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Do Weather Conditions Drive China's Carbon-Coal-Electricity Markets Systemic Risk? A Muti-Timescale Analysis

Yi Zhao (Co-first author, 1928435304@qq.com)
College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

Xingyu Dai (Co-first author, star19950818@foxmail.com)*
College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

Dongna Zhang (dongnazhang6688@gmail.com)
Department of Accounting and Financial Management, Newcastle Business School, Northumbria University, Newcastle upon Tyne, UK.

Qunwei Wang (Corresponding author, wqw0305@126.com)
College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

Yaru Cao (cyr0414@126.com)
College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
Research Center for Soft Energy Science, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

* Yi Zhao and Xingyu Dai contributed equally to this work and are considered to be co-first authors.

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Abstract: This paper uses the wavelet coherency method to reveal the timescale-varying driving mechanism of 12 different types of weather conditions data on risk measures of China's Carbon-Coal-Electricity (CCE) system. First, we find that temperature may be a major factor influencing the co-movement pattern of China's CCE system on a long-term timescale, but cannot affect information spillover pattern of the CCE system. Second, snowfall, cloud, and wind levels could influence the long-term variation of the CCE system's risk measurement. Third, none of the selected weather condition indicators could influence the short- and medium-run CCE systemic risk.

Keywords: Carbon-coal-electricity markets system; Weather conditions; Multi-timescale analysis; Wavelet coherency; Dynamic equicorrelatioin

1. Introduction

Carbon, coal, and electricity markets have complex pairwise interactions (Ahonen et al., 2022; Dai et al., 2021), and China is a prime example of this phenomenon. Participants in China's carbon market are primarily from the power generation sector, which is responsible for over 40% of carbon emissions. In comparison Compared to that, 68% of China's electricity generation is derived from coal-based thermal power (China Electricity Council, 2021). As a result of the reform in China's energy and power sector, the government has gradually marketized the electricity and energy[1] pricing mechanism. At the critical crossroad in recent China's "dual carbon" target, energy transition, and electricity price marketization process, these facts increase the urgency of risk management work on systemic risks of China's carbon-coal-electricity (CCE) markets system.

The weather, which could affect the operation of the carbon, coal, and electricity markets simultaneously, is a potential non-negligible contributor to the systemic risk of China's CCE. Evidence suggests that extreme temperatures can impact CO2 price levels (Batten et al., 2021), and an unexpected temperature change could have the same effect (Mansanet-Bataller et al., 2011). Not only does cold weather increase oil and carbon consumption, but it also increases the price of electricity in the EU (Agnello et al., 2020; Alberola et al., 2008; Liu and Chen, 2013). In addition to temperature, wind speed substantially affects electricity prices (Mosquera-López et al., 2017). Since 2019, the La Nina phenomenon has frequently impacted China's power supply security. The complexity of the systemic risk of weather conditions in China's CCE market may exceed current understanding.

The nonlinear pattern of weather conditions' influence on China's CCE markets system varies across heterogeneous timescales. The dynamic patterns of returns on the carbon, coal, and electricity markets vary on short-, medium-, and long-run timescales.

[1] The float has been expanded from the current upward float of no more than 10% and downward float of no more than 15% to no more than 20% in principle for both upward and downward floats (Sino-German Energy Partnership, 2021).

This is because market participants hold varied opinions (Dai et al., 2020; Dai et al., 2021; Dai et al., 2022; Tong et al., 2022). Further, weather conditions also have periods. In addition to the seasonal-length cycle, wind and tide fluctuations also exhibit the characteristics of a monthly-length cycle. Several studies have revealed the temporal differences in the relationship between the carbon, energy, and electricity markets (Dai et al., 2021). However, there is still a lack of comprehension regarding the multi-timescale characteristics of CCE markets' systemic risk, as well as the multi-timescale interaction between CCE market systems and weather conditions.

Based on the preceding discussion, this study addresses two major issues. How might varying weather conditions impact China's CCE market system under varying risk measures? What is the impact of a multi-timescale weather pattern on China's CCE market system? We construct dynamic equicorrelation (DECO) and DY spillover index as the risk measure of China's CCE markets system. We use wavelet coherency to reveal the multi-timescale pairwise relationship between 12 types of weather conditions and CCE's DECO and DY index.

