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Heterogeneous response of the stock market to CO_2 emissions in China

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CO_2 emissions have been a great challenge in China, especially in recent years. Meanwhile, the CO_2 emissions allowance price cannot accurately reflect the CO_2 emissions information in China because of the limited efficiency in China's carbon market. Accordingly, this study constructs a CO_2 emissions index and provides an empirical investigation of the heterogeneous response of stock markets to CO_2 emissions. With a quantile regression approach, we document that the effect of CO_2 emissions on stock returns is significant in 2021, while it is insignificant in 2019 and 2020. In addition, its influence is more significant at the upper and lower quantiles than at the median quantile. Our findings indicate that investors and the government should pay more attention to carbon risk in the future and under extreme market conditions.

KEYWORDS

CO_2 emissions, quantile regression approach, stocks returns, the carbon emissions trading scheme, heterogenous response

1 Introduction

CO_2 emissions are a great challenge for China, the largest carbon emitter in the world. The government has adopted tightening carbon emissions policies for energy firms to cut CO_2 emissions, such as a continuous decline in the benchmark of CO_2 emissions starting in 2021, which is significantly lower than in 2020 and 2019. The CO_2 emissions allowance decreased significantly. Energy firms must reduce carbon emissions or pay for excess carbon emissions. Meanwhile, the global CO_2 emission allowance price has risen sharply, and the price of the European Union carbon allowance (EUA) increased from 33.7 euros to 88.9 euros per ton at the end of 2021. In addition, investor attention to CO_2 emissions is increasing, indicating that the effect of CO_2 emissions on stock returns in 2021 is more significant than before.

The effect of CO_2 emissions on stock returns is based on the CO_2 emissions allowance price in China (Wen et al., 2020; Zhao et al., 2022; Pan et al., 2022; Bolton and Kacperczyk, 2021; Dutta et al., 2018), but the efficiency of China's carbon market is limited (Fang and Cao, 2021; Wen et al., 2022; Zhang et al., 2020). This indicates that the price of Chinese carbon emission allowances (CEA) cannot accurately reflect CO_2 emissions information, and the response of stock returns to CO_2 emissions is inaccurate. Furthermore, we need to obtain more CO_2 emissions components from other measurements. Rohleder et al. (2022) and Oestreich and Tsiakas (2015) investigate the effects of carbon emissions on the stock

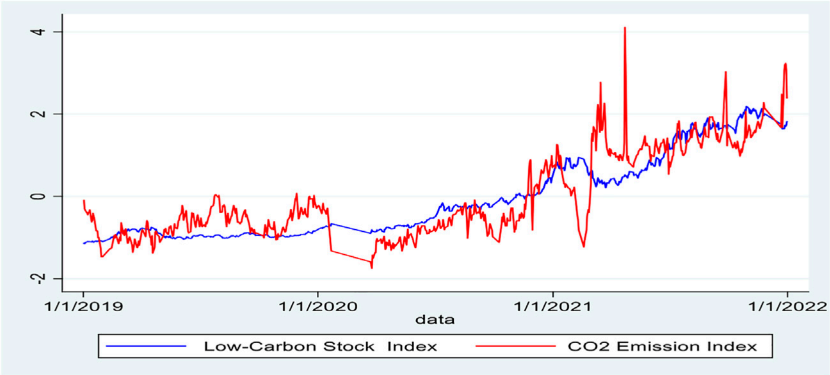

FIGURE 1
The fluctuation trend of the CO_2 emissions index and the Low Carbon Index. Note: The blue line shows the Low Carbon Index, and the red one shows the CO_2 emissions index.

market based on CO_2 emissions. In addition, Chen et al. (2022) and Guastella et al. (2022) report that CO_2 emissions attention is the driver of stock returns, which means that attention to CO_2 emissions cannot be neglected. This indicates that we should extract more CO_2 emissions components from CO_2 emissions allowance price, CO_2 emissions, and CO_2 emissions attention.

Accordingly, this paper contracts a CO_2 emissions index to investigate the heterogeneous response of the stock market to carbon emissions from 2019 to 2021 in China. The panel quantile regression approach was employed in this paper, providing more complete results and demonstrating the possible heterogeneity. The research is carried out in the following steps. First, we used principal component analysis to construct a CO_2 emissions index based on the CO_2 emissions, CO_2 emissions allowance price, and investor attention to CO_2 emissions. Second, we make an empirical analysis to examine the heterogeneous response of the stock returns to CO_2 emissions.

The contributions of our work are as follows. First, our empirical results show that the effect of CO_2 emissions on stock returns is significant in 2021 and insignificant in 2019 and 2020. Zhu et al. (2018) and Daskalakis et al. (2009) report that the influence of CO_2 emissions on stock returns is different at the different phases of volatility behavior in the EUA market. However, little research has paid attention to the heterogeneous response of the stock market to CO_2 emissions in China in different years.

Second, using the principal component analysis method to construct a CO_2 emissions index based on CO_2 emissions, CO_2 emissions allowance price, and investor attention to CO_2 emissions accurately reflects CO_2 emissions information in China. All the empirical results help the government and investors to understand the variation of carbon risk in recent years. The government and investors should pay more attention to CO_2 emissions in the future and in extreme stock market conditions.

The remainder of the paper is organized as follows. Section 2 is a review of the literature. Section 3 introduces the construction of the CO_2 emissions index. Section 4 is empirical results. Section 5 is the conclusions.

TABLE 1 Descriptive statistics.

