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Lead-lag relations between the Chinese carbon and energy markets: Evidence from extreme climate shocks☆

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ABSTRACT

We examine how lead-lag relationships between China's carbon market and energy markets change during extreme climate events. We show that extreme climate events strengthen the lead-lag relationship between markets, especially during extreme cold and heat periods during which energy demand spikes.

1. Introduction

The Chinese government has placed a significant emphasis on the development of carbon emissions markets. As of 30 June 2023, the cumulative turnover of carbon emission allowances has grown to 237 million tonnes. This turnover is explained by China's heavy dependence on energy commodities. As these commodities are primarily sourced on international energy markets, this may result in increased dependence between prices of China's carbon contracts and international energy commodities.[1]

The relationship between prices of carbon and energy commodities has been the subject of several studies.[2] To some extent, prices of carbon and energy commodities are driven by the same factors. Think factors such as energy consumption and of carbon emission reduction policies. A reduction in carbon emission quota will reduce demand for fossil fuels thereby affecting both carbon and energy markets. Increased investor focus on climate risk enhances volatility spillover relationships among carbon and energy markets (Chen et al., 2024a). The dependence on the same factors leads to information being transmitted to both markets, thereby forming relationships between them. Another example is the exchange rate. Chen et al. (2024b) argue that a change in the exchange rate may

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[1] In 2021, 72% of China's crude oil consumption was supplied by non-Chinese sources and 46% for gas. The China Energy Development Report shows that China's coal consumption increased with 7.7% in 2023 and that the dependence on other energy sources rose as well.

[2] See for instance Dhamija et al. (2018), Hammoudeh et al. (2014), and Koch et al. (2014

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affect the economies of both countries, thereby changing energy demand and the demand for carbon permits. The opposite relationship might hold as well, as the intensity of carbon emissions affects the expansion of international trade and therefore the exchange rate.

Few studies suggest that the relationship between energy and carbon prices might change due to market frictions caused by exogenous shocks from - for instance - extreme weather. Chen et al. (2023) find that stock prices from energy-intensive companies lead carbon prices, but that this relationship reverses under the influence of exogenous shocks. Wu and Qin (2023) focus on extreme risk spillovers to carbon markets from traditional fossil energy and new energy markets in China. They find evidence for reversing relationships when carbon-intensive energy markets face extreme market conditions.

Shocks from extreme weather events attract public attention to the carbon market, resulting in the carbon market leading the stock market (Chen et al. 2024b). Few studies have the impact of extreme weather shocks on this lead-lag relationship. According to Chen et al. (2024b), shocks from extreme weather events may amplify the trading volume on carbon markets, thereby increasing carbon price volatility, and ultimately turning the carbon market from a risk receiver to a risk transmitter.

The purpose of this work is to understand this lead-lag relationship better as climate risk plays a crucial role in driving financial market fluctuations and influencing cross-market connections (Venturini 2022). Climate risk directly bears on carbon markets, and numerous studies have confirmed the impact that the risk of climate change has on carbon prices.[3]

2. Data

We use prices from Chinese carbon markets and the prices of energy commodities to research changes in the lead-lag relationships between carbon and energy markets due to extreme weather events leading to a better understanding of the consequences of climate risk. For carbon, we use the prices on the Guangdong carbon emission trading market (GDC) from 1 January 2018 through 31 December 2022, as the Guangdong carbon emission trading market is more liquid (Chen et al. 2024b) than other Chinese carbon markets.[4] For domestic energy markets, we use the DCE (Dalian Commodity Exchange) Coking Coal Futures, the SHFE (Shanghai Futures Exchange) Crude Oil Futures, and the Natural Gas Sector Stock Index as the sample of prices of Chinese coal (DCOAL), oil (DOIL) and gas (DGAS) markets respectively. We use the ICE Rotterdam Coal Futures, ICE Brent Crude Oil Futures, and NYMEX Natural Gas Futures as the samples of the international coal (FCOAL), oil (FOIL), and gas (FGAS) prices respectively. The daily closing prices of all markets are obtained from the Wind database.[5]