The contribution of this study is two-fold. To the best of our knowledge, this is the first study to identify the exogenous risk driver of China's CCE markets system, as well as the first study to investigate the impact of weather conditions on China's CCE markets. Secondly, our findings reveal the time-varying and timescale-varying influence pattern of weather conditions on China's CCE markets system, thereby enhancing the understanding of the impact of weather conditions on economic systemic risks.

The remainder of this study is as follows. Section 2 describes the data selection and model, Section 3 provides empirical results, and Section 4 draws a conclusion.

2. Data and Methodology

2.1 Data selection

In this study, we select three types of China's overall weather conditions: the hot indicators, the cold indicators, and the natural conditions. Each type of weather condition is comprised of many sub-indices, as shown in Table 1. The data sources for the weather conditions is from International Energy Agency (IEA). The rationale behind classifying the weather conditions variables into three types is threefold. First, the hot indicator represents the hot temperature that has a direct impact on energy production, transmission and demand. On one hand, the hot temperature can reduce the capacity of energy extraction and transmission lines. In particular, the thermal efficiency of power plants can be affected significantly by the hot temperature. On the other hand, the rising use of cooling devices tends to increase the electricity demand and prices due to the hot temperature.

Second, the cold indicator represents the cold temperature which has extensive impacts on energy production and distribution process. Energy usage can also be driven up by the increased demand for heating during cold temperatures, which in turn impacts the prices of electricity. Third, the natural conditions weather variables impact the production of renewable energy from sources such as solar power, wind power, hydro power and tidal power. As electricity can be generated from renewable energy without giving rise to carbon dioxide emissions, which leads to reduced energy-related carbon dioxide emissions relative to fossil fuels and influences the carbon market dynamics in China.

Table 1

Weather conditions index selection.

Weather conditions	Weather variables	Definition
Hot indicator	➢ *CDDhum*	CDDhum is cooling degree days from temperature corrected by humidity (reference temperature 65 °F)
	➢ *CDDThold23*	CDDThold23 is cooling degree days (reference temperature 23 °C and threshold temperature 26 °C).
	➢ *CDDwet*	CDDwet is cooling degree days from wet bulb temperature (reference temperature 65 °F).
Cold indicator	➢ *HDD*	HDD is heating degree days with the reference temperature as 18 °C.
	➢ *HDDThold20*	HDDThold20 is heating degree days (reference temperature 20 °C and threshold temperature 17 °C).
	➢ *HDDwind*	HDDwind is the heating degree days corrected by wind speed (reference temperature 14 °C).
Nature conditions	➢ *Cloud*	Cloud is the proportion of a grid box covered by a cloud.
	➢ *Evaporation*	Evaporation is the accumulated amount of water that has evaporated from the earth's surface
	➢ *Precipitation*	Precipitation is the accumulated liquid and frozen water, comprising the rain and snow that falls to the earth’s surface.

➢	*RH*	RH is the relative humidity based on 2 meters of air and dew temperatures.
➢	*Snowfall*	Snowfall is the accumulated snow that falls to the earth’s surface.
➢	*Wind10int*	Wind10int is the horizontal speed of air at the height of ten meters above the earth's surface.

To comprehensively evaluate the development of China's carbon market, we chose Beijing, Hubei, Guangdong, Shanghai, and Shenzhen, the provincial pilot carbon markets with the highest trading volume (Liu et al., 2021), to construct a trading volume weighted China's composite carbon market index. The carbon price data sources are from *Wind* database. After the launch of China's national carbon market on 16 July 2021, we will construct a weighted composite carbon market index using China's national carbon market and the five pilot carbon markets. This is done by taking the proportion of carbon quota turnover in each carbon market to the total turnover in each of the six carbon markets and multiplying the weight of each market by the average daily price of carbon quota traded in each carbon market. We use steaming coal futures as a proxy for China's coal market because China's coal accounts for the largest share of primary energy consumption and electricity production. As a proxy variable for China's electricity market, we select the *Shenwan* thermal power generation stock index and from *Wind* database.

All variables are daily data, and the timespan is from 27 September 2013 to 31 December 2021. This paper uses a logarithmic transformation to calculate the return series. Let the returns of China’s composite carbon price index, steaming coal price, and electricity stock index be $\boldsymbol{R}_t = \left(r_{C,t}, r_{En,t}, r_{El,t}\right)'$, which three make up China’s CCE system.