	R	$R_i - Rf$	SMB	HML	CI
Mean	0.0010	0.0009	0.0001	−0.0005	0.0016
Standard Deviation	0.0298	0.0109	0.0082	0.0066	0.1128
Kurtosis	4.5961	3.4232	1.7915	0.7702	17.9113
Skewness	−0.1105	−0.0960	−0.6458	0.4087	−1.0800
Minimum	−0.2005	−0.0595	−0.0380	−0.0217	−0.9428
Maximum	0.2013	0.0563	0.0251	0.0237	0.6564
Observations	93,149	93,149	93,149	93,149	93,149

2 Literature review

The paper reviews the previous literature on the effect of CO_2 emissions on stock returns from three main aspects. The first focuses on the relationship between CO_2 emissions and CO_2 emissions allowance. The CO_2 emissions and CO_2 emissions allowance prices interact with each other. On the one hand, CO_2 emissions significantly impact the variation of the CO_2 emissions allowance prices. Benz and

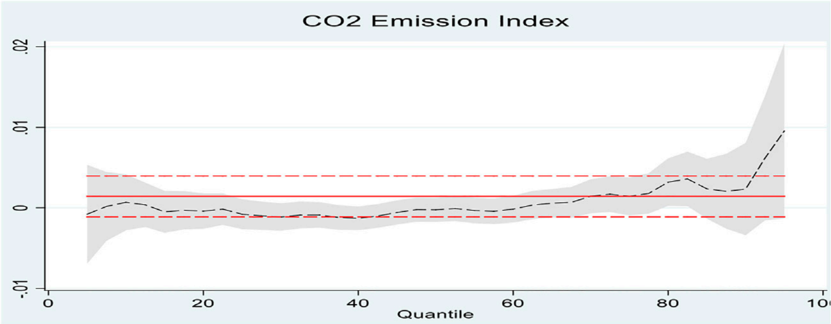

FIGURE 2
Quantile regression results for the CO_2 emissions index–low-carbon stock prices in 2019. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

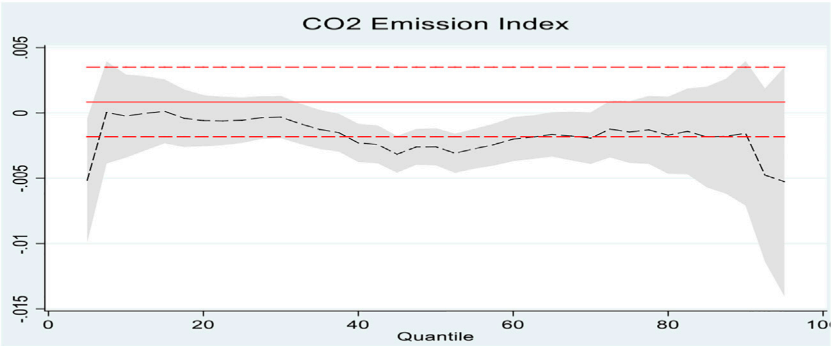

FIGURE 3
Quantile regression results for the CO_2 emissions index–low-carbon stock prices in 2020. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

Trück (2009) show that the skewness, excess kurtosis and different phases of volatility behavior of CO_2 emissions allowance returns come from fluctuations in demand for CO_2 emissions. On the other hand, the variation of CO_2 emissions allowance price also significantly impacts CO_2 emissions. Forbes and Zampelli (2019) report that increases in the carbon allowance price significantly reduce carbon emissions. Meanwhile, Li et al. (2022) believe that a significant impact occurs if the CO_2 emissions allowance price exceeds 300 RMB/TCO_2. From the above literature, we can conclude that the CO_2 emissions and the price of CO_2 emissions allowance are highly correlated, but they reflect the CO_2 emissions information differently.

The second aspect focuses on the response of the stock returns and carbon emissions. The relationships among CO_2 emissions allowance price, stock returns, and volatility are complicated. First, there are no consensus opinions about the response of stock returns to carbon emissions. Da et al. (2016) believe that EU ETS has a statistically significant positive long-run impact on the aggregated power-sector-stock market return decreasing the firm's profitability. However, Tian et al. (2016) show that the positive relationship between EUA returns and returns of electricity companies is different for carbon-intensive companies. It is favorable for less carbon-intensive producers and negative for high carbon-intensive producers. Moreover, Xu et al. (2022) report that the relationship between the return of carbon-intensive industries and the carbon allowance is uncertain. The return is positive in Shenzhen and Shanghai pilots and negative in Beijing, Guangdong, and Hubei pilots. Second, the volatility spillover between carbon emissions allowance price and stock returns is also uncertain. Alkathery and Chaudhuri (2021) report significant volatility spillover effects and co-movement between carbon emission allowance prices and energy stock markets in the three GCC. Zhu et al. (2018)

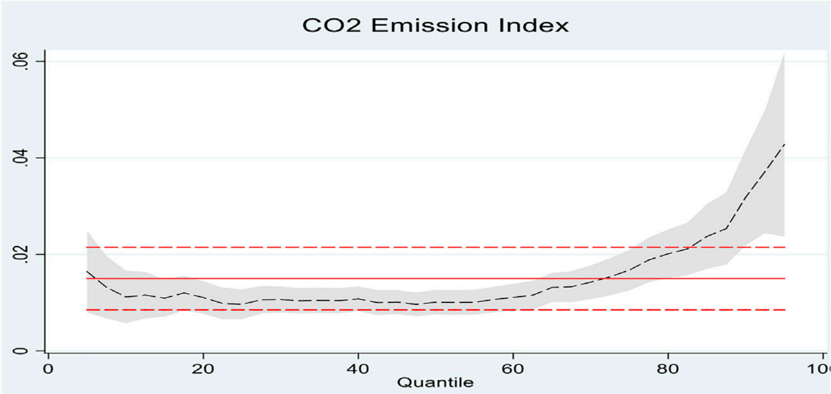

FIGURE 4
Quantile regression results for the CO_2 emissions index–low-carbon stock returns in 2021. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

and Daskalakis et al. (2009) believe that the influence of CO_2 emissions on stock returns is different at the different phases of volatility behavior in the EUA market. However, less attention is to the heterogeneous response of stock returns to CO_2 emissions in different years in China.

