension m:

$$X_i = \{x(i),\ldots,x(i+m-1)\}, i = 1,\cdots,N-m. \quad (4)$$

$$Y_i = \{y(i),\ldots,y(i+m-1)\}, i = 1,\cdots,N-m. \quad (5)$$

We then obtain $Z_i = \{X_i, Y_i\}$.

Step 2: Produce the Hilbert Space. We choose the kernel function k to be an inhomogeneous polynomial $k_p(x,y) = (\alpha x y^T + c)^P$, where p is an integer, α and c are constants. Then we use the kernel to obtain the Gram matrix K_X with element as $K(X_i, X_i)$. The range of K_X is then the Hilbert Space H_X we wanted. The matrix K_Z and the Hilbert Space H_Z can be defined similarly.

Step 3: Obtain the estimation of the original series. We use the linear regression

$$\widetilde{x_i} = \sum_{j=1}^{m} \alpha_j x(i+m-j) \quad (6)$$

$$\widetilde{x_i}^* = \sum_{j=1}^{m} \alpha_j{}^* x(i+m-j) + \sum_{j=1}^{m} \beta_j{}^* x(i+m-j) \quad (7)$$

Then the estimation of the original series is built as $\tilde{x} = (\tilde{x}_{m+1},\ldots,\tilde{x}_N)$ and $\tilde{x}^* = (\tilde{x}^*_{m+1},\ldots,\tilde{x}^*_N)$. The $\tilde{x}_i$ is the projection of x on H_X. In other words, calling P the projector on the space H_X, we have $\tilde{x} = Px$. Similarly, using both x and y, the values of the linear regression form the vector $\tilde{X}^* = P'x$ the $\widetilde{x_i}^*$ is the projection of x on H_Z.

Step 4: Calculate the prediction error. Let $\widetilde{K} = K_Z - PK_Z - K_Z P + PK_Z P$ and $H_X^{\perp}$ be the range of this matrix. We can decompose $H_Z = H_X \oplus H_X^{\perp}$ and let $P^{\perp}$ be the projector on $H_X^{\perp}$. The error of prediction is given by

$$\varepsilon_x = \|x - \tilde{x}\|^2 = 1 - \tilde{x}^{\mathsf{T}}\tilde{x}. \quad (8)$$

$$\varepsilon_{xy} = \varepsilon_x - \|P^{\perp}x\|^2. \quad (9)$$

Step 5: Calculate the Granger Causality index. We calculate the eigenvectors $t_1,\ldots,t_m$ of $\widetilde{K}$ with nonvanishing eigenvalues. Let r_i be the Pearsons correlation coefficient of Y and t_i . Then we define the Granger Causality index as

$$\delta(Y \to X) = \frac{\sum_i r_i^2}{1-\tilde{x}^{\mathsf{T}}\tilde{x}} \quad (10)$$

To avoid false causalities, we use the Bonferroni correction [21] to select the eigenvectors t_i with the expected fraction of false positive equal to 0.05.

C. Data

The data is the daily transaction price obtained from the carbon trading website (http://k.tanjiaoyi.com/). As China's national carbon market is under construction, this study selects seven carbon pilot markets as sample areas. Since there are multiple types of carbon prices in the Shenzhen market, this chapter takes the average of different types data as the representative carbon price in the Shenzhen pilot market. The experimental data is covers from August 2015 to December 2020 (excluding holidays). The coal data comes from the coal index. It can be obtained from China Energy Network (https://www.china5e.com/) and correspond with carbon market.

IV. EXPERIMEATAL RESULTS

We use the sliding window technique to calculate the entropy sequence of prices. We use a fixed window width Nw = 240, which is about one year. Window step size is a single trading day. Specifically, we calculate the sample entropy of the first window,