Table 1 shows the descriptive statistics of daily changes in the log prices of the commodities. The changes in the log prices for international coal, oil, and gas markets (FCOAL, FOIL, FGAS) have a higher standard deviation than their Chinese equivalents (DCOAL, DOIL, DGAS). The changes in the log prices for the gas contracts (DGAS, FGAS) have the lowest standard deviation, whereas the log price changes of the coal contracts (DCOAL, FCOAL) exhibit the highest standard deviations. All series exhibit excess kurtosis. The ADF tests indicate that all return series are stationary at the 1 % significance level.

Table 2 shows the extreme weather events in China. We categorize them into events A, B, C, and D, where categories B and C (extreme heat and cold) embed energy demand increasing events and categories A and D (heavy rainfall and extreme storms) embed climate events with a not clear impact on energy demand. We expect to see more links between carbon and energy markets for event categories B and C than for event categories A and D.

3. Methodology

We use the thermal optimal causal path methodology (hereafter: TOP) to identify the lead-lag structure between the Chinese carbon and energy markets. Sornette and Zhou (2005) introduced TOP to examine the lead–lag relationship between the S&P 500 index and U. S. Treasury bonds.[6] TOP is effective in detecting local lagged dependence, especially when the dependence relationship is nonlinear and experiences intermittent changes. This is what applies for our study as we examine the lead-lag relationship between carbon and energy prices, which might change due intermittent frictions caused by extreme weather conditions. We provide a brief intuitive discussion about the TOP method here and refer to Sornette and Zhou (2005), Chen et al. (2023), and Ren et al. (2023) for more details.

Let $R_{i,t}$ be the difference in the log price of commodity i between time t and $t\text{-}1$ (logarithmic return). We normalize $R_{i,t}$ by dividing by its standard deviation such that the log price changes of two commodities i and j have comparable values. Then, we introduce two times $t1$ and $t2$ ($t1, t2 = 1 \ldots T$) and the distance matrix $E_{i,j}$ with cells $\varepsilon(t1,t2) = |R_{i,t1}\text{-}R_{j,t2}|$. Consider the situation where $R_{j,t=}R_{i,t\text{-}k}$, i.e. the return of commodity i perfectly leads the return of commodity i by k periods. Then, the distance $\varepsilon(t-k,t) = |R_{i,t-k}\text{-}R_{j,t}|$equals zero. The distance matrix shows this k-period dependence with a line (a path) of zeros which is parallel to the main diagonal. However, detecting the exact form of the lead-lag relationship in the distance matrix is not that simple in practice. The relationship might be more complex,

[3] We refer to Batten et al. (2021), Benz and Trück (2009), Mansanet-Bataller et al. (2007).

[4] The average daily volume on the Guangdong carbon market is >2.5x the average daily volume of the second biggest market (Tianjin).

[5] See https://www.wind.com.cn

[6] The TOP method has been widely used to examine the non-linear relationships in financial and commodity markets. See for instance Wang et al. (2017), Gao et al. (2020), Yang and Shao (2020), Yao and Li (2020), Jin and Guo (2021), Chen et al. (2023), Ren et al. (2023), and Chen et al. (2024a).

Table 1
Descriptive statistics and unit root tests of the logarithmic return of each commodity.