The third aspect is that investor attention is a driver of the variation of financial markets. Fang et al. (2014) adopt the Baidu index as the proxy for individual investor attention to stocks and find that investor attention improves the stock return in the short term. Ben-Rephae and Israelsen (2017) report that institutional attention responds more quickly to significant news events, leads to retail attention, and facilitates permanent price adjustment. Moreover, their relationship affects other variables, such as the uncertainty avoidance index of national culture (Shear et al., 2020; Ren et al., 2022). In addition, more and more research demonstrates that investor attention to climate risk significantly impacts financial market variation. Liu et al. (2021) find that investor attention to air pollution reduces the prices of the polluting stocks, for the investors receive more attention on trading days with air pollution. Ding et al. (2022) find that investor attention to climate change has significant causal effects on the spillovers among carbon, fossil energy, and clean energy markets. Moreover, the effect of investor attention on green assets becomes more significant. Pham and Huynh (2020) and Pham and Cepni (2022) find that investor attention to the green bond significantly impacts the green bond's return and volatility, and the relationship becomes more significant. Chen et al. (2022) report that climate attention is becoming more important for state-owned and high-carbon-emission firms. All the above empirical results indicate that investor attention has a significant role in the return on the stock market and green assets, but less attention is given to the linkages between investor attention on CO_2 emissions and the stock market in China.

In general, the literature on the heterogeneous response of stock returns to CO_2 emissions in different years is relatively scarce in China. The challenge of a decreasing benchmark of corporate carbon emissions in 2021, rapidly rising investor attention to CO_2 emissions in China and the soaring price of EUA suggests that the response of stock returns to CO_2 emissions will become more significant. How will China's CO_2 emissions affect the stock returns in different years? It has been 4 years since carbon neutrality was launched in China, and an empirical study on the heterogeneous response of stock returns to CO_2 emissions in different years is needed.

3 Construction of the CO_2 emissions-index

3.1 Data and calculations

The research on the effect of CO_2 emissions on the stock market is mainly based on CO_2 emissions and CO_2 emissions allowance prices. Meanwhile, investor attention to climate risk also significantly impacts asset price fluctuations (Pham and Cepni, 2022; Ding et al., 2022), which indicates that investor attention to carbon risks cannot be neglected. In addition, investor attention to carbon emission is closely related to CO_2 emissions and CO_2 emissions allowance prices. Accordingly, a CO_2 emissions index based on the CO_2 emissions, the carbon emission allowance price, and investor attention to CO_2 emissions is considered.

The sample period covers from 1 January 2019 to 31 December 2021 with 1,096 observations. The CO_2

TABLE 2 Effect of the CO_2 emissions index on the return of low-carbon stocks.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019							
$R_i - Rf$	1.2080***	1.1629***	1.1395***	1.0662***	1.0178***	0.9929***	0.9901***
	(0.0322)	(0.0183)	(0.0116)	(0.0079)	(0.0155)	(0.0302)	(0.0573)
SMB	0.9882***	0.9042***	0.8778***	0.7618***	0.7417***	0.8346***	0.9067***
	(0.0470)	(0.0268)	(0.0169)	(0.0115)	(0.0226)	(0.0440)	(0.0836)
HML	−0.1128	0.0283	0.1604***	0.2826***	0.3260***	0.2593***	0.0926
	(0.0879)	(0.0500)	(0.0316)	(0.0214)	(0.0423)	(0.0823)	(0.1562)
CI	−0.0008	0.0007	−0.0004	−0.0002	**0.0032****	**0.0023**	**0.0095***
	(0.0031)	(0.0018)	(0.0011)	(0.0008)	(0.0015)	(0.0029)	(0.0055)
Constant	−0.0280***	−0.0198***	−0.0124***	−0.0021***	0.0101***	0.0210***	0.0357***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0006)
Observations	31,190	31,190	31,190	31,190	31,190	31,190	31,190
Panel A: 2020							
$R_i - Rf$	1.2017***	1.1482***	1.0755***	0.9959***	0.9780***	0.9803***	1.0204***
	(0.0301)	(0.0202)	(0.0124)	(0.0090)	(0.0187)	(0.0351)	(0.0556)
SMB	1.2135***	1.0871***	0.9204***	0.7455***	0.7558***	0.7740***	0.8986***
	(0.0496)	(0.0333)	(0.0204)	(0.0149)	(0.0308)	(0.0578)	(0.0916)
HML	0.2700***	0.3148***	0.3222***	0.4182***	0.4752***	0.4327***	0.3836***
	(0.0595)	(0.0400)	(0.0245)	(0.0178)	(0.0370)	(0.0694)	(0.1099)
CI	**−0.0052****	**−0.0002**	**−0.0006**	**−0.0026*****	**−0.0017**	**−0.0016**	**−0.0053**
	(0.0024)	(0.0016)	(0.0010)	(0.0007)	(0.0015)	(0.0028)	(0.0045)
Constant	−0.0303***	−0.0221***	−0.0140***	−0.0027***	0.0112***	0.0237***	0.0390***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0004)	(0.0006)
Observations	28,031	28,031	28,031	28,031	28,031	28,031	28,031
Panel C: 2021							
$R_i - Rf$	1.6023***	1.4525***	1.2794***	1.0722***	1.1358***	1.2311***	1.3362***
	(0.0508)	(0.0327)	(0.0203)	(0.0153)	(0.0303)	(0.0597)	(0.1147)
SMB	1.3094***	1.2173***	1.1073***	0.9350***	0.9032***	0.8564***	0.9333***
	(0.0475)	(0.0305)	(0.0190)	(0.0143)	(0.0283)	(0.0558)	(0.1072)
HML	0.5231***	0.5109***	0.5044***	0.5287***	0.6840***	0.8382***	0.9221***
	(0.0576)	(0.0371)	(0.0231)	(0.0174)	(0.0343)	(0.0677)	(0.1301)
CI	**0.0164*****	**0.0112*****	**0.0111*****	**0.0101*****	**0.0201*****	**0.0318*****	**0.0428*****
	(0.0043)	(0.0028)	(0.0017)	(0.0013)	(0.0026)	(0.0051)	(0.0097)
Constant	−0.0426***	−0.0306***	−0.0194***	−0.0028***	0.0171***	0.0348***	0.0590***
	(0.0004)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0005)	(0.0010)
Observations	33,954	33,954	33,954	33,954	33,954	33,954	33,954

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Bold values represent the impact of carbon emissions on stock prices.