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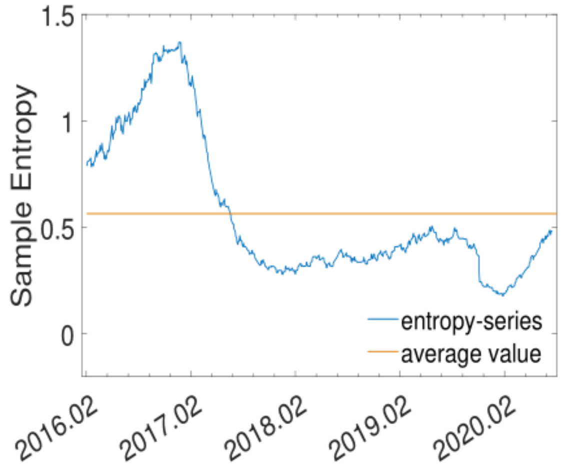
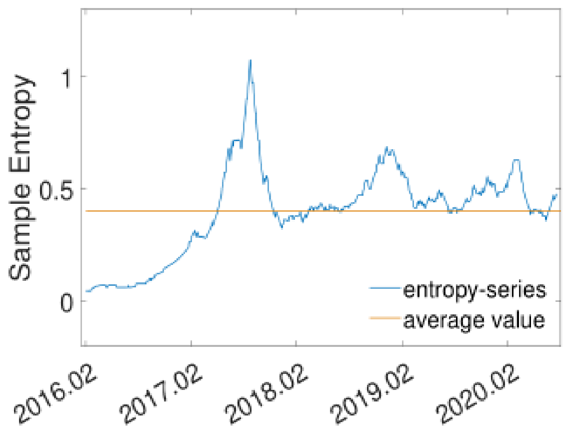
covering the sequence from the first point to the 240th point. And then, the window slides forward by deleting the first point and adding the 241st point.

Fig.1 shows the evolution of sample entropy. First, the entropy curves among seven carbon markets vary at different levels, indicating different market complexity. The average entropy are ranked as Guangdong (1.4877), Hubei (1.4654), Shenzhen (1.4183), Shanghai (0.6599), Beijing (0.5641), Chongqing (0.4009), and Tianjin (0.0860). Furthermore, the entropy curves of Guangdong, Shenzhen and Hubei fluctuate greatly. Therefor, leading by Guang-dong pilot, the three marker have higher market complexity than the other four carbon markets. Tianjin pilot performs the worst as its entropy is almost zero before 2019. It shows that China's carbon market is not mature [22].

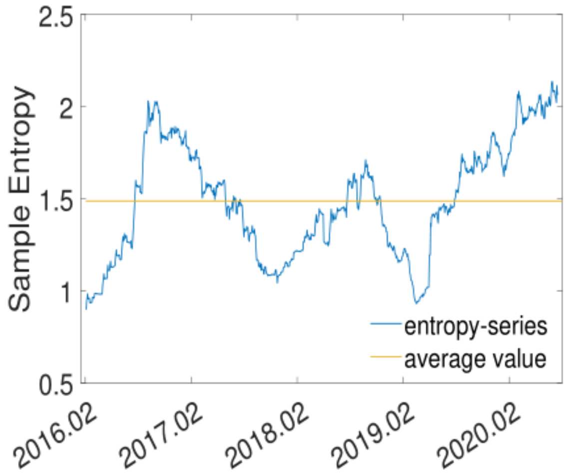
Second, the coal market has the highest complexity. Compared with the carbon pilot markets, the entropy curve of the coal market is the closest to the white noise entropy curve as we can see in Fig.1(h). which indicates this market has a highest complexity. The entropy curve of the coal market remains at a high level from June 2016 to June 2017. Also, it can be observed from February 2018 to June 2019. The average coal entropy series value is 2.1627.