2.2 Methodology

We calculate two systemic risk measures of China’s CCE markets. The first is dynamic equicorrelation (DECO) ρ_t of Engle and Kelly (2002) and Wang et al. (2020), which is an index describing the level of how each market in the CCE system co-move together, and a risk measure reflecting the co-movement pattern among each market in CCE system. The value of DECO ρ_t varies between -1 and 1. If DECO is closer to 1, then market price returns for the CCE system exhibit a stronger linear co-movement in the same direction. If DECO ρ_t is closer to -1, there is a stronger linear co-movement in the opposite direction. If DECO ρ_t is closer to 0, there is a weaker linear co-movement in China's CCE system.

The second systemic risk measure calculated is the total returns information spillover index, or total DY spillover index S_t (Dai et al., 2021; Diebold and Yilmaz, 2012). Unlike DECO ρ_t, the DY spillover index S_t describes the degree of pairwise influence among each market returning in China's CCE system. The value of S_t varies from 0% to 100%. A high S_t indicates that the return fluctuations of one market in the CCE system significantly affect the return fluctuations of another market.

DECO ρ_t reflect the co-movement effect, and DY S_t reflects the spillover effect in China's CCE markets system. Our calculated measures, whether DECO ρ_t or DY S_t, are dynamic and can reflect the risk pattern of the CCE system at any time. The key factor of modeling is to determine how the weather conditions index W_t affects CCE system's S_t or ρ_t at different times and timescales. More details can be found in supplementary data.

The wavelet coherency method might satisfy our modeling requirements (Tong et al., 2022). Given a wavelet function $\psi(\cdot)$ and a timeseries y_t, the continuous wavelet

$$y \quad \infty \quad 1 \quad {}^{*}\left(\underline{t-\tau} \right) \quad {}^{*}$$

transform of $_t$ is $W_{y_t}(s,\tau)=\int_{-\infty} y(t)\frac{1}{\sqrt{|s|}}\psi\left(\frac{\quad}{s}\right)dt$, where $\psi(\cdot)$ is a conjugate function of $\psi(\cdot)$. The wavelet coherency between CCE systems risk measure X_t and weather conditions Y_t can be represented as the ratio of the cross-spectrum to the product of each series spectrum which may be denoted as follows:

$$R^2(s,\tau)=\frac{\left|S\left(s^{-1}W_{x_t y_t}(s,\tau)\right)\right|^2}{S\left(s^{-1}\left|W_{x_t}(s,\tau)\right|^2\right)S\left(s^{-1}\left|W_{y_t}(s,\tau)\right|^2\right)} \tag{1}$$

The value of $R^2(s,\tau)$ is between 0 to 1. The closer the value of $R^2(s,\tau)$ is to one, the more significant the correlation relationship between CCE risk measure X_t and weather conditions Y_t at timescale S. The angle $\phi_{x_t y_t}$ of the $W_{x_t y_t}(s,\tau)$ is called phase-difference, that is:

$$\phi_{xy}=\arctan\left(\frac{\mathrm{Im}\left(S\left(W_{x_t y_t}(s,\tau)\right)\right)}{\mathrm{Re}\left(S\left(W_{x_t y_t}(s,\tau)\right)\right)}\right) \tag{2}$$

A zero phase difference indicates that the time series move together at the specified time-frequency. If $\phi_{xy}\in(0,\pi/2)$, then CCE risk measure X_t and weather conditions Y_t at timescale s move in the same direction, but Y_t leads X_t. If $\phi_{xy}\in\left(-\pi,-\frac{\pi}{2}\right)$, then X_t and Y_t move in the opposite direction, and the weather conditions lead to CCE risk measure at timescale S. Section 3 uses arrows pointing to different directions (↗ or ↙) to represent ϕ_{xy}.

3. Empirical analysis

This section presents the wavelet coherency computation result between weather conditions and two risk measures of China's CCE market systems. According to the influence period of weather conditions on China's CCE market risk measure, we categorize the timescale as short-run (period less than 64 days), medium-run (period between 64 and 256 days), and long-run (period over 256 days). Because of the cyclical nature of weather conditions change, commodity markets are all affected to some extent by seasonal cycles of one year's length(Singh et al., 2019). 256 days represents a time scale of one year, 64 days represents a time scale of one season. so the medium-run and long-run divisions are based on a time point of 256 days. the medium-run and short-run divisions are based on a time point of 64 days.