Variables	Mean	Std. Dev.	Min	Median	Max	Skew.	Kurt.	ADF test
R_{GDC}	0.0017	0.0266	−0.1739	0.0007	0.1755	0.0204	9.4420	−26.5982***
R_{DCOAL}	0.0004	0.0280	−0.3775	0.0008	0.1305	−3.1598	41.4929	−20.6150***
R_{DOIL}	0.0003	0.0256	−0.1413	0.0008	0.1154	−0.1778	5.8809	−31.2695***
R_{DGAS}	0.0003	0.0183	−0.0869	0.0009	0.0681	−0.4367	5.4372	−31.0797***
R_{FCOAL}	0.0010	0.0367	−0.4508	0.0004	0.5009	0.6327	13.8070	−32.6494***
R_{FOIL}	0.0002	0.0311	−0.2798	0.0022	0.1908	−1.2549	19.2273	−32.2911***
R_{FGAS}	0.0013	0.0683	−0.3118	0.0003	0.4210	0.3286	17.2693	−33.5138***

Note: *** denotes the 1 % significance level.

due to a time lag that may not be constant over time, and noisy observations such that lead-lag relationships are not clearly visible as zeros in the distance matrix. The "optimal" path in the distance matrix is found by applying a recursive procedure that searches for the path with the lowest average distance (or energy as it is called within TOP) to some point in the matrix.[7] The result is a probability that a point (being a time and a lead/lag period) in the matrix will be reached. The key insight is that the method works with such a probability as it allows for different routes towards a point in the distance matrix. The optimal lead-lag order Ord_t is the average of the probabilities of all possible paths that could reach a point, where a positive value for Ord_t means that $R_{i,t}$ leads (is ahead of) variable $R_{j,t}$ and vice versa. The advantage of this averaging approach is that it reduces the influence of noise in the data on the result.

4. Results

Fig. 1 shows the lead-lag order estimates between the log price changes of the carbon and the energy commodities. Panel (a) shows the lead-lag order for carbon and domestic coal, which is positive on average but negative during some periods. At this point, we observe that the estimates are not constant, which we expected to see when climate events cause these relationships to change.

The lead-lag relationships are shown Fig. 2 as networks with arrows indicating the direction of the relationship and the numbers the estimate for Ord_t. Panel (a) shows the estimates obtained from the whole sample. The arrow pointing from DCOAL to GDC means that the lead-lag relationship between DCOAL (domestic coal) and GDC (carbon) is 3.4 on average, indicating that the prices on the Chinese coal market lead the prices on the Chinese carbon market by 3.4 days on average.

On average, the price changes of DCOAL, FCOAL, FGAS lead the price change of carbon by 3.4, 1.6, and 3.2 days respectively. The price change of carbon leads the foreign oil market by 1 day on average. There is no clear relationship between the carbon and DGAS and DOIL markets on average.

Although we observe a weak or no relationship between carbon and oil markets, panels (b) and (e) in Fig. 1. hint at a decrease in the lead-lag order between the Chinese carbon and oil markets over time. As the liquidity of China's carbon emissions trading market increased, and corporations are beginning to use the carbon market to manage their carbon emissions, carbon price dynamics may affect the consumption of oil. This may result in crude oil prices being more sensitive to the price of carbon emission allowances.

Fig. 1. clearly shows that the order of the lead-lag relationship varies over time. We argue that some of this variation might be caused by weather events. For instance, extreme cold and heat events result in increased demand for heating and cooling, both resulting in increased demand for energy for which more carbon permits need to be purchased.

Fig. 2 shows the network diagrams for the different climate categories. Panels (b), (c), (d), and (e) show the networks for event categories A, B, C, and D. We expect to observe more intense relationships between carbon and energy markets for events categories B and C as those events lead to an increase energy demand. Fig. 2. shows that this is the case indeed. Panels (c) and (d) show more lines than panels (a) and (d); the lead-lag network is more intense. During extreme storms (event category D in panel (e)) the carbon market leads the international oil market (weakly) and lags the international gas market. For the rest, no relationships. This differs from extreme heat events in panel (c) where GDC leads and lags with all other markets except for foreign coal. We conclude that the extreme heat and cold events have the greatest impact on the lead-lag relationship between markets. The markets become more linked after such events. Extreme rainfall and storms do not lead to clear increases in energy consumption and do not lead to increased dependencies between energy markets.

