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Dynamic Risk Spillover Effect between the Carbon and Stock Markets under the Shocks from Exogenous Events

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Abstract: Based on the DY spillover index model, we explore the static and dynamic risk spillover relationships between the Chinese carbon and stock markets from the perspective of the entire market and different industry levels. Furthermore, we examine the impact of diverse types of exogenous events on the risk spillover effects. The empirical results of the sectoral stock market show that the carbon market is the primary risk taker, and the risk spillover to the carbon market is mainly from high-carbon-emitting industries, such as the oil and electricity industries. However, the risk spillover relationship will be reversed under the shocks from exogenous events. The shocks from different types of exogenous events enhance the risk spillover from the carbon market to the stock market, specifically to the oil sector. The Sino–U.S. trade war and the COVID-19 outbreak are more impactful than government policies. These findings help investors to understand the risk conduct patterns among different financial sub-markets, and have implications for regulators to strengthen market risk management.

Keywords: carbon emission trading market; risk spillover; stock market; exogenous shock

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1. Introduction

A carbon market is essential for the attainment of carbon neutrality and a low-carbon development mechanism with the carbon market at its core can utilize the market to achieve the efficient allocation of resources. Carbon markets trade carbon dioxide emission rights as a commodity, allowing companies to sell their surplus carbon emission allowances to companies with higher abatement costs, thereby reducing the total cost of abatement to society. As the world's second-largest economy, China's consumption of fossil energy is enormous, and the massive emissions of CO_2 have led to increased global warming and frequent extreme weather. The Chinese government is attempting to reduce CO_2 emissions and aims to peak CO_2 emissions before 2030 and to become carbon neutral by 2060 as proposed at the 26th United Nations Climate Change conference. The current Chinese carbon market consists of eight regional carbon emissions trading markets and one national market, and is expected to be the world's largest carbon emission trading market in the near future. As one of the important financial instruments, China's carbon emission market is growing in size, and its connectedness with other financial markets is bound to increase, e.g., the stock market [1]. In addition, the complex external environment of the financial market and the frequent occurrence of various exogenous shocks have led to intricate relationships among the components of financial markets. Therefore, it is necessary to explore the risk of spillover relationships between the Chinese carbon market and other financial markets, which helps regulators to strengthen the risk management of the financial market and also be of great value for investors to optimize their investment portfolios.

There is a large body of research focusing on the risk spillover effect between carbon and other financial markets. Several studies have addressed the risk spillover relationship among the carbon and energy futures markets, including oil, gas, and coal futures markets [2–11]. Specifically, Liu and Chen confirmed the existence of volatility spillovers between carbon and petroleum, coal, and gas markets [7]. However, Zhang and Sun argued that there are only significant unidirectional volatility spillovers from the coal to the carbon market [8]. Based on volatility spillovers, Ji et al. discovered that Brent crude oil prices considerably influence carbon price changes and that significant time-varying features exist between returns and volatility [9]. Cao et al. argued that there is a mutually constraining relevance between the electricity market and the carbon market, a relevance that reduces the cost of generation technologies and provides positive incentives for clean energy generation technologies [10]. Yuan and Yang utilized the GAS-DSC-Copula model to reveal that EUA carbon markets are likely to be subject to risk spillovers from uncertainties in financial markets, particularly from uncertainties in crude oil markets [11]. While these findings have extensively explored the risk spillover relationship between carbon and energy markets from diverse perspectives, they have not considered the influence of external shocks on the risk spillover relationship between the two. With the continuous development and utilization of new energies [12], e.g., the wind and geothermal energies, there are also some studies that focus on the risk spillover relationship between the carbon market and the new energy market [13,14]. These studies found that the new energy stock market also acts as the net information transmitter to the carbon market in China. In addition, Anupam et al. also investigated the links between ethanol and carbon emission markets, and found that carbon emission prices affect Brazilian ethanol prices positively [15].

In terms of the stock market, the existing research has focused on the correlation between carbon and stock markets from the perspective of the overall markets. Rising short-term carbon trading prices increase the marginal cost of firms [16]. In the long term, however, the rise in emissions costs raises the cost of entry for firms, relatively increases the competitiveness of existing firms, promotes investment and innovation in abatement technologies, and further increases the value of firms and the long-term value of their shares. Thus, the positive correlation between carbon prices and stock returns has been recognized by some studies [17,18]. However, other studies have concluded that the association is insignificant [19,20] or even negative [21]. Some studies have suggested a non-linear relationship between the two markets [22]. Therefore, generally, the correlation between the two markets has not been consistently ascertained.

From the perspective of the sector level of stock markets, Wen et al. investigated the asymmetric relationship between the Chinese carbon market and the overall and sector levels of stock markets and found that carbon emission trading price is significantly related to some energy-intense sectors and the financial sector stock market [23]. Asif et al. investigated the directional predictability between carbon trading and sectoral stocks in China under different market conditions [24]. Li et al. investigated the spillover effect between the carbon market and the power sector in China from a systematic perspective and found that the carbon market is a net receiver of information from the power sector [25].

There is also some literature on the relationship between the carbon and stock markets from a theoretical perspective. On the one hand, the resource allocation function possessed by the carbon market will increase emission reduction costs in high-carbon-emitting industries, which in turn affects corporate stock performance [16]. On the other hand, the flow of capital and message prolongs the credit chain between markets, which can cause financial risks to accumulate and be transmitted between markets [26]. Additionally, as the external environment of financial markets becomes more complex, shocks from major external events often cause the dramatic fluctuation of asset price [27], and then exacerbate risk transmission among markets and even trigger financial systemic risks [28,29], such as government policy [30], the Sino–U.S. trade war, and the COVID-19 outbreak [31]. Numerous empirical studies have demonstrated that major public health emergencies and uncertainties in economic and environmental policies can have a prominent effect on the carbon and stock markets [32–35].