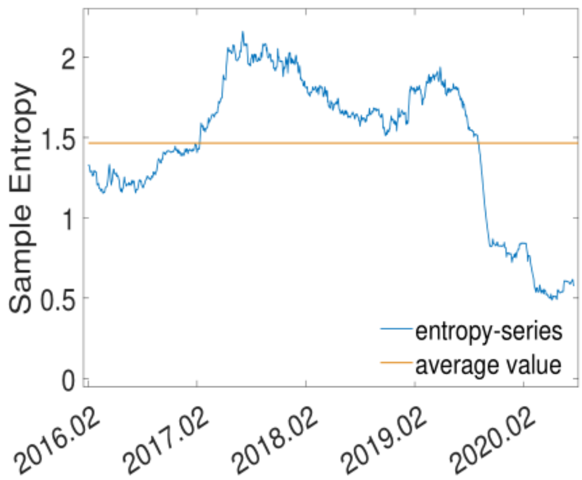
(a)Beijing



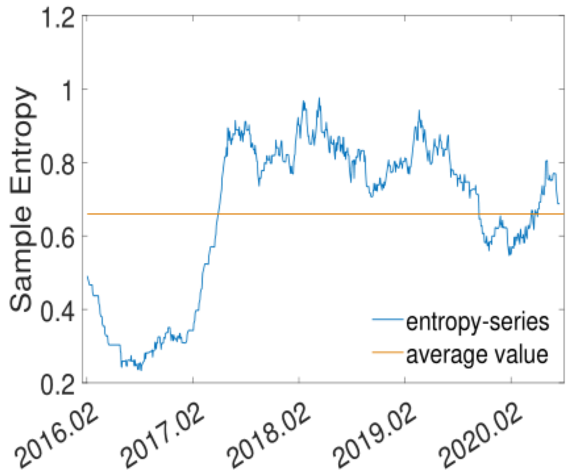
(b)Chongqing



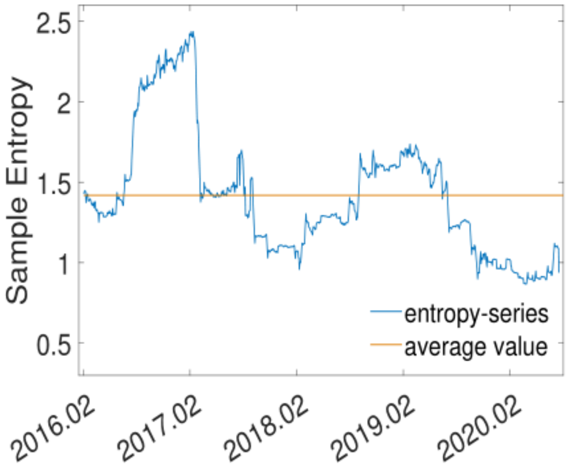
(c)Guangdong



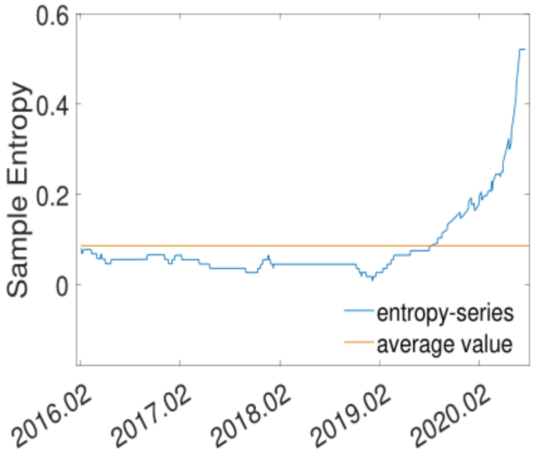
(d)Hubei



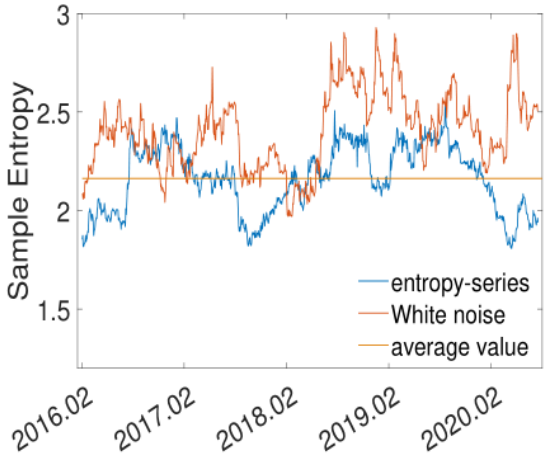
(e)Shanghai



(f)Shenzhen



(g)Tianjin



(h)Coal

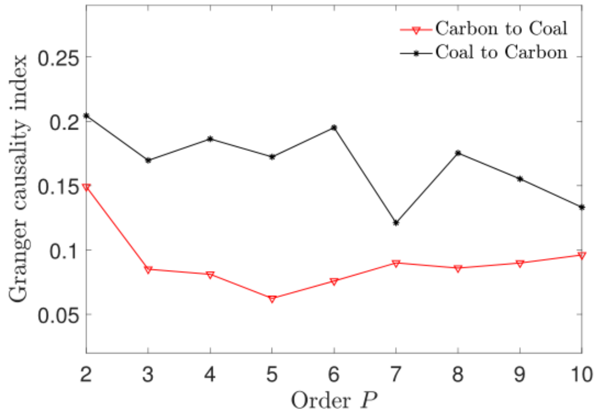
Figure 1: Entropy sequence of China's carbon market and coal market

We now turn to calculate the Granger causality index of the carbon markets and coal market from two directions using different nonlinear order. Applying the entropy sequence to calculate the index, the Granger causality index between carbon and coal market are provided in Fig.2, where we choose m = 2, consistent with sample entropy calculation. Fig.2 shows the Granger causality index at different order, which order P from 2 to 10.