TABLE 3 Impact of the year 2021 on the return of low-carbon stocks.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
$R_i - Rf$	1.2918***	1.2149***	1.1475***	1.0519***	1.0456***	1.0540***	1.0905***
	(0.0219)	(0.0135)	(0.0083)	(0.0059)	(0.0119)	(0.0234)	(0.0416)
SMB	1.2031***	1.0984***	1.0042***	0.8553***	0.8226***	0.8733***	0.9297***
	(0.0269)	(0.0165)	(0.0101)	(0.0073)	(0.0146)	(0.0286)	(0.0509)
HML	0.3427***	0.3791***	0.4021***	0.4797***	0.5597***	0.5842***	0.5714***
	(0.0365)	(0.0224)	(0.0138)	(0.0099)	(0.0198)	(0.0389)	(0.0691)
CI	0.0025	0.0034***	0.0019***	0.0006	0.0041***	0.0056***	0.0093**
	(0.0019)	(0.0012)	(0.0007)	(0.0005)	(0.0011)	(0.0021)	(0.0037)
D1	−0.0129***	−0.0093***	−0.0059***	−0.0005***	0.0065***	0.0128***	0.0218***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0005)	(0.0009)
Constant	−0.0293***	−0.0210***	−0.0132***	−0.0022***	0.0107***	0.0223***	0.0375***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0005)
Observations	93,175	93,175	93,175	93,175	93,175	93,175	93,175

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

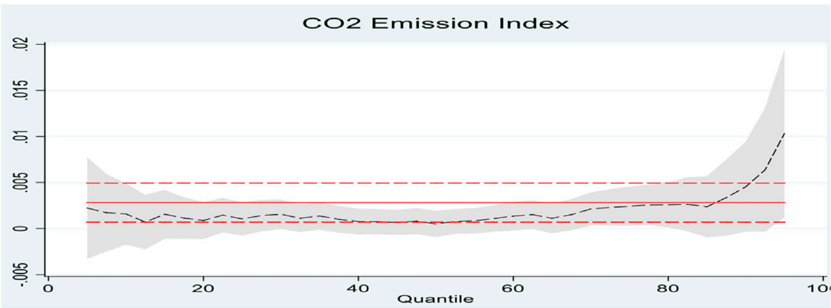

FIGURE 5
Quantile regression results for CO_2 emissions index−energy stock return in 2019. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

emissions in China are obtained from: https://www.carbonmonitor.org.cn/. The price of the CO_2 emissions allowance consists of the price of EUAs and carbon emission allowances in the Hubei carbon market (HBEAs). For that, the efficiency in China's carbon market is limited, and EUA pricing efficiency performance is better (Fang and Cao, 2021; Wen et al., 2022). The data are obtained from the Wind database. In addition, investor attention to CO_2 emissions is obtained from the Baidu search index based on web crawler technology, and the search keywords include "CO_2 emissions" and "low carbon policy."

Each CO_2 emissions variable includes a carbon emissions component and other idiosyncratic components. One issue in forming an index is determining the effective information of the variable. Variables that exhibit strong relationships may reflect a given shift in carbon emissions better than others. Hence, the study uses principal component analysis to construct the CO_2 emissions index based on the above four variables, where each index component has first calculated the log return. According to the empirical results, the first principal component explains 54.547% of the sample variance; it indicates that it captures much of the standard

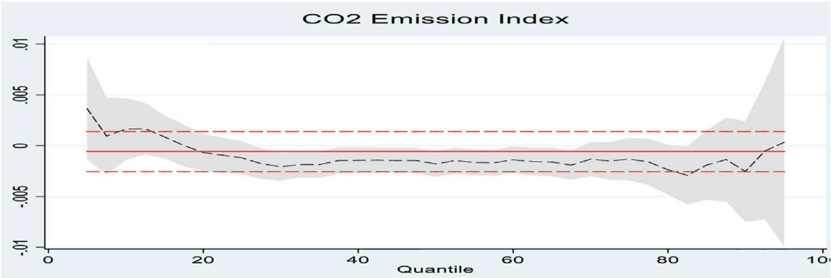

FIGURE 6
Quantile regression results for the CO_2 emissions index–energy stock returns in 2020. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

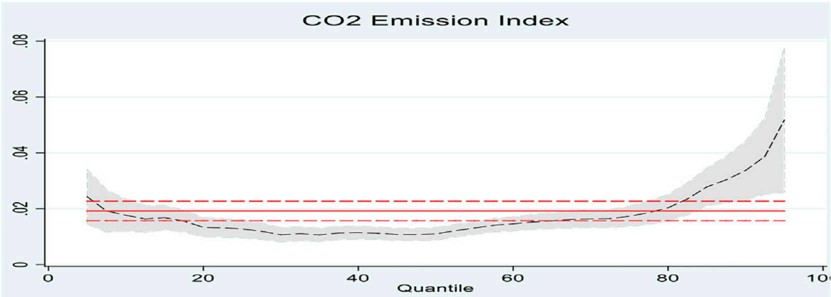

FIGURE 7
Quantile regression results for the CO_2 emissions index–energy stock returns in 2021. Note: The solid red line represents the OLS coefficient; the two red dashed lines depict the conventional 95% confidence intervals for the OLS coefficient. The shaded gray area plots a 95% pointwise confidence band for the quantile regression estimates.

variation and reflects most carbon emission information. The coefficients of each variable are as follows:

$$CI = 0.701*HBEA + 0.943*EUA + 0.149*CE + 0.874*IACE.$$

Here, CI is the carbon emission index, $HBEA$ is the price of carbon emission allowance in the Hubei carbon market, EUA is the price of Europe's carbon emissions, CE is the CO_2 emissions in China, and $IACE$ is the investor attention to CO_2 emissions. All parameters in the principal component analysis are positive, indicating they are positively correlated. Meanwhile, the size of the parameters shows that $HBEA$, EUA, and $IACE$ contain a large amount of information with a high contribution.