It can be seen from the above literature that although there is abundant research on the risk spillover relationship between the carbon and stock markets, there are still some research gaps. Firstly, there is relatively limited empirical evidence of the static and dynamic connectedness characteristics between the carbon market and the overall and sector levels of stock markets. In particular, differences in enterprises' demands for carbon emission allowances may lead to different characteristics in the relationships between the carbon market and the high-carbon-emitting sectors and the low-carbon-emitting sectors. Secondly, in the context of the changing external market environment, it is necessary to clarify the risk spillover relationship between the carbon and stock markets, which is crucial for investors to comprehend the laws of the market and for regulators to prevent systemic risks. The goal of this work is to fill these gaps.

From the perspective of the overall and the sector levels, this study explores the quiescent and dynamic risk spillover relationship between the Chinese carbon and stock markets based on the DY spillover index model [36–38]. Additionally, it examines the impact of different types of exogenous event shocks on the risk spillover effect based on the event study method, e.g., government policy, the Sino–U.S. trade war, and the COVID-19 outbreak. The empirical results show that the carbon market is the primary risk taker, and the risk spillover to the carbon market is mainly from high-carbon-emitting industries, such as the oil and electricity industries. However, the risk spillover relationship will be reversed under the shocks from exogenous events. Specifically, environmentally related policy events can reinforce risk spillovers from the carbon to stock markets in high-carbon-emitting sectors. The Sino–U.S. trade war has increased risk spillovers from the carbon to stock markets in varying sectors and has negatively impacted high-carbon-emitting sectors. A shock from the epidemic could also lead to a spillover of risk from the carbon market to the stock market. Generally, the Sino–U.S. trade war and the COVID-19 outbreak are more impactful than government policies.

Our study makes several contributions. It complements the work on the dynamic connectedness between the carbon emission trading market and the financial market. From both an overall and sectoral perspective, we draw an explicit conclusion related to the relationship among the carbon and stock markets through a comprehensive study with broader coverage of research objectives. In addition, by considering the impact of diverse types of exogenous event shocks, we depict the complete picture of the relationship between the two markets in different market environments. Our research is helpful for regulators to stabilize the carbon market, and promote the carbon market to play a better role in reducing carbon emissions. The empirical results can also potentially help investors to facilitate the design of portfolio allocation strategies by considering the carbon asset.

The remainder of this paper is organized as follows. Section 2 displays the empirical methodology. Section 3 analyzes the empirical results and draws specific conclusions. Section 4 presents the conclusion and discussion.

2. Empirical Methods

2.1. Risk Spillover Index Model

We calculate the index using the spillover index model developed by Diebold and Yilmaz (2012) [37], which is widely used in the study of risk spillover effects among variables [6,9,13,14,25]. One of the advantages of this model is that the calculation of spillover indices does not depend on the order in which the variables enter the model. On this basis, we use a rolling time window approach to calculate a dynamic risk spillover index [39]. Assuming that the time series is smooth, an N-dimensional vector autoregressive model with lag order p $VAR(p)$: $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, can be transformed into a moving average $x_t = \sum_{i=1}^{\infty} \mathrm{A}_i \varepsilon_{t-i}$. Where x_t is a column vector consisting of the logarithmic return on the market price of carbon or the price of a stock, ϕ_i denotes the $N \times N$ coefficient matrix, and A_i is an N-dimensional unit matrix. ε_t is the equation residuals. When $i < 0$, $A_i = 0$; when $i > 0$, the coefficient A_i follows the recursive formula: $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$.

Hence, based on the generalized forecast error variance decomposition, the relative degree of contribution of the j-th variable to the movement in series x_t can be observed. The proportion of the x_t forward H-step forecast error variance of market i that is caused by the x_j shock to market j is $\theta_{ij}^{g}(H)$. Thus, the relative variance contribution of the prior period is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_i\right)} \tag{1}$$

where $\theta_{ij}^{g}(H)$ denotes the spillover index of x_j over x_i, σ_{jj}^{-1} is the standard deviation of the forecast error of market j, and e_i is column i in the $N \times N$ dimensional unit matrix. The relative variance contribution rates satisfy the following conditions: $\theta_{ij}^{g}(H) < 1,\ \sum_{j=1}^{n}\theta_{i,j}(H) = N$ and $\sum_{i,j=1}^{n}\theta_{i,j}(H) = N$. When $i \neq j$, the total spillover index measures the impact of the shock on all variables and is expressed as follows:

$$TS^{g}(H) = 100 \times \frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)} = 100 \times \frac{1}{N}\sum_{i=j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H) \tag{2}$$

The decomposition of the total spillover index into spillovers to and from other markets can be used to analyze the direction of risk spillovers between the carbon and stock markets. We define market spillover to other markets as the output spillover index $DS_{.\leftarrow i}^{g}(H)$ and market spillover to other markets as the input spillover index $DS_{i\leftarrow .}^{g}(H)$:

$$DS_{.\leftarrow i}^{g}(H) = 100 \times \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ij}^{g}(H)} = 100 \times \frac{1}{N}\sum_{i,j=1}^{n}\theta_{i,j}\widetilde{\theta}_{ij}^{g}(H) \tag{3}$$

$$DS_{i\leftarrow .}^{g}(H) = DS_{.\leftarrow i}^{g}(H) = 100 \times \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\theta}_{ji}^{g}(H)} = 100 \times \frac{1}{N}\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H) \tag{4}$$