Figure 1 shows the The DECO index and DY index of China's CCE system. The DECO is a risk metric that reselects the price co-movement pattern among China's CCE markets. The DY index represents the price information spillover between China's markets. These two indicators show a convergence of movements, as they both reflect the movement of CEE market prices. It can be seen that both indicators show more significant fluctuations after 19 years, which could be explained by the entry of the national carbon market.

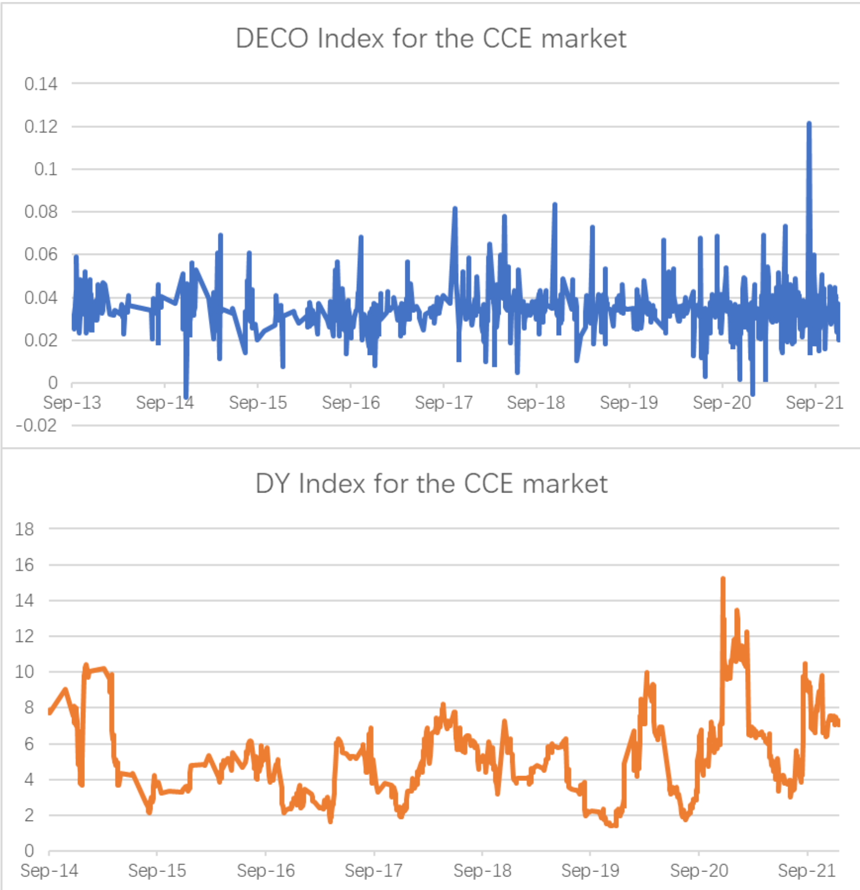

Figure 1. The DECO index and DY index of China's CCE system.

The impact pattern of weather conditions on the DECO of China's CCE markets varies over time and scale as depicted in Figure 2. We find that the change in the hot indicator leads to the change in the DECO of China's CCE system in the long run. There are huge islands in the first row of Figure 2 over 256 days-length timescales whose arrows most point to ↙, which uncovers that the increasing (decreasing) of the hot index will improve the negative (positive) co-movement pattern among the markets in

China’s CCE system.

This phenomenon occurs because a change in the hot index affects the wintertime temperature. Compared with summer, China consumes more coal and electricity in winter. If winters become colder in the long run, coal consumption for district heating will increase, and coal prices will rise. At the same time, the long-term profits of power generation companies will increase, and production activities will become more frequent, which will also contribute to the increase in carbon prices. This transformation process has led to a rise in the DECO of China's CCE system.