3.2 Effectiveness of the CO_2 emissions-index in describing the trend

Next, we will examine whether the CO_2 emissions index effectively describes the fluctuation trend of carbon emissions. The analysis is based on the China Low Carbon Index price and the actual conditions of carbon emissions. The China Low Carbon Index is highly correlated with CO_2 emissions (Zhu et al., 2022). This index is proposed by the Beijing Environment Exchange and clean technology investment fund Vantage Point Partner. It is the first low-carbon stock index and includes all the low-carbon firms in China. Let us suppose that the stock market in China is a semi-strong efficient market. If so, the China Low Carbon Index price reflects the information on CO_2 emissions. Figure 1 shows the tendency of the China Low Carbon Index and the CO_2 emissions index.

It is easy to find that the CO_2 emissions index is low and stable in 2019 and 2020 and increases sharply in 2021. The China Low Carbon Index variation shows similar fluctuation trends. Since 2021, it has grown rapidly, and before that, it remains stable. This indicates that the China Low Carbon Index variation accurately reflects the fluctuations in CO_2 emissions, and the CO_2 emissions index effectively shows the trend of carbon emissions.

The CO_2 emissions index trend also reflects actual conditions of carbon emissions. The CO_2 emissions, the CO_2 emissions allowance prices, and investor attention to CO_2 emissions in China maintain slow growth in 2019 and 2020 and peak in 2021. Moreover, a challenging benchmark for energy firms cutting CO_2 emissions begins in 2021, and the benchmark target is

TABLE 4 Effect of the CO_2 emissions index on the return of the energy stocks.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019							
$R_i - Rf$	1.0892***	1.0395***	0.9778***	0.8876***	0.8442***	0.8665***	0.8773***
	(0.0290)	(0.0175)	(0.0106)	(0.0074)	(0.0130)	(0.0257)	(0.0480)
SMB	0.8365***	0.7664***	0.6800***	0.5698***	0.5191***	0.5967***	0.7041***
	(0.0424)	(0.0256)	(0.0154)	(0.0109)	(0.0189)	(0.0376)	(0.0701)
HML	0.2004**	0.2514***	0.3043***	0.3463***	0.3604***	0.4501***	0.4014***
	(0.0796)	(0.0480)	(0.0290)	(0.0204)	(0.0356)	(0.0707)	(0.1317)
CI	0.0022	0.0016	0.0009	0.0005	0.0026**	0.0045*	0.0103**
	(0.0028)	(0.0017)	(0.0010)	(0.0007)	(0.0013)	(0.0025)	(0.0046)
Constant	−0.0245***	−0.0174***	−0.0107***	−0.0015***	0.0083***	0.0173***	0.0292***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0005)
Observations		26,612	26,612	26,612	26,612	26,612	26,612
Panel B: 2020							
$R_i - Rf$	0.9957***	0.9193***	0.8807***	0.8252***	0.8180***	0.8794***	0.9131***
	(0.0317)	(0.0193)	(0.0115)	(0.0080)	(0.0155)	(0.0314)	(0.0652)
SMB	0.8251***	0.6882***	0.5749***	0.4711***	0.4543***	0.5448***	0.6990***
	(0.0523)	(0.0318)	(0.0190)	(0.0133)	(0.0256)	(0.0519)	(0.1077)
HML	0.4894***	0.4828***	0.4875***	0.5555***	0.6636***	0.8100***	0.9185***
	(0.0627)	(0.0381)	(0.0228)	(0.0159)	(0.0307)	(0.0622)	(0.1292)
CI	0.0036	0.0016	-0.0007	−0.0018***	−0.0024*	−0.0025	0.0003
	(0.0025)	(0.0015)	(0.0009)	(0.0006)	(0.0012)	(0.0025)	(0.0052)
Constant	−0.0255***	−0.0176***	−0.0109***	−0.0017***	0.0090***	0.0195***	0.0333***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0007)
Observations	23,464	23,464	23,464	23,464	23,464	23,464	23,464
Panel C: 2021							
$R_i - Rf$	1.5448***	1.3475***	1.1576***	0.9137***	0.9486***	0.9968***	1.1538***
	(0.0586)	(0.0343)	(0.0209)	(0.0138)	(0.0284)	(0.0628)	(0.1551)
SMB	1.1359***	1.0826***	0.9251***	0.7058***	0.6398***	0.5097***	0.4677***
	(0.0548)	(0.0321)	(0.0196)	(0.0129)	(0.0266)	(0.0588)	(0.1452)
HML	1.0003***	0.8675***	0.7767***	0.7637***	0.9753***	1.1455***	1.3202***
	(0.0662)	(0.0387)	(0.0237)	(0.0156)	(0.0322)	(0.0710)	(0.1753)
CI	**0.0243*** **	**0.0177*** **	**0.0133*** **	**0.0110*** **	**0.0203*** **	**0.0337*** **	**0.0517*** **
	(0.0050)	(0.0029)	(0.0018)	(0.0012)	(0.0024)	(0.0054)	(0.0132)
Constant	−0.0389***	−0.0271***	−0.0164***	−0.0020***	0.0139***	0.0307***	0.0538***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0005)	(0.0013)
Observations	26,895	26,895	26,895	26,895	26,895	26,895	26,895

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Bold values represent the impact of carbon emissions on stock prices.