Furthermore, we examine the relative magnitude of risk spillover in market i in both the input and output directions. We define the difference between $DS_{.i}^{g}(H)$ and $DS_{i.}^{g}(H)$ as the net spillover index $N_i^{g}(H)$ for market i. When $N_i^{g}(H) = DS_{.i}^{g}(H) - DS_{i.}^{g}(H) > 0$, it indicates that market i is a net exporter of risk spillover. When $NS_i^{g}(H) = DS_{.i}^{g}(H) - DS_{i.}^{g}(H) < 0$, it indicates that market i is a net importer of risk spillover. Considering the net spillover effect between markets, the net spillover index from market i to market j is defined as the difference between the spillover index from market i to market j and the spillover index from market j to market i:

$$NS_{ij}^{g}(H) = 100 \times \left(\frac{\widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N}\widetilde{\theta}_{ik}^{g}(H)} - \frac{\widetilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N}\widetilde{\theta}_{jk}^{g}(H)}\right) = 100 \times \frac{\widetilde{\theta}_{ji}^{g}(H) - \widetilde{\theta}_{ij}^{g}(H)}{N} \tag{5}$$

where $NS_{ij}^{g}(H)$ is the net spillover index of market i to market j. When $NS_{ij}^{g}(H) > 0$, it indicates that there is a net spillover from market i to market j. When $NS_{ij}^{g}(H) < 0$, it indicates that there is a net spillover from market j to market i. The value indicates the size of the net spillover effect between markets.

2.2. Event Study Method

The efficient markets hypothesis suggests that the market will react in advance if the event is anticipated by the market in advance. Therefore, the event window should include the trading day before the event occurs. If the event is not anticipated by the market in advance, the event window should only include the trading days after the event has occurred. Figure 1 shows that, the event study method usually denotes $t = 0$ as the date of the event, $t \in [T_1,\ T_2]$ as the event window, and $t \in [T_0, T_1]$ and $t \in [T_2, T_3]$ as the estimation and post-event windows, respectively. Following the works [40,41], we select [−15, +15] as the event window to test the effect of exogenous event shocks on the risk spillover effect. The estimation window is set to [−45, −15] in this study because the estimation window is set to effectively avoid crossover effects of events and changes in the data structure. Additionally, given that some exogenous event shocks cannot be fully anticipated by the market, this study sets the ex-post window at [+15, +45] to capture the market's response to the unanticipated event shocks.

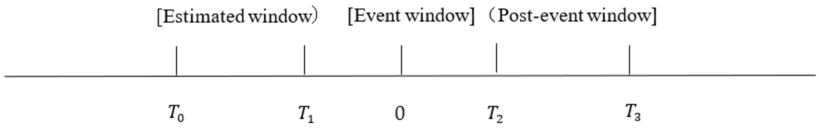

Figure 1. Event Study Method.

Referring to the studies [41,42], we use a GARCH(1,1) model to simulate the normal change of the risk spillover index within the event window, and define the abnormal spillover effect as the difference between the actual spillover effect within the event window and the normal spillover effect in the absence of exogenous event shocks:

$$\Delta ASE_{i,t}^{j} = \Delta SE_{i,t}^{j} - D\left(\Delta SE_{i,t}^{j}\right) \tag{6}$$

where $\Delta ASE_{i,t}^{j}$ denotes the abnormal risk spillover from market i to market j at moment t, $\Delta SE_{i,t}^{j}$ denotes the actual spillover from market i to market j at moment t, and D denotes the normal spillover from market i to market j at moment t. We also give the cumulative value of the anomaly within the event window as $Accum\_\Delta ASE_{i}^{j} = \sum_{t=T_1}^{T_2} \Delta ASE_{i,t}^{j}$.

3. Empirical Evidence

3.1. Data Collection

The daily data of the carbon emission trading market and the stock market from the WIND database are used in our present study, and the sampling period is from 1 January 2015 to 31 December 2020, for a total of 1270 trading days. Considering that market illiquidity and the missing data would usually make biased and incorrect empirical results, we select the Guangdong carbon emission trading market (CT) to represent the Chinese carbon market. As a regional carbon emission trading market with a sound regulatory system, effective supervision, and high participation of market players, the Guangdong carbon market is the most active compared with other regional carbon markets. For the stock, we choose the Chinese CSI 300 index(CSI) to reflect the overall situation of the stock market, which is considered to be one of the most representative stock market indicators in China [43]. We select oil (OPI), electricity (PI), steel (SI), chemicals (CI), and non-ferrous metals (NFMI) as high-carbon-emitting sectors, and banks (BI) as low-carbon-emitting sectors based on the high-energy-consuming industries released by China's National Bureau of Statistics in 2013, to investigate the risk spillover between the carbon and sectoral markets. We use the Shewan Primary Sector Index to represent the sectoral markets.

The estimation of the risk spillover index is made according to the logarithmic return on the closing price of each market. We define the return series as $R_t = ln(P_t/P_{t-1})$, where P_t is the closing price of each market on day t. Table 1 shows that the mean of the carbon emissions trading market is significantly smaller than the overall stock market, whereas the standard deviation is larger than the overall stock market. This indicates that the carbon market is more volatile. The possible reason is that compared with the stock market, China's carbon market has been operating for a relatively short period and the corresponding trading mechanism is not as developed as the stock market. The standard deviation of the market across sectors reveals that returns in high-carbon-emitting sectors are considerably volatile compared with those in low-carbon-emitting sectors. From the skewness and kurtosis, the skewness of returns in each market is less than 0 and the kurtosis is significantly greater than 3. The Jarque-Bera test shows that the JB statistic for each market is significant at the 1% level, indicating that the return series for each market deviates significantly from a normal distribution. Additionally, the ADF test shows that the return series for each market is smooth and does not have unit roots.