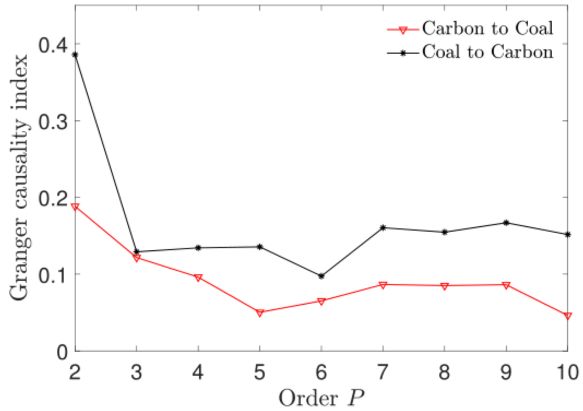
First, form the different order, we observe that all Granger causality indies are different from zero. This suggests that there is bidirectional causality between the carbon market and the coal market. There is a causality relationship between the markets and they affect each other.

Second, the Granger causality index from the coal market to the carbon market is clearly greater than that from the opposite direction. It shows that the coal market is more affect to the carbon market. Therefore, the carbon market is the result of the coal market, which suggest that the coal market impacts on the changes of the carbon market. The fluctuation of coal market is the key factor affecting the carbon market.

Third, we can see that when order P changes, the relationship between the market have no change. As can be seen from the Fig.3, the index lines the coal market to carbon market is mostly bigger than the carbon market to coal market, very rarely changes. Through the results, we can see that the nonlinear order P has little effect on the Granger causality index. Next, we take 3 as the nonlinear order P for calculation.



(a)Beijing



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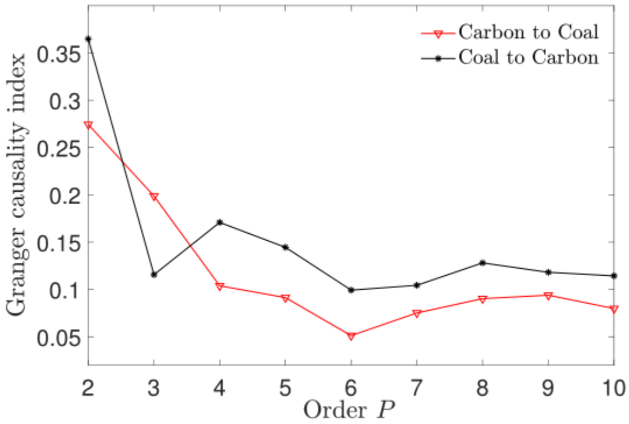
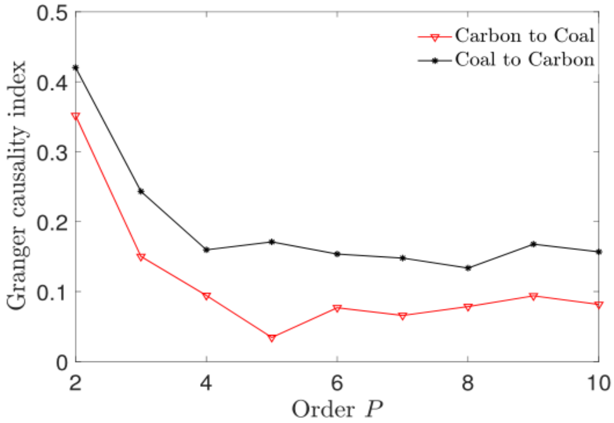
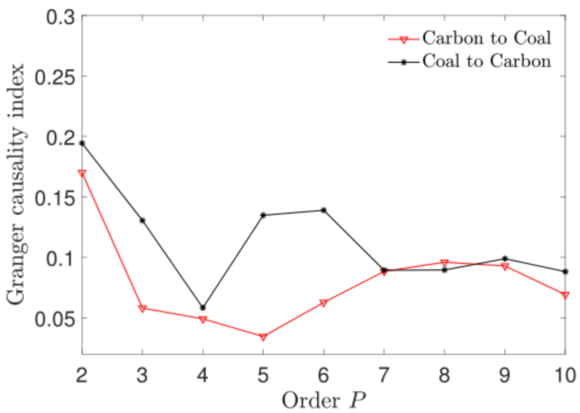