TABLE 5 Effect of CEA price on the energy stock return.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019–2020							
$R_i - Rf$	1.0827***	1.0047***	0.9388***	0.8641***	0.8329***	0.8626***	0.8916***
	(0.0221)	(0.0137)	(0.0078)	(0.0054)	(0.0100)	(0.0209)	(0.0408)
SMB	0.8793***	0.7787***	0.6660***	0.5447***	0.5170***	0.5890***	0.7212***
	(0.0341)	(0.0211)	(0.0120)	(0.0083)	(0.0155)	(0.0322)	(0.0630)
HML	0.4525***	0.4454***	0.4609***	0.4928***	0.5451***	0.6499***	0.6941***
	(0.0506)	(0.0314)	(0.0179)	(0.0123)	(0.0230)	(0.0479)	(0.0936)
CEA	0.0005	0.0005	0.0002	0.0001	−0.0003	0.0005	0.0007
	(0.0008)	(0.0005)	(0.0003)	(0.0002)	(0.0003)	(0.0007)	(0.0014)
Constant	−0.0252***	−0.0176***	−0.0108***	−0.0016***	0.0087***	0.0183***	0.0310***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
Observations	49,632	49,632	49,632	49,632	49,632	49,632	49,632
Panel B: 2021							
$R_i - Rf$	1.5848***	1.4295***	1.2152***	0.9447***	0.9929***	1.0785***	1.3444***
	(0.0566)	(0.0355)	(0.0205)	(0.0134)	(0.0278)	(0.0624)	(0.1366)
SMB	1.1355***	1.0973***	0.9354***	0.7063***	0.6349***	0.5269***	0.4477***
	(0.0537)	(0.0336)	(0.0195)	(0.0127)	(0.0264)	(0.0592)	(0.1296)
HML	0.9686***	0.8687***	0.7980***	0.7554***	0.9724***	1.1142***	1.2128***
	(0.0649)	(0.0406)	(0.0235)	(0.0153)	(0.0319)	(0.0715)	(0.1565)
CEA	**−0.0285****	**−0.0248*****	**−0.0312*****	**−0.0177*****	**−0.0210*****	**−0.0361*****	**−0.0738****
	(0.0126)	**(0.0079)**	**(0.0046)**	**(0.0030)**	**(0.0062)**	**(0.0139)**	**(0.0305)**
Constant	−0.0385***	−0.0271***	−0.0164***	−0.0022***	0.0139***	0.0308***	0.0537***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0005)	(0.0012)
Observations	26,895	26,895	26,895	26,895	26,895	26,895	26,895

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Bold values represent the impact of carbon emissions on stock prices.

significantly lower than in 2020 and 2019. It indicates that CO_2 emissions will become more valuable to the enterprise in 2021 than 2019 and 2020. Both indicate that the CO_2 emissions index effectively and accurately describes the carbon emissions trend.

4 Empirical results

4.1 Quantile regression model

Quantile regression (QR) was introduced by Koenker and Bassett (1978) and developed by Koenker and Hallock (2001). QR does not require an economic variables sequence to conform to a normal distribution. QR determines the model for the selected quantiles in the conditional distribution of the dependent variable (Carreras and Coenders, 2020; Palma et al., 2020; Sirin and Yilmaz, 2020; Xu and Lin, 2020). In this study, seven quantiles are selected $\tau = (5\%, 10\%, 20\%, 50\%, 80\%, 95\%)$. These quantiles are divided into three categories. The lower quantiles (0.05, 0.10, 0.20) indicate that the market's return is low, and investors will gain comparatively low profits; the median quantile (0.50) indicates the market's return stays under normal level. The upper quantiles (0.80, 0.90, 0.95) mean that the market's return is high. The quantile regression (QR) model is formulated as follows:

TABLE 6 Effect of CEA price on low-carbon stocks return.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019–2020							
$R_i - Rf$	1.2077***	1.1581***	1.1147***	1.0401***	0.9975***	0.9878***	1.0159***
	(0.0216)	(0.0137)	(0.0084)	(0.0062)	(0.0119)	(0.0225)	(0.0410)
SMB	1.1153***	1.0061***	0.9110***	0.7767***	0.7657***	0.8403***	0.9231***
	(0.0335)	(0.0213)	(0.0130)	(0.0096)	(0.0185)	(0.0349)	(0.0636)
HML	0.1429***	0.2229***	0.2782***	0.3722***	0.4145***	0.3815***	0.3094***
	(0.0490)	(0.0311)	(0.0191)	(0.0141)	(0.0271)	(0.0510)	(0.0930)
CEA	−0.0007	−0.0001	0.0003	0.0000	−0.0001	−0.0003	−0.0026*
	(0.0007)	(0.0005)	(0.0003)	(0.0002)	(0.0004)	(0.0008)	(0.0014)
Constant	−0.0294***	−0.0210***	−0.0133***	−0.0023***	0.0105***	0.0221***	0.0372***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
Observations	56,806	56,806	56,806	56,806	56,806	56,806	56,806
Panel B: 2021							
$R_i - Rf$	1.6418***	1.4958***	1.3203***	1.1040***	1.1958***	1.3392***	1.5232***
	(0.0520)	(0.0340)	(0.0208)	(0.0152)	(0.0316)	(0.0599)	(0.1109)
SMB	1.2876***	1.2298***	1.1108***	0.9394***	0.9007***	0.8566***	0.8705***
	(0.0485)	(0.0316)	(0.0193)	(0.0142)	(0.0294)	(0.0558)	(0.1033)
HML	0.4800***	0.4879***	0.4936***	0.5144***	0.6243***	0.7268***	0.8284***
	(0.0593)	(0.0387)	(0.0237)	(0.0174)	(0.0360)	(0.0683)	(0.1264)
CEA	**−0.0024**	**−0.0034**	**−0.0027**	**−0.0057***	**−0.0018**	**0.0006**	**−0.0088**
	(0.0115)	**(0.0075)**	**(0.0046)**	**(0.0034)**	**(0.0070)**	**(0.0133)**	**(0.0246)**
Constant	−0.0420***	−0.0304***	−0.0193***	−0.0028***	0.0173***	0.0350***	0.0589***
	(0.0004)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0005)	(0.0009)
Observations	32,436	32,436	32,436	32,436	32,436	32,436	32,436

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Bold values represent the impact of carbon emissions on stock prices.

$$Q_{R_{it}}(\tau|\alpha_i, x_{it}) = \alpha_i + \beta_{1\tau}\left(R_m - r_f\right) + \beta_{2\tau}SMB_t + \beta_{3\tau}HML_t + \beta_{4\tau}CI_t + \varepsilon_t \quad (1)$$

where α is the quantile point, R_{it} is the return of portfolios i, $R_{it} - rf_t$, and SMB_t and HLM_t are well-known portfolio return series downloaded from Ken French's website. $R_{it} - rf_t$ is the excess daily return. SMB_t is the daily return of a portfolio that is long on small stocks and short on large stocks, and HLM_t is the daily return of a portfolio that is long on high book-to-market stocks and short on low book-to-market stocks, CI_t is the CO_2 emissions index. β_4 is the impact of the CO_2 emissions index on stock returns. If it is positive and significant, it indicates that the CO_2 emissions index brings excess return.