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

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	JB	ADF
$R_{CT,t}$	1.08×10^{-4}	0.050	−0.446	0.341	−0.547	12.2070	4550 ***	−31.558 ***
$R_{CSI,t}$	2.82×10^{-4}	0.016	−0.091	0.099	−0.535	9.1351	2053 ***	−25.169 ***
$R_{OPI,t}$	-9.94×10^{-4}	0.017	−0.105	0.103	−0.275	10.3011	2837 ***	−26.407 ***
$R_{PI,t}$	-2.75×10^{-4}	0.016	−0.081	0.094	−0.401	10.7696	3228 ***	−25.311 ***
$R_{SI,t}$	-1.87×10^{-4}	0.020	−0.093	0.118	−0.317	6.9273	838 ***	−26.658 ***
$R_{CI,t}$	3.30×10^{-4}	0.019	−0.085	0.099	−0.485	7.8332	1286 ***	−23.197 ***
$R_{NFMI,t}$	1.10×10^{-4}	0.022	−0.089	0.106	−0.220	6.4984	658 ***	−24.270 ***
$R_{BI,t}$	0.65×10^{-4}	0.015	−0.105	0.087	−0.118	9.8582	2492 ***	−24.973 ***

Notes: $R_{CT,t}$ and $R_{CSI,t}$ denote the logarithmic returns of the Guangdong carbon emission trading and overall stock markets, respectively. $R_{OPI,t}$, $R_{PI,t}$, $R_{SI,t}$, $R_{CI,t}$, $R_{NFMI,t,}$ and $R_{BI,t}$ denote logarithmic returns of the oil, electricity, steel, chemicals, non-ferrous metals, and bank sectors, respectively. *** indicates significance at the 1% level.

3.2. Analysis of Static Risk Spillover Effects

First, we examine the static risk spillover effect between the carbon and stock markets. Tables 2 and 3 provide the risk spillover indices of the carbon market to the overall stock market and the different sector markets, respectively. The column variables denote the individuals receiving the spillover and each pillar denotes the index of output spillover from one particular market to another (To). The row variables indicate the source of the spillover, with each row indicating the input spillover index of one market to another (From). The diagonal line indicates the market's spillover to itself.

Table 2. Static risk spillover relationship between the carbon and overall markets.

	CT	CSI	From
CT	99.1373	0.8627	0.8627
CSI	1.3810	98.6190	1.3810
To	1.3810	0.8627	1.1218
Net	0.5183	−0.5183	

Notes: The column variables of Table 1 denote the individuals receiving the spillover and each pillar denotes the index of the output spillover from one particular market to another (To). The row variables indicate the source of the spillover, with each row indicating the input spill-over index of one market to another (From). The diagonal line indicates the market's spillover to itself.

Table 2 shows that the carbon market has a risk spillover index of 1.381 to the overall stock market, a reverse risk spillover index of 0.8627, and a net inter-market spillover index of 0.5183. Thus, risks spillover from the carbon to the overall stock market primarily. However, considering the industry-level results, the net spillover index for carbon markets in Table 3 is −3.1648, indicating that carbon markets are the main risk takers. The oil and electricity sectors have the largest risk premiums to the carbon market, at 1.4274 and 0.9697, respectively. Oil is a main fossil energy source and oil's price significantly affects carbon's price. Additionally, China is currently dominated by thermal power generation, which accounts for more than 71% of the country's electricity production in 2021, and is a significant source of greenhouse gas generation. Thus, risks are mainly transmitted from the oil and electricity markets to the carbon market. Compared with other high-carbon-emitting sectors, the carbon market has the smallest net risk premium to the banking sector at −0.2644. Banks influence the production activities and CO_2 emissions of companies through financial instruments, such as green credits, which in turn influence carbon prices. This may be the main reason for the spillover of risk from the banking sector to the carbon market. However, this indirect effect is weaker than in other high-carbon-emitting sectors.

Table 3. Static risk spillover relationship between the carbon and stock markets across sectors.

	CT	OPI	PI	SI	CI	NFMI	BI	From
CT	94.5664	1.4274	0.9697	0.8534	0.7953	0.7958	0.7920	5.6336
OPI	0.4598	38.0214	13.6338	12.7272	12.1597	10.7477	12.2505	61.9786
PI	0.3384	9.6958	28.4504	17.1517	19.5165	16.7793	8.0679	71.5496
SI	0.3419	9.3058	18.0224	28.0366	18.1639	18.4982	7.6312	71.9634
CI	0.3313	8.7459	19.8300	17.4078	27.1025	21.0104	5.5721	72.8975
NFMI	0.2697	8.0249	17.9119	18.5623	22.0278	27.8217	5.3816	72.1783
BI	0.5276	14.1463	13.2806	11.4424	8.6567	7.8601	44.0863	55.9137
To	2.2688	51.3461	83.6484	78.1448	81.3198	75.6914	39.6953	58.8449
Net	−3.1648	−10.6325	12.0988	5.9815	8.4223	3.5131	−16.2183	

Notes: The column variables of Table 1 denote the individuals receiving the spillover, and each pillar denotes the index of output spillover from one particular market to another (To). The row variables indicate the source of the spillover, with each row indicating the input spill-over index of one market to another (From). The diagonal line indicates the market's spillover to itself.

3.3. Analysis of Dynamic Risk Spillover Effects

We further test the risk spillover relationship between the carbon and overall stock markets and different sector markets from a dynamic perspective. We employ a rolling time window way to calculate the dynamic spillover index, with a window width of 100 trading days and a step length of one trading day. Figure 2a,b show the directional spillover and net spillover indices, respectively. The dynamic net spillover index between the two shows that the risk spillover relationship between the two evolves in an alternating positive and negative manner and reaches local peaks at certain periods, such as around April 2017, when the net spillover index is as low as approximately −7.5, and around 31 December 2019, when the net spillover index is as high as approximately 12.5. The likely reason for this is that different exogenous events can cause shocks to different markets, which in turn result in changes in the risk spillover relationships between markets over time.