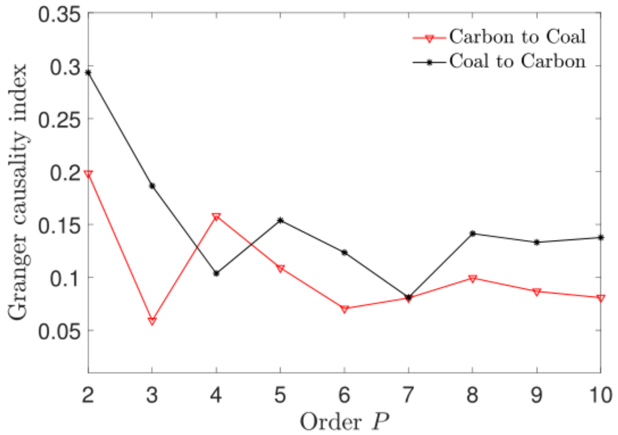
(c)Guangdong



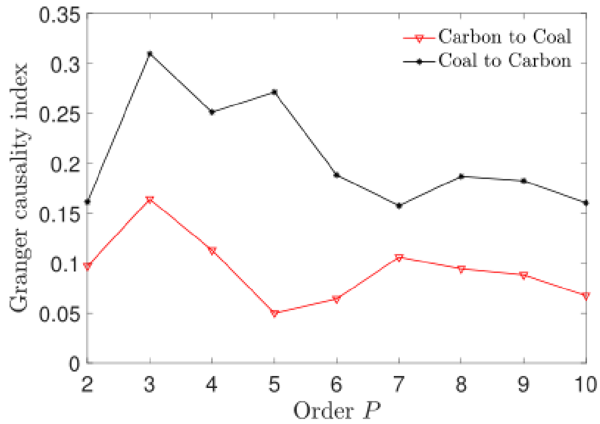
(d)Hubei



(e)Shanghai



(f)Shenzhen



(g)Tianjin

Figure 2: Granger causality index of entropy sequence with different order P

We compute the Granger causality index between the markets for different time scales, which are depicted in Fig.3. The Moving-Average technology is applied in many fields. For an arbitrary time series $x(i)$,$1 \leq \mathrm{i} \leq \mathrm{N}$, where N is the length of the time series. The moving averaged time series $\mathrm{x}(\mathrm{i},\tau)$ at the scale factor τ is calculated as[23]

$$\mathrm{x}(\mathrm{i},\tau) = \frac{1}{\tau}\sum_{j=1}^{i+\tau-1} P(j), 1 \leq i \leq N-\tau+1. \quad (11)$$

This study calculates sample entropy values and Granger index for the scale factors from 1 to 60. We select time scales τ=1, 5, 20 and 60, which represent the scales of a day, a week, a month and a quarter.

At time scale τ= 20, the Guangdong, Hubei and Shanghai markets affect the coal market. Shown in Fig.3, which the Granger causality index of the carbon market to coal market is bigger than the opposite direction. Through the result of Fig.1, we get that this three market have high complexity. Guangdong, Hubei and Shanghai markets have developed well in Chinascarbon market and are in a leading position.

The causality of the carbon market and coal market are similar between the small time scales ($\tau \leq 5$) and large time scales($\tau = 60$) . The coal market has influence over the carbon market at time scales of 1, 5 and 60. When the time scale($\tau = 1$), Guangdong market has an impact on the coalmarket. However, the remaining six carbon market are still affected by the coal market. The carbon market is not mature in China, and its ability to control the coal market is insufficient. At the present stage in China, the coal market still affects the carbon makes. This relationship will not change in the short term.