The previous results indicate that the lead-lag relationships between the carbon and energy markets are not constant over time and might depend on climate events. We question whether the observed lead-lag orders are strong enough to support hedging or trading decisions. To examine this, we construct two trading strategies based on the lead-lag relationships and examine the two strategies in bear and bull markets.

Fig. 3 shows that we can distinguish, roughly speaking, two markets: a neutral or bear market (stable or declining prices of energy commodities) between April 1, 2019 and April 1, 2020 and a bull market (strong rising prices) between March 1, 2021 to March 1, 2022. In the strategy 1, we analyze hedged positions with GDC and different energy commodities. Position i/GDC is long in 1 unit of commodity i and short in h units of GDC, where the hedge ratio h is calculated conform Antonakakis et al. (2020). Columns (2) to (5) in

[7] In TOP, one needs to set the parameter T. The method might suffer from information loss, when T is set too high. When T is set too low, the result might suffer from overfitting. We have calculated our result with different settings for T ($T = 5, 10, 15$) and found the results to be consistent for those settings. We choose to only show the results for $T = 10$ to save space without losing consistency.

Table 2
Details and dates of four categories of extreme weather events.

Event category	Event	Event date
A: Extreme heavy rainfall events	During early summer, continuous heavy rainfall in southern China leads to widespread urban flooding.	June 18, 2018
	During the summer, frequent rainfall occurs in the upper reaches of the Yellow River in China, leading to flooding in Lanzhou, Gansu province.	July 20, 2018
	In January and February, southern China experiences unusually cloudy and rainy weather with limited sunshine.	February 10, 2019
	Southern China experiences the longest pre-flood season since 1961.	March 9, 2019
	Continuous heavy rainfall leads to a major landslide in Shuicheng City, Guizhou Province, China.	July 1, 2019
	The autumn rainy season in the western region of China is noticeably longer, with an increased number of rainy days.	August 27, 2019
	The plum rain season and the amount of plum rainfall in the middle and lower reaches of the Yangtze River in China are both the highest in history.	June 9, 2020
	This summer, China has experienced abundant precipitation and severe flood situations.	June 25, 2020
	In mid-August, frequent heavy rainfalls occurred in the Sichuan Basin of China, resulting in disasters in some areas.	August 18, 2020
	Precipitation in northern China is above average and ranks as the second highest in history.	June 21, 2021
	Henan Province in China experiences a super heavy rainstorm, breaking the record for the highest hourly precipitation in mainland China.	July 17, 2021
	The Songliao River Basin in China experiences extreme rainfall, resulting in a breach of the embankment in the Panjin section of the Rao Yang River.	July 2, 2022
	During the peak of summer, localized short-duration heavy rainfall leads to significant casualties.	July 15, 2022
B: Extreme heatwave events	A record-breaking hot summer triggers a high-temperature warning for 33 consecutive days.	July 14, 2018
	Yunnan Province in China experiences high temperatures and scarce rainfall, resulting in severe consecutive droughts during the spring and summer seasons.	March 1, 2019
	Severe consecutive autumn drought occurs in the middle and lower reaches of the Yangtze River in China.	July 21, 2019
	Southern China experiences high temperatures and reduced rainfall, leading to the ongoing development of meteorological drought.	July 27, 2020
	Since 1961, the strongest heatwave "scorching" China leads to the first issuance of a red alert for high temperatures by the China Meteorological Administration.	June 13, 2022
	The Yangtze River basin experiences a "reverse drought" during the flood season, and artificial rainfall is being employed to support drought-affected areas.	August 18, 2022
C: Extreme cold wave events	At the end of January, a cold wave hits the central and eastern regions of China, triggering heavy snowfall.	January 24, 2018
	A severe spring cold wave hits the central and eastern regions of China, resulting in severe frost damage.	March 7, 2018
	In mid-February, snowfall covers 1/7 of the land area in northern China.	February 13, 2019
	In early winter, a cold wave and snowstorm hit northeastern China, resulting in disasters in some areas.	November 17, 2020
	After the onset of autumn, many parts of China frequently experience strong cold wave weather.	November 4, 2021
	Beijing Winter Olympics affected by low temperatures and snowfall, meteorological departments spare no effort to provide support and ensure smooth operations.	February 11, 2022
	Frequent autumn cold waves result in a cliff-like drop in temperatures, causing adverse effects on public transportation and agricultural and pastoral production.	October 3, 2022
D: Extreme storm events	Within a month, three typhoons consecutively affect Shanghai, China.	July 22, 2018
	Typhoon "Mangkhut" makes a strong landfall in the More significant Bay Area of China, including Guangdong, Hong Kong, and Macau.	September 16, 2018
	In early July, Kaiyuan City in Liaoning Province, China, experiences a rare and powerful tornado attack.	July 17, 2019
	Super Typhoon "Lekima" severely impacts eastern China.	August 10, 2019
	In the span of half a month, three consecutive typhoons affect northeastern China, which is historically rare.	August 27, 2020
	Typhoon "In-Fa" lingers over mainland China for an extended period, setting a new historical record.	July 25, 2021
	In December, a super typhoon impacts the South China Sea, which is historically rare.	December 16, 2021
	Typhoon "Mei Fa" makes landfall in Liaoning Province, China, marking the northernmost autumn typhoon landfall in our country since 1949.	September 14, 2022
	Multiple tornadoes occur in scattered areas, and for the first time, the meteorological department successfully issues forecasts and warnings for these tornado events.	July 2, 2022