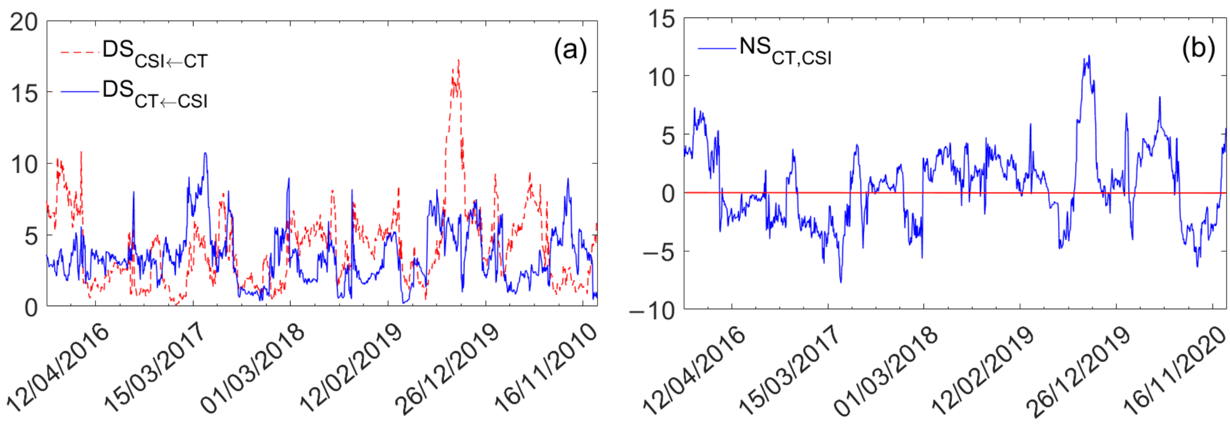

Figure 2. Dynamic evolution of the volatility spillover index between the carbon (CT) and overall stock (CSI) markets: (**a**) shows the directional volatility spillover index between CT and CSI, and (**b**) presents the net volatility spillover index between CT and CSI.

Figure 3a to f show the dynamic net spillover indices of the carbon market to the oil, electricity, steel, chemicals, non-ferrous metals, and banking sectors, respectively. The net spillover between the carbon emissions trading and stock markets of the different sectors shows alternating positive and negative time evolution. The net spillover from the carbon market to the oil and electricity sectors was less than 0 for most trading days and reached minimum values of −17 and −15, separately, reflecting that the oil and electricity sectors had the strongest risk spillover effects to the carbon market. This result is compatible with the results in Table 3.

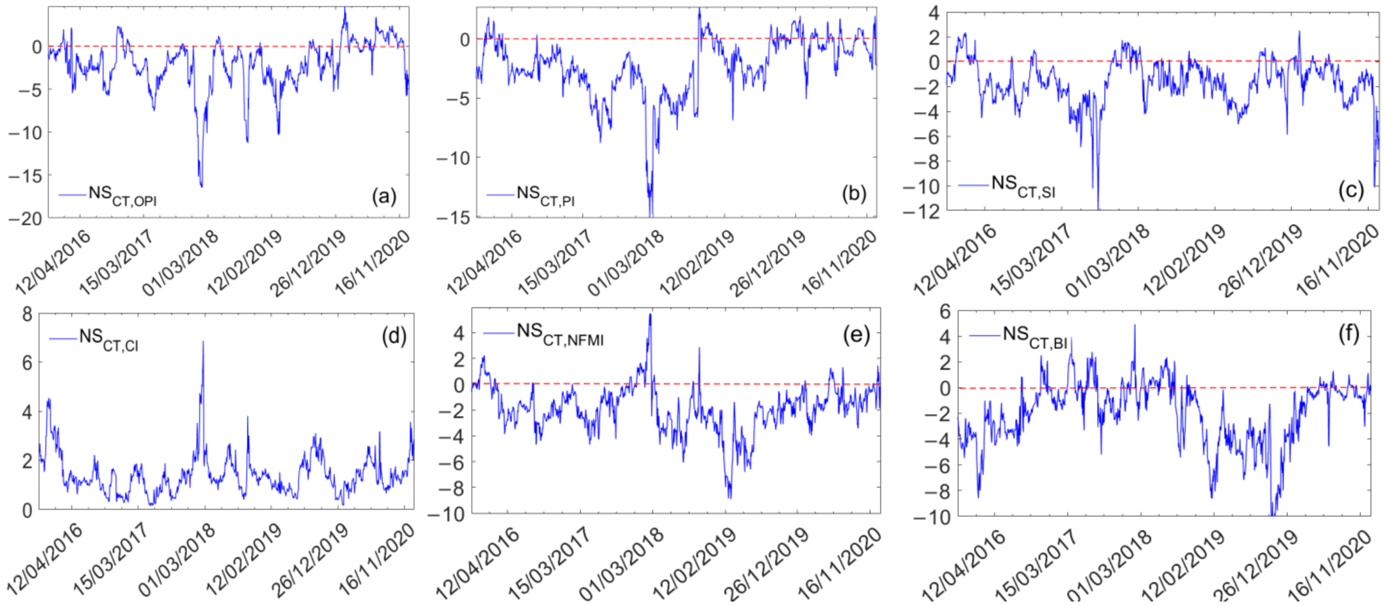

Figure 3. Dynamic evolution of the net volatility spillover index between the carbon (CT) and stock markets across sectors: (**a**–**f**) present the net volatility spillover index between CT and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

3.4. Analysis of Exogenous Event Shocks Affecting Risk Spillover Effects

Subsequently, we examine the impact of varying types of exogenous event shocks on inter-market risk spillover relationships from multiple perspectives, including government policy, the Sino–U.S. trade war, and the COVID-19 outbreak. Government policies related to environmental protection may affect the carbon market by influencing the structure of industries and energy sources, which in turn affects the risk spillover relationships between markets. The Sino–U.S. trade war has had a significant effect on both Chinese energy import prices and domestic securities markets. The COVID-19 outbreak, which for a period caused economic stagnation, had a major impact on the carbon and stock markets. Therefore, we have selected different types of exogenous events from various perspectives, including government policies, the Sino–U.S. trade war, and the COVID-19 outbreak. Table 4 shows the specific descriptions of each type of exogenous event.