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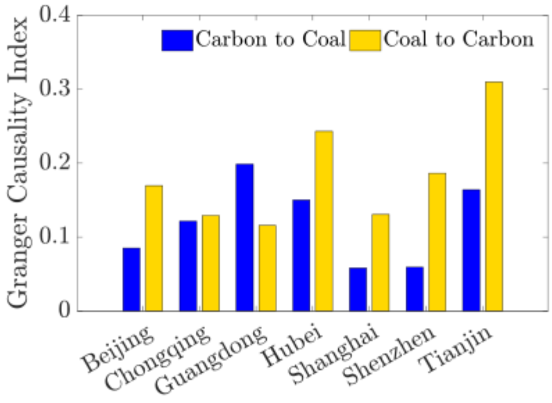
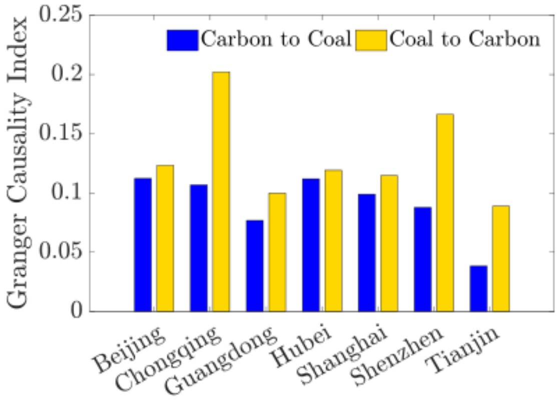
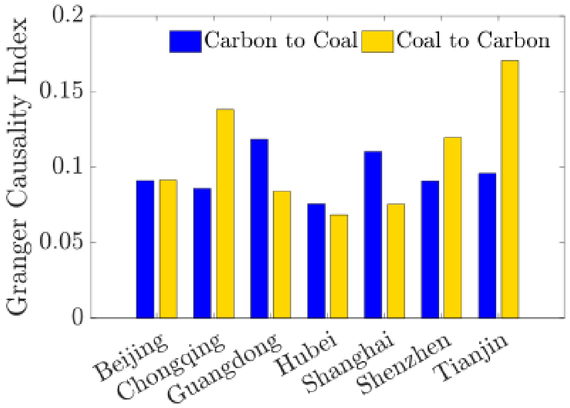


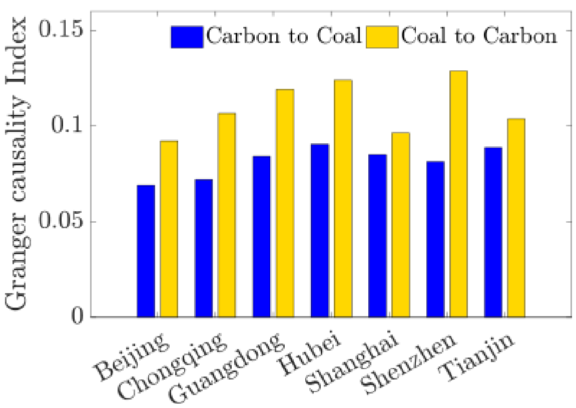
(a)τ = 1



(b)τ = 5



(c) τ = 20



(d) τ = 60

Figure 3: Multi-scale grange causality index of market in different time scales

V CONCLUSIONS

This paper mainly investigates the nonlinear causality between the carbon market and the coal market using Granger causality index. Moving average algorithm is applied to calculate the multi-scale Sample entropy entropy value of the market. Polynomial kernel method is used to calculate the Granger causality index of the entropy value sequence. Influence on the index is analyzed from two aspects of nonlinear order and time scale.

We have the following conclusions. Compared with the carbon pilot markets, the coal market has the highest complexity. The coal market is the leader in that the coal market affects seven carbon markets. Such influence is consistent on time scales 1, 5, 20 and 60. At time scale 20, there have three markets affect the coal market. The entropy-based Granger causality shows that the carbon market is affected by the coal market at all the time scales.

The results of this paper can provide references for decision makers and investors. First, effective measurements should be carried out to develop the carbon market. The result of entropy analysis shows a low complexity of all carbon pilots. Therefore, we should improve carbon market laws and regulations and increase the enthusiasm for carbon market transactions. At the same time, a differentiated development strategy is formulated according to the development status of each carbon market. As Guangdong, Shenzhen, and Hubei are relatively better developed, their experience should be learned and extended to the national carbon market.

Second, investors should make decisions according to their marker role.The result of time scale 1, 5 and 60 shows that the coal market affect to the carbon market. On the contrary, τ= 20 shows that there have three carbon market affect the coal market. Therefore , small companies and large institutes should pay attention to the coal market while medium investors should focuses on the carbon market.

However, this study still has some limitations. This article studies the causal relationship between the carbon market and the coal market from the perspective of complexity. It does not consider the causal relationship between markets in a special period. In addition, this article does not consider the causal relationship between other energy markets and carbon markets. Therefore, changes in the causal relationship between the carbon market and other energy markets in a special period could become a further research direction.

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