Table 3 show the cumulative returns of the positions during the bear and bull markets. The positions perform better during bull than bear markets. Column (4) shows that the portfolios DCOAL/GDC, FCOAL/GDC and FGAS/GDC perform better than the other portfolios, possibly explained by DCOAL, FCOAL and FGAS leading GDC as indicated by the average lead-lag orders shown in column (1). These results suggest that, in a bull market, a long position in commodity i and a short position in commodity j, when commodity i leads commodity j might yield higher returns.

This motivated us to examine the performance of positions wherein we explicitly use the estimated lead-lag orders to construct the position. Position i-GDC is long in 1 unit of commodity i and short in h units of GDC when commodity i leads GDC. Columns (6) and (7) show the cumulative returns of these positions. For all commodities, these positions result in a positive performance, but with better results during bull than bear markets. Column (7) also shows that the positions with the high order commodities generally perform

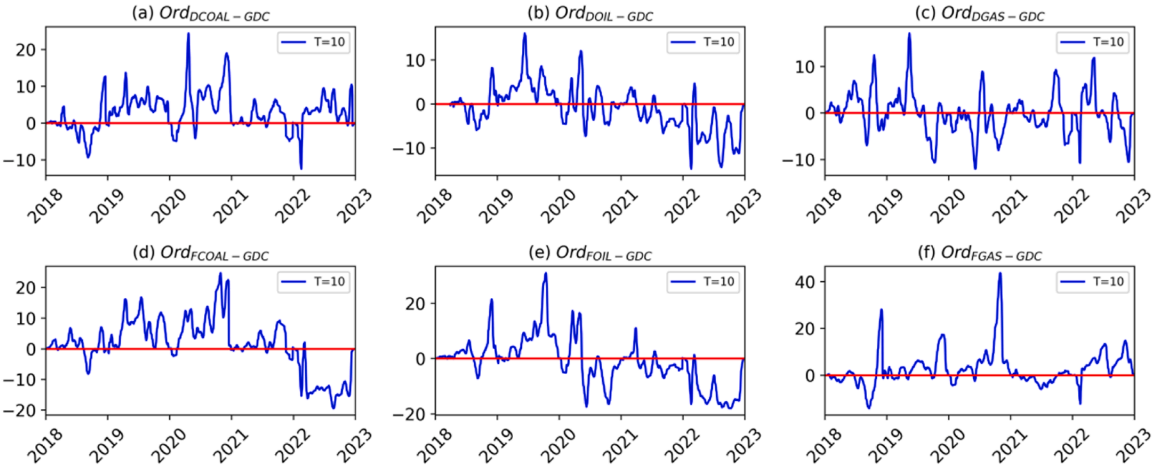