4.2 Descriptive statistics

Table 1 reports descriptive statistics for 154 low-carbon stocks in China from 1 January 2019 to 31 December 2021. The skewness and kurtosis of all variables are presented to explain using the QR approach. The kurtosis coefficient of the return is greater than 3, and the skewness is negative for the

TABLE 7 Effect of the CO_2 emissions index on the energy stock return.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019–2020							
$R_i - Rf$	1.0809***	1.0038***	0.9415***	0.8659***	0.8334***	0.8626***	0.9033***
	(0.0220)	(0.0138)	(0.0079)	(0.0054)	(0.0099)	(0.0205)	(0.0376)
SMB	0.8779***	0.7753***	0.6627***	0.5475***	0.5214***	0.5899***	0.7197***
	(0.0339)	(0.0211)	(0.0122)	(0.0083)	(0.0152)	(0.0316)	(0.0578)
HML	0.4520***	0.4426***	0.4631***	0.4958***	0.5436***	0.6445***	0.7076***
	(0.0505)	(0.0315)	(0.0181)	(0.0124)	(0.0226)	(0.0470)	(0.0861)
CO_2	0.0020	−0.0010	−0.0040	−0.0079***	−0.0090***	−0.0180***	−0.0463***
	(0.0067)	(0.0042)	(0.0024)	(0.0017)	(0.0030)	(0.0063)	(0.0115)
Constant	−0.0252***	−0.0176***	−0.0108***	−0.0016***	0.0087***	0.0185***	0.0315***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0004)
Observations	49,632	49,632	49,632	49,632	49,632	49,632	49,632
Panel B: 2021							
$R_i - Rf$	1.5775***	1.4105***	1.1887***	0.9511***	1.0057***	1.1143***	1.2941***
	(0.0587)	(0.0353)	(0.0209)	(0.0133)	(0.0283)	(0.0623)	(0.1379)
SMB	1.1324***	1.0935***	0.9335***	0.6965***	0.6266***	0.5114***	0.4786***
	(0.0558)	(0.0335)	(0.0199)	(0.0127)	(0.0269)	(0.0592)	(0.1312)
HML	0.9573***	0.8753***	0.7919***	0.7715***	0.9926***	1.1330***	1.2882***
	(0.0677)	(0.0407)	(0.0241)	(0.0154)	(0.0326)	(0.0718)	(0.1590)
CO_2	0.0406*	0.0361***	0.0332***	0.0407***	0.0783***	0.1414***	0.1941***
	(0.0230)	(0.0138)	(0.0082)	(0.0052)	(0.0111)	(0.0244)	(0.0541)
Constant	−0.0387***	−0.0273***	−0.0166***	−0.0023***	0.0135***	0.0297***	0.0523***
	(0.0005)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0005)	(0.0012)
Observations	26,895	26,895	26,895	26,895	26,895	26,895	26,895

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

dependent variable stock returns, indicating that the stock returns' unconditional distribution is asymmetric.

4.2 Heterogeneous response of stock returns to the CO_2 emissions index based on low-carbon stocks

The CO_2 emissions index maintains slow growth in 2019 and 2020 and increases significantly in 2021. This means that with the increase in the CO_2 emissions index, the effect of the CO_2 emissions on stock returns is also more significant. Meanwhile, the empirical research indicates that the influence of CO_2 emissions on stock returns changes at the different phases of volatility in the EUA market (Zhu et al., 2018; Daskalakis et al., 2009; Ren., 2022). Therefore, we will investigate the response of the low-carbon stocks return to carbon emissions. Figures 2–4 show Eq. 1 slope coefficients for the different CO_2 emissions index–low-carbon stock return pairs in 2019, 2020, and 2021. Table 2 shows more details about them.

It is easy to find that a heterogeneous response of low-carbon stock returns to the CO_2 emissions index exists in different years. Figures 2, 3, and panels A and B of Table 2 show that the impact of the CO_2 emissions index on the low-carbon stock returns is insignificant in 2019 and 2020. In

TABLE 8 Effect of the CO_2 emissions index on the low-carbon stocks return.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	QR_5	QR_10	QR_20	QR_50	QR_80	QR_90	QR_95
Panel A: 2019–2020							
$R_i - Rf$	1.2095***	1.1581***	1.1149***	1.0413***	0.9970***	0.9864***	1.0250***
	(0.0217)	(0.0139)	(0.0085)	(0.0063)	(0.0118)	(0.0224)	(0.0418)
SMB	1.1176***	1.0053***	0.9097***	0.7731***	0.7643***	0.8467***	0.9243***
	(0.0335)	(0.0214)	(0.0131)	(0.0097)	(0.0182)	(0.0345)	(0.0644)
HML	0.1443***	0.2215***	0.2794***	0.3725***	0.4131***	0.3864***	0.3207***
	(0.0491)	(0.0314)	(0.0193)	(0.0142)	(0.0267)	(0.0507)	(0.0946)
CO_2	0.0003	0.0061	−0.0047*	−0.0097***	−0.0043	−0.0022	−0.0079
	(0.0066)	(0.0042)	(0.0026)	(0.0019)	(0.0036)	(0.0068)	(0.0126)
Constant	−0.0294***	−0.0211***	−0.0133***	−0.0022***	0.0105***	0.0221***	0.0372***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0005)
Observations	56,806	56,806	56,806	56,806	56,806	56,806	56,806
Panel B: 2021							
$R_i - Rf$	1.6531***	1.4929***	1.3288***	1.1113***	1.2052***	1.3571***	1.5572***
	(0.0494)	(0.0345)	(0.0201)	(0.0150)	(0.0311)	(0.0599)	(0.1129)
SMB	1.2763***	1.2312***	1.1094***	0.9352***	0.8968***	0.8278***	0.8914***
	(0.0462)	(0.0323)	(0.0188)	(0.0140)	(0.0290)	(0.0560)	(0.1056)
HML	0.5253***	0.4860***	0.4956***	0.5214***	0.6395***	0.7711***	0.8642***
	(0.0568)	(0.0397)	(0.0231)	(0.0173)	(0.0357)	(0.0689)	(0.1298)
CO_2	0.0545***	0.0131	0.0360***	0.0336***	0.0664***	0.1219***	0.1200***
	(0.0193)	(0.0135)	(0.0078)	(0.0059)	(0.0121)	(0.0234)	(0.0441)
Constant	−0.0423***	−0.0304***	−0.0195***	−0.0030***	0.0168***	0.0344***	0.0582***
$R_i - Rf$	1.6531***	1.4929***	1.3288***	1.1113***	1.2052***	1.3571***	1.5572***
Observations	32,436	32,436	32,436	32,436	32,436	32,436	32,436