The long-run impact of hot temperature indicators on China’s CCE markets system’s DECO mainly happens before 2020. We could find that the arrows over 256 days-length in *CDDhum*, *CDDhum23*, and *CDDwet* in Figure 2 do not point to ↙ suddenly since 2020, given that China has experienced a series of warm winters since that year. On a long-run scale, the arrival of a warm winter will decrease electricity and coal consumption, thereby decreasing the DECO of the CCE system. Besides, we find that there are few arrows pointing to ↗ or ↙ in subfigures of *CDDhum*, *CDDhum23*, and *CDDwet*, which implies hot indicator could not affect the DECO of China’s CCE system.

According to the definition, the value of cold indicators fluctuates in the opposite direction of hot indicators. As shown in the subfigures for *HDD*, *HDDThold20*, and *HDDwind*, the arrows in *CDDhum*, *CDDhum23*, and *CDDwet* point in the opposite direction. These evidences also indicate that temperature changes affect DECO on a long-run scale, and that long-run cold temperature has a greater impact on the DECO of the Chinese CCE system than long-run hot temperature.

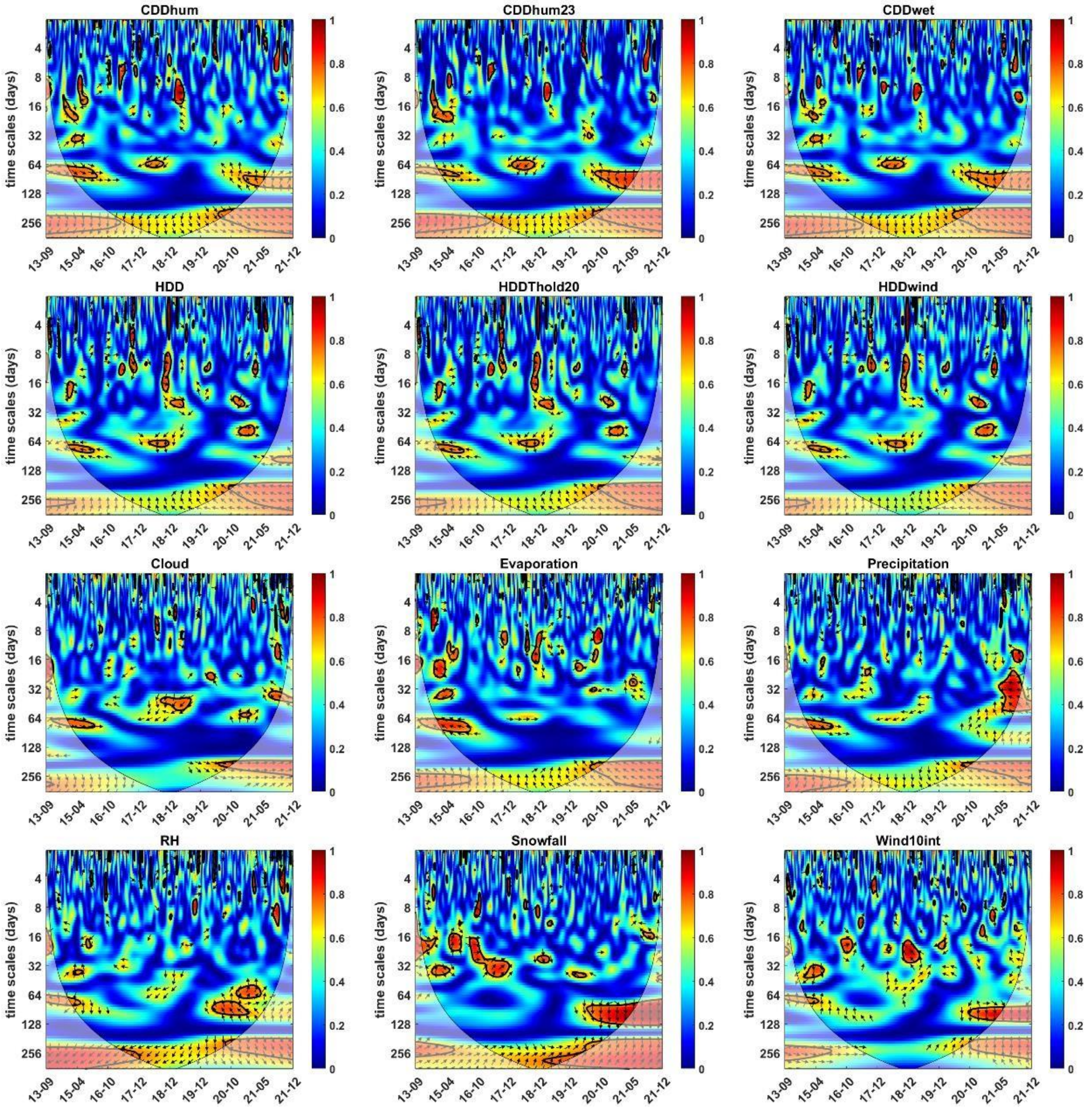

Figure 2. Wavelet coherency between weather indicators and the DECO of China's CCE system.