Fig. 1. The lead-lag order estimates. Panels (a) - (f) show the lead-lag orders between DCOAL and GDC, DOIL and GDC, DGAS and GDC, FCOAL and GDC, FOIL and GDC, FGAS and GDC, respectively.

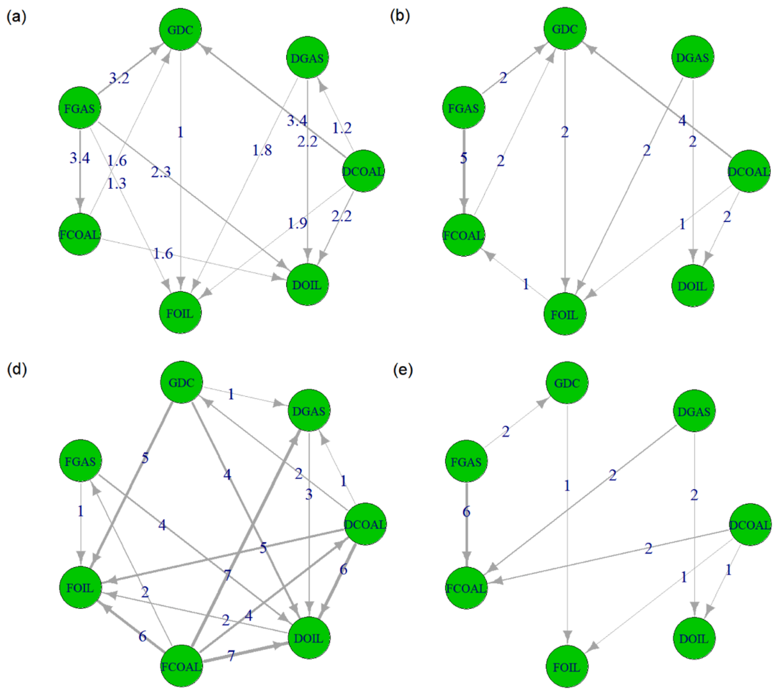

Fig. 2. Lead-lag networks: panel (a) shows the lead-lag network based on the lead-lag relation during the sampling period (2018–2022), panels (b)-(e) show those networks after the shocks of event categories A to D: extreme heavy rainfall, extreme heatwave, extreme cold wave, and extreme storm respectively. A node represents a market, and a line points from market i to j if market i leads (is ahead of) market j. The thickness of a line reflects the lead-lag order from market i to j, with a thicker line indicating a greater the order. We calculate the orders for each line as follows. For each event in an event category (see Table 2 for the details), we estimate the lead-lag order between markets i and j over the 10 trading days after the event. Then, over all the events within an event category we calculate the average lead-lag order. This is repeated for all event categories. We do not show a line when the order of the relationship is <1.

better than the other positions (although DOIL-GDC performs high as well although having a negative lead-lag order on average).