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

comparison, Figure 4 and panel C of Table 2 show that the effect of the CO_2 emissions index on the low-carbon stock returns is positive and significant in 2021. Meanwhile, the effect of the CO_2 emissions index on the low-carbon stock returns is more significant at the upper and lower quantiles than at the median quantiles. Moreover, the influence is more significant at the high percentiles than at the lower percentiles. The coefficient of CI is 0.015 at the 5% quantile, and it increased to 0.0428 at the 95% quantile.

4.3 Heterogeneous response of stock returns to the CO_2 emissions based on dummy variable

A dummy variable D_1 is defined to investigate whether the year 2021 has a significant impact on the return of the low-carbon stocks. If the sample is in 2021, $D_1 = 1$, otherwise, $D_1 = 0$. We add D_1 to Eq. 1, and the model is as follows: $Q_{R_{it}}(\tau|\alpha_i, x_{it}) = \alpha_i + \beta_{1\tau}(R_m - r_f) + \beta_{2\tau}SMB_t + \beta_{3\tau}HML_t + \beta_{4\tau}CI_t + \beta_{5\tau}D_1 + \varepsilon_t$. Table 3 reports the results.

We find that the coefficient of D_1 is significant, and it has asymmetric effects at lower and upper quantiles. It is significantly negative at the 5%, 10%, 20%, and 50% quantiles and significantly positive at the 80%, 90%, and 95% quantiles. Meanwhile, the coefficient of D_1 is the lowest at 50% quantiles, while it is more significant at extremely high and low quantiles. These findings indicate that the year 2021 significantly influences the return of low-carbon stocks return, and its impact is greater at the extremely high and low quantiles. This provides further empirical evidence for the heterogeneous response of low-carbon stock returns to the CO_2 emissions index in different years.

4.5 Heterogeneous response of stock returns to the CO_2 emissions index based on energy stocks

The energy industry is the largest source of carbon emissions in China, and the energy sector return is highly correlated with CO_2 emissions in China (Dutta et al., 2018; Wen et al., 2020; Kangyin Dong et al., 2021; Chen et al., 2022). Next, we will investigate the heterogeneous response of the CO_2 emissions index on energy stocks return in different years. The energy stock return is the log return obtained from the CSMAR database. Figures 5–7 and Table 4 show the results.

The empirical results demonstrate that the effect of the CO_2 emissions index on energy stock returns is heterogeneous. Figure 5 and Panel A of Table 4 show that the influence was significant and positive at the high quantiles in 2019. Figure 6 and Panel B of Table 4 show that the result was insignificant in 2020. Figure 7 and Panel C of Table 4 demonstrate that the results were significant and positive in 2021. Meanwhile, the impact of the CO_2 emissions index on the energy stock returns is more significant in the upper and lower quantiles than in the median quantiles. Moreover, its impact is more significant in the high quantiles than in the low quantiles, similar to the results of 4.3. Therefore, we can infer that the heterogeneous response of low-carbon stock returns to the CO_2 emissions index exists in different years and quantiles.

4.6 Heterogeneous response of stock returns to CO_2 emissions and the price of CEA

The construction of the CO_2 emissions index is based on CO_2 emissions and the price of CEA. Most empirical research uses these data to investigate the effect of CO_2 emissions on stock returns. Next, we will retest the heterogeneous response of stock returns to the CO_2 emissions based on CO_2 emissions and CEA price. Tables 5–8 report the results.

All empirical results support that the response of stock returns to CO_2 emissions is heterogeneous. Table 5 reports that the effect of the CEA price on the return of the energy stocks is heterogeneous. On the one hand, it was negative and significant in 2021 but not in 2019, 2020. The influence is more significant at high and low quantiles than in the median quantiles, and its impact is more significant at the high quantiles than at the low quantiles. However, Table 6 shows that the effect of CEA price on the return of the low-carbon stocks is insignificant in different years and at different quantiles. Tables 7, 8 demonstrate that the effect of CO_2 emissions on the return of the energy stocks and low-carbon stocks is heterogeneous. Its influence is positive and significant in 2021, while not in 2019 and 2020. In addition, the impact at high and low quantiles is also more significant than at the median quantiles.

5 Conclusion

This paper constructs a CO_2 emissions index and uses a QR approach to investigate the heterogeneous response of the stock returns to CO_2 emissions based on daily data from 2019 to 2021. Our results suggest that heterogeneous effects do exist. The CO_2 emissions index maintains low growth in 2019 and 2020 and surges in 2021. Meanwhile, the effect of CO_2 emission on stock returns is significant and positive in 2021, while it is insignificant in 2019 and 2020. This may be related to the rapidly rising carbon emission index. In addition, the response is more significant at the lower and upper quantiles than at the median quantiles, and its influence is more remarkable in upper quantiles than in lower quantiles. This implies that the carbon risk is positively priced in 2021, especially in extreme market conditions.

Based on the above empirical results, we derive two policy implications. First, the effect of CO_2 emissions on stock returns is significant in 2021 while insignificant in 2019 and 2020, and the low-carbon and energy stocks have similar results. Thus, all firms should be committed to cutting carbon emissions against the carbon risk. Meanwhile, the government and investors should pay more attention to CO_2 emissions in the future. The carbon emissions allowance becomes an especially valuable resource for power companies. Second, as market circumstances change, the effect of CO_2 emissions on stock returns becomes more significant at the upper and lower quantiles. Thus, investors must adopt different investment strategies depending on the market circumstances.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

MW: analysis of the data, TL: writing part of the paper, WL: writing and revising the paper.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.1074262/full#supplementary-material

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