Figure 4 shows the trend in the outlier of the net spillover index between the carbon and overall stock markets for the 15 trading days before and after the event in response to the government policy shock. Figure 4a shows that the net spillover index increased the day after A1 was released and increased from −4.2 to approximately 1.7 over the subsequent 15 trading days. In Figure 4b, the net spillover index increases from 0 to approximately 1 after the notification is issued. Owing to the close timing of the release of events A1 and A2, the net spillover index experienced a significant movement before event A2 occurred. These results suggest that environmentally related policy events can reinforce risk spillovers from the carbon to the overall stock market. This could be because such policies can increase the pressure on companies to reduce carbon emissions, which in turn can cause carbon prices to take the lead in volatility.

Table 4. Description of the different types of exogenous events.

Event	Serial	Event Description	Dates
Policies	A1	Three-year action plan to fight air pollution	3 July 2018
	A2	Resolution to promote the difficult battle of pollution prevention and control following the law	30 July 2018
Sino–U.S. trade war	B1	U.S. imposes tariffs on USD 60 billion of Chinese imports	26 March 2018
	B2	U.S. Department of Commerce puts 11 Chinese companies on the "entity list"	20 July 2020
COVID-19 outbreak	C1	Lockdown imposed in Wuhan	23 January 2020

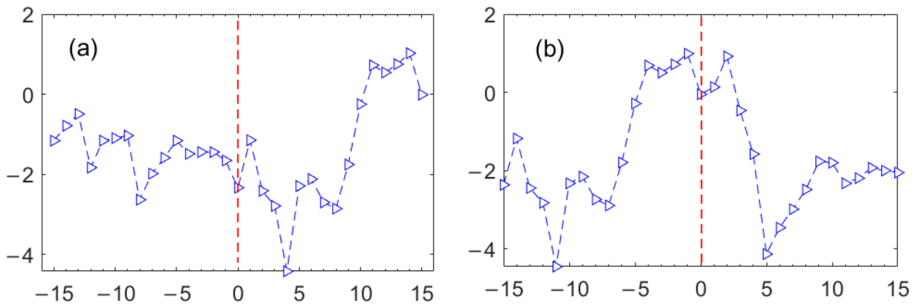

Figure 4. Strike of government policies on the outlier of net spillover effect: (**a**,**b**) show the outlier of the net spillover index between the carbon and overall stock markets after the shocks of government policies A1 and A2.

Figures 5 and 6 show the outliers of the net spillover of the carbon and stock markets of various industries within 15 trading days before and after the occurrence of A1 and A2, respectively. Figure 5a to f show the effect of event A1 on the net spillover from the carbon to the oil, electricity, steel, chemicals, non-ferrous metals, and banking sectors, respectively. Figure 6a–f show the impact of event A2, respectively. In Figure 5a, the outlier value of net spillover from the carbon market and oil plate rapidly increases from −3 to a level greater than 0 after event A1. Additionally, the net spillover outliers in Figure 5b,d,e reach a local maximum around the event date because of the presence of certain market expectations. Similarly, in Figure 6a–e, there is an obvious rising trend in the net spillover outliers—all occurring after event A2. These results suggest that shocks from policy events can reinforce risk spillovers from carbon to stock markets in high-carbon-emitting sectors. In Figures 5f and 6f, the outliers of the net spillover from the carbon and banking sector did not change significantly before and after the event date compared with the stock market of high-carbon-emission industries.

Figures 7 and 8 show the outliers of the net spillover from the carbon and stock markets of various industries within 15 trading days before and after the occurrence of events B1 and B2, respectively. Figure 7a–f show the strike of event B1 on the net spillover from the carbon to the oil, electricity, steel, chemicals, non-ferrous metals, and banking sectors, respectively. Figure 8a–f show the impact of event B2. In Figures 7 and 8, most of the net spillover outliers had an upward trend before the date of the event. The Sino–U.S. trade war has experienced several frictions and conflicts since March 2018, and the market is extremely sensitive to and anticipates adjustments in tariff policy, which may be the main reason for the net spillover outliers beginning to move well in advance of the event date. Additionally, Figures 7 and 8 show that the carbon market has a large variation in net spillover outliers with the oil, electricity, and chemicals sectors, and a relatively small variation in net spillover outliers with the banking sector. Generally, the Sino–U.S. trade war has increased risk spillovers from the carbon to stock markets in varying sectors and has negatively impacted high-carbon-emitting sectors.