Note: In each subfigure, the horizontal and vertical axis represents the timespan and timescale, respectively. Arrows pointing up to the north-east (↗) or south-west (↙) indicate that weather conditions change drives the systemic risks change in China's CCE markets system in the same or opposite direction. Red and orange indicate time-frequency regions with strong co-movements, whereas blue and green indicate regions with weak co-movements.

Among the nature conditions indices, the most remarkable findings are that *RH* and *Snowfall* significantly influence the change of DECO. In the subfigure of *RH,* we find that there are islands where the arrows point to ↙ around at the medium-run timescale and a large island where the arrows point to ↙ at the long-run timescale, suggesting that there may be a significant negative correlation between *RH* and DECO.

A large number of arrows point to ↗ above the time period of 256 days-length timescales, indicating a significant positive correlation between *Snowfall* and DECO at the long-run timescale. However, *Evaporation*, *Precipitation*, and *Wind10int* have nearly no striking arrows in the 5% significance black area.

There are significantly fewer regions with strong co-movements between weather conditions and CCE's DY index compared to the results of DECO as shown in Figure 3.

CDD, *CDDThold23*, and *CDDwet* have a few islands where the arrows point to ↙ in the time period of 16-32 days- and 64-256 days-length timescale. Besides, *HDD*, *HDDThold20*, and *HDDwind* have a small distribution of islands where arrows point to ↗ in the time period of 16-256 days-length timescale. All of these indicators suggest that temperature has a negligible effect on information diffusion between markets in China's CCE systems. This is primarily the mechanism for price information spillover between markets in China's CCE systems, which are complex and driven by economic growth. Temperatures are not crucial influencing variables.

Considering the influence pattern of natural conditions on the DY index of China’s CCE system, both *Cloud and Snowfall* have islands where arrows point to ↙ at over 128 days-length timescales, indicating that cloud and snow weather slightly affects the DY of China’s CCE markets and is negatively correlated with changes of DY index, other natural conditions do not show a significant risk driving effect on information spillover pattern among markets in China’s CCE system.

By combining the results of DY and DECO, it is possible to conclude that the effect of weather conditions on the DECO between China's CCE markets is greater than the effect on DY. DY may be influenced by weather conditions more persistently and stably (as can be seen from the consistency of the arrow direction). When analyzing the effects of temperatures on China's CCE markets, the temperature situation should be given more consideration. *Cloud*, *Snowfall*, and *RH* are key risk drivers for China's CCE markets' systemic risk management work, among all the other weather conditions considered in this paper.