5. Conclusions

This paper shows that the lead-lag relationship between the Chinese carbon markets and energy markets time-varying characteristics. We argue that at least some of this variation is caused by exogenous climate shocks. Extreme cold and heat events strengthen

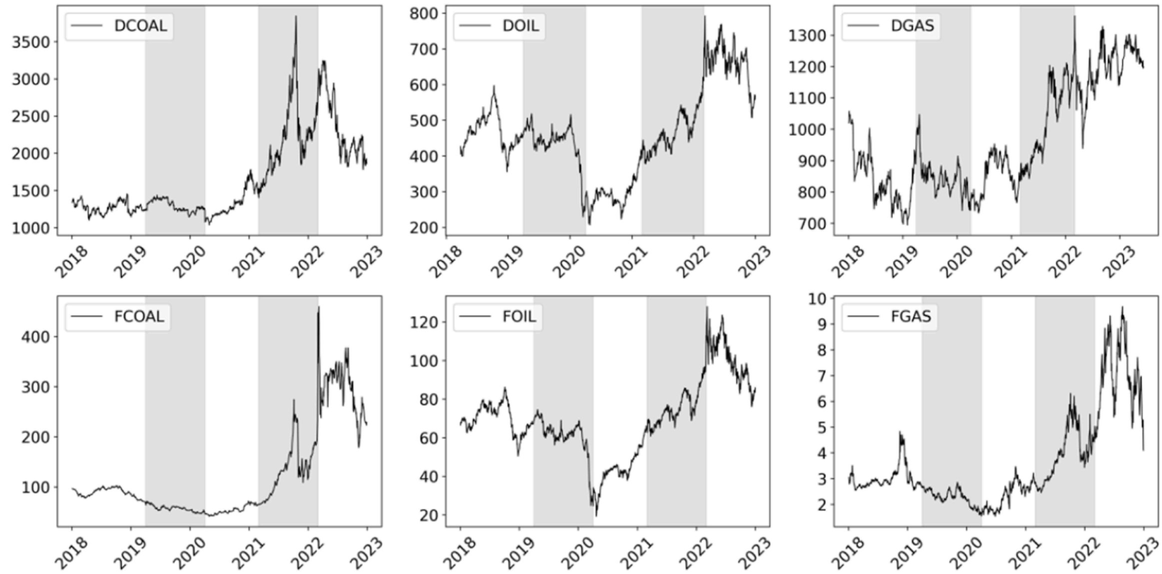

Fig. 3. Price trend of different energy markets. We select the period from April 1, 2019 to April 1, 2020 as the market being in a bear market phase, and select the period from March 1, 2021 to March 1, 2022 as the market being in a bull market phase.

Table 3
The average lead-lag order and cumulative returns of portfolios at different market stages.

	Order	Bear		Bull		Bear	Bull
i	i-GDC (1)	i/GDC (2)	GDC/i (3)	i/GDC (4)	GDC/i (5)	i-GDC (6)	i-GDC (7)
DCOAL	3.4230	0.0005	0.0014	0.0034	0.0030	0.1500	0.3163
DOIL	-0.7666	-0.0016	0.0012	0.0030	0.0029	0.1339	0.3704
DGAS	0.0852	-0.0007	0.0015	0.0016	0.0032	0.0587	0.1478
FCOAL	1.6189	-0.0022	0.0014	0.0081	0.0026	0.1172	0.2830
FOIL	-1.0358	-0.0017	0.0015	0.0015	0.0026	0.1297	0.2347
FGAS	3.1875	-0.0017	0.0016	0.0065	0.0027	0.0998	0.4245

the lead-lag relationship between markets, probably due to increased demand for energy and therefore carbon credits. Our goal was not to delve deep in the economic mechanisms through which climate risk changes lead-lag relationship. We argue that future research is needed to understand this better. What we do observe is that companies can use this knowledge to improve trading and hedging strategies in carbon and energy markets. Furthermore, policy makers should keep in mind that carbon policies might enforce a lead-lad relationship, that can change dur to climate events, which makes the impact of policies more uncertain.

CRediT authorship contribution statement

Jingbo Li: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhang-Hangjian Chen:** Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Xiang Gao:** Writing – original draft, Supervision, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Ronald Huisman:** Writing – review & editing, Writing – original draft, Conceptualization. **Kees Koedijk:** Writing – review & editing, Conceptualization.

Data availability

Data will be made available on request.

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