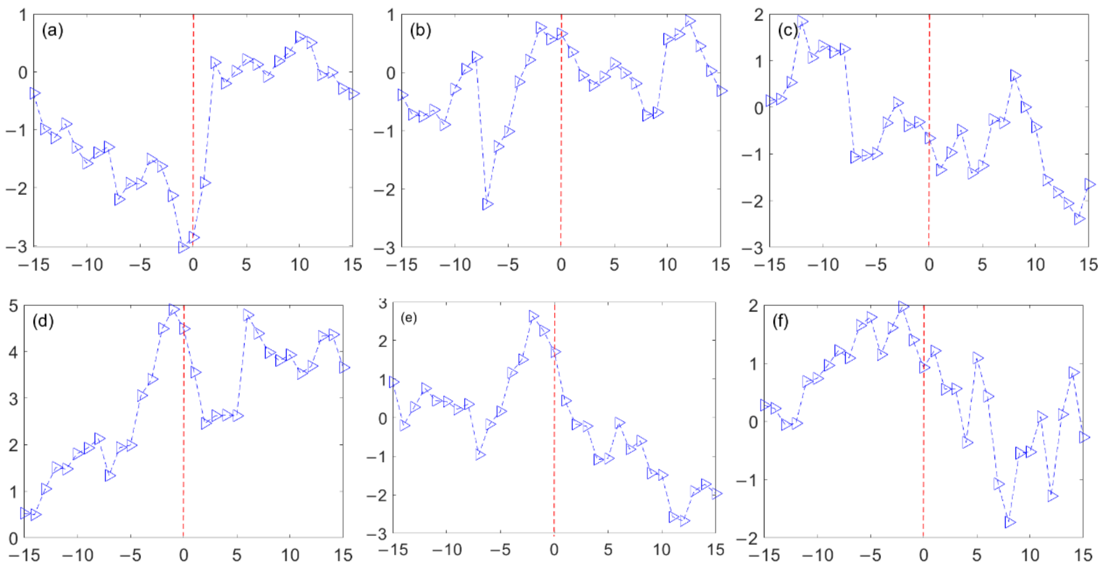

Figure 5. Strike of the government policy A1 on the outlier of net spillover effect: (**a**–**f**) show the outlier of the net spillover between the carbon market (CT) and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

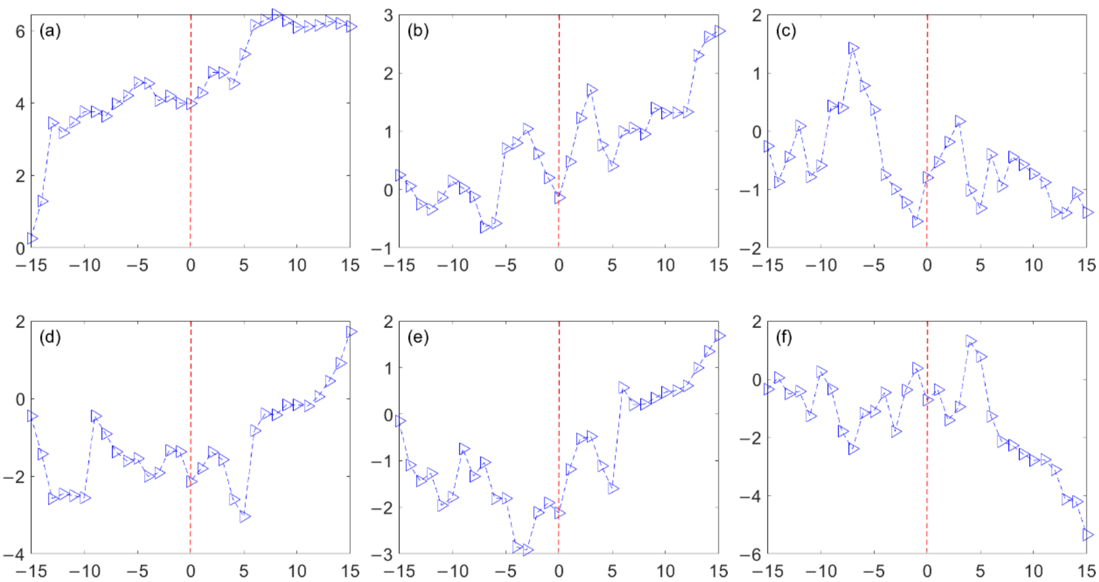

Figure 6. Strike of the government policy A2 on the outlier of net spillover effect: (**a**–**f**) show the outlier of net spillover between the carbon market (CT) and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

Figure 9 indicates the outliers of the net spillover from the carbon and stock markets of various industries within 15 trading days before and after event C1. Figure 9a–f show the strike of event C1 on the net spillover from the carbon to the oil, electricity, steel, chemicals, non-ferrous metals, and banking sectors, respectively. In Figure 9a, there is an obvious rising trend in the carbon market and oil sector net spillover outliers in the 10 trading days before and after the lockdown was imposed in Wuhan. Figure 9b,c,e,f show a distinct upgrade trend in the carbon market and electricity, steel, non-ferrous metals, and banking sector net spillover outliers in the five trading days after the event. In early 2020, as the pandemic continued to spread, a large number of enterprises faced shutdowns and work stoppages, and Wuhan had been closed down for 76 days. This may have influenced the demand of enterprises for carbon emission allowances, which caused the carbon market to fluctuate continuously for a period of time, leading to the increase in volatility spillovers from the carbon market to the stock market. Although there was also a shock to the stock market from the COVID-19 outbreak, the stock market reacts more quickly to new information and the volatility of the market does not last long. In general, the COVID-19 outbreak strengthened the spillover of the carbon market to other stock markets, especially to the oil sector.

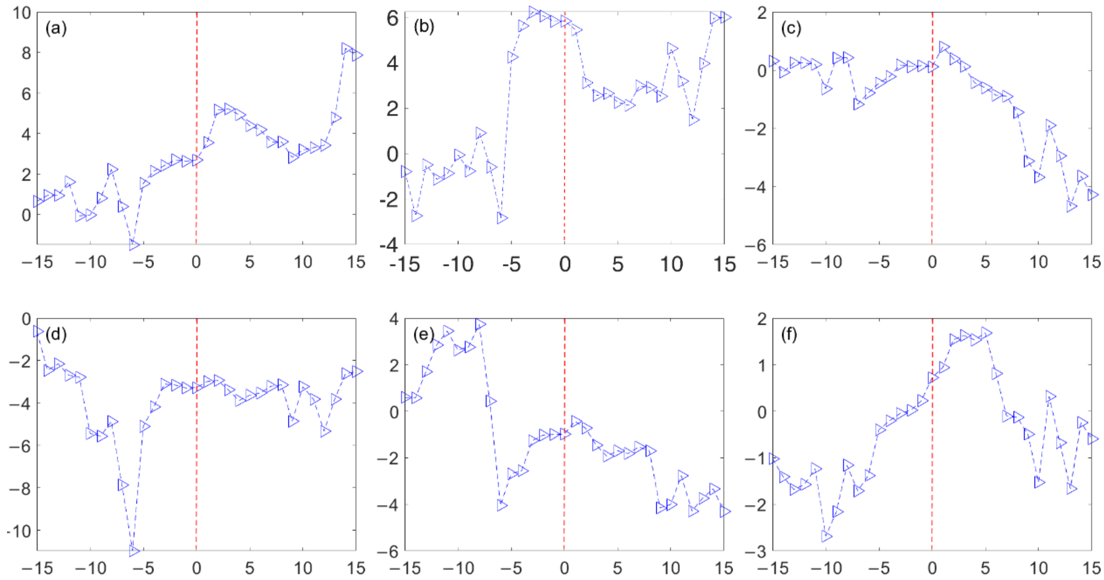

Figure 7. Strike of the event of the Sino–U.S. trade war B1 on the outlier of net spillover effect: (**a**–**f**) show the outlier of net spillover between the carbon market (CT) and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