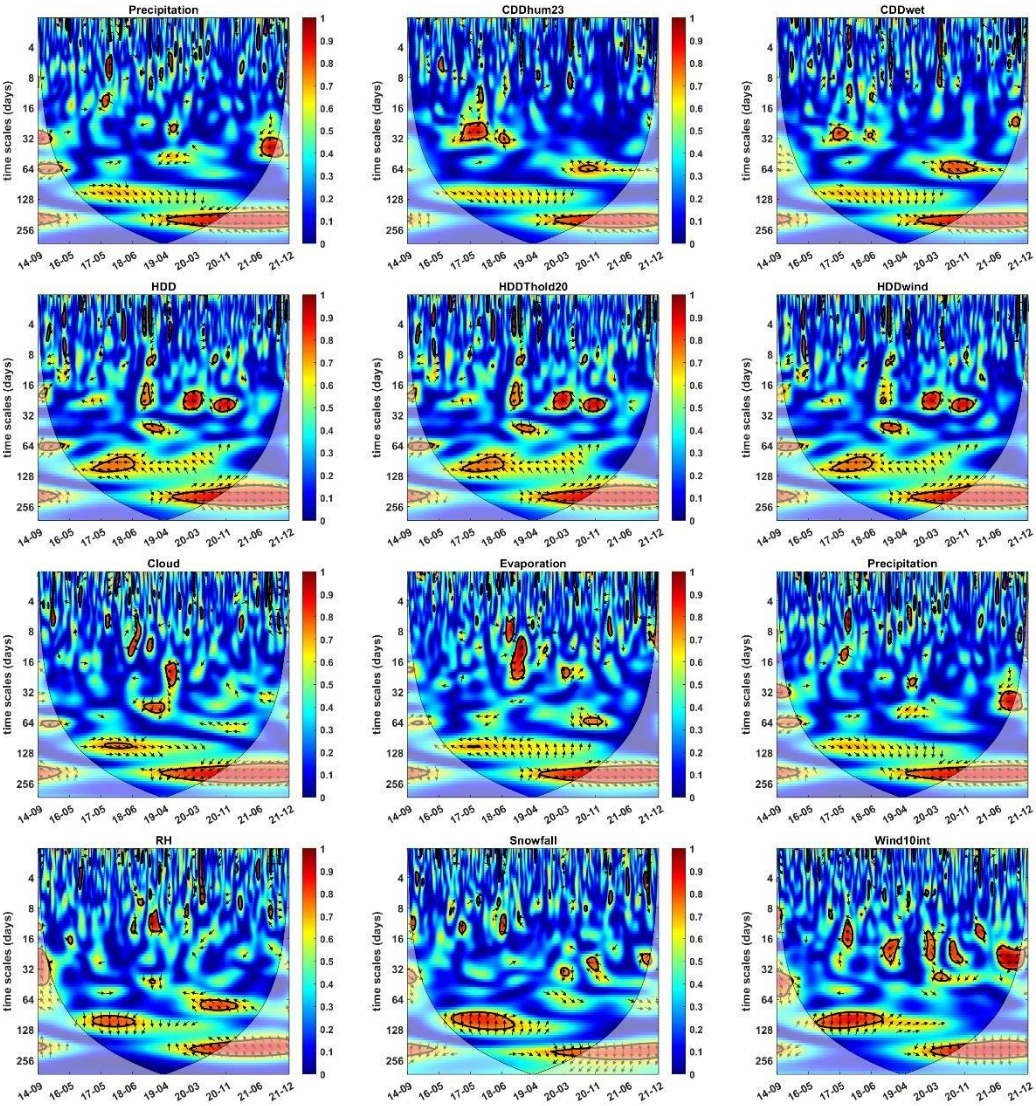

Figure 3. Wavelet coherency between weather indicators and the DY of China's CCE system.

Note: See Figure 2.

4. Conclusion

This paper investigates the influence pattern of weather conditions on the systemic risk of China's carbon-coal-electricity (CCE) markets. China's carbon, coal, and electricity markets are highly interdependent, and the CCE system plays a crucial role in China's current economic development, which is the primary motivation for researching this characteristic. Moreover, weather conditions are a significant factor that may affect the operation of China's CCE markets system. The following are our conclusions.

First, temperature could be a very important factor influencing the long-run co-movement pattern of China's CCE markets system. When the temperature is lower, the market returns in the CCE system co-move in a closer direction. The higher the temperature, the more likely it is that market returns in the CCE system will move in opposite directions. This influence pattern is significant in the cold winter years. However, the temperature may not impact the price information spillover pattern among markets in China’s CCE system.

Secondly, nature conditions, relative humidity, and snowfall level would affect the co-movement pattern of markets in China's CCE system, while cloud and snowfall levels are long-run drivers influencing the price information spillover pattern of China's CCE markets system. We conclude that evaporation, wind speed, and precipitation may not be risk factors for China's CCE system.

Thirdly, it is possible that none of the weather conditions analyzed in this study are short- or medium-run drivers of systemic risk in China's CCE markets.

The study of the systemic risk of CCE can provide a new perspective for identifying market risk and financial risk, thus facilitating the improvement of the performance of regulators' duties. On the other hand, in the process of constructing relevant portfolios, understanding the information spillover between the carbon market, coal market and power companies is beneficial for investors to grasp the correlation between different markets, achieving resource allocation and adjust their business strategies in their portfolios. Focusing on the role of weather conditions in driving the CCE market can also integrate weather conditions factors into risk management, making the risk management framework more complete.

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