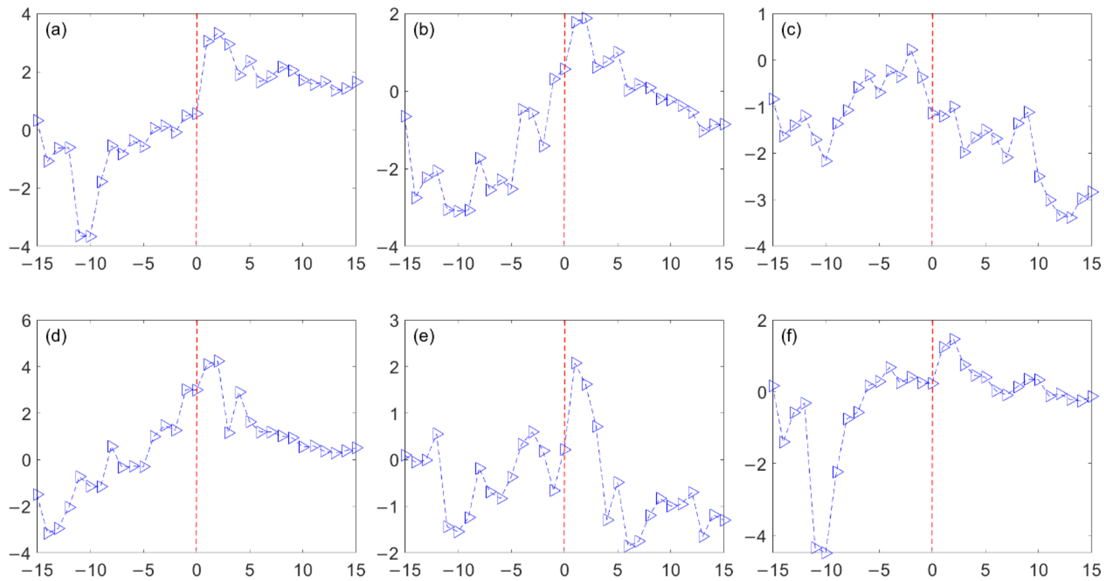

Figure 8. Strike of the event of the Sino–U.S. trade war B2 on the outlier of net spillover effect: (**a**–**f**) show the outlier of net spillover between the carbon market (CT) and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

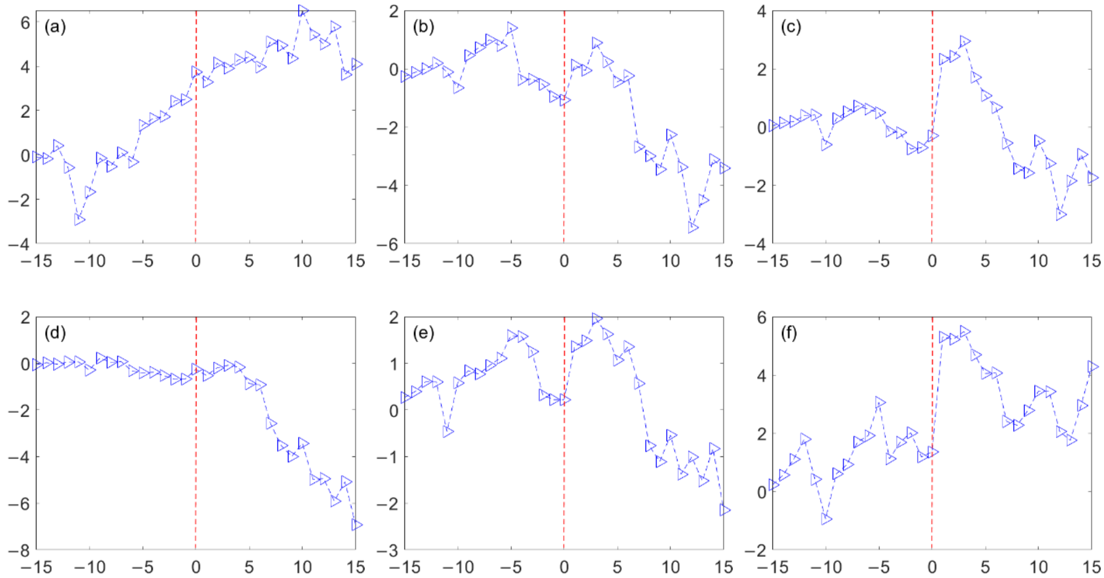

Figure 9. Strike of the COVID-19 outbreak on the outlier of net spillover effect: (**a**–**f**) show the outlier of net spillover between the carbon market (CT) and oil (OPI), electricity (PI), steel (SI), chemicals (CI), non-ferrous metals (NFMI), and banking (BI) sectors, respectively.

To further compare the impact of different types of exogenous event shocks, we provide the cumulative outliers of the net spillover from the carbon market to the stock market in different sectors over the five trading days following the event, as shown in Table 5. Table 5 shows that the cumulative outliers for net spillover are generally larger and mostly greater than zero for shocks to events B1, B2, and C1 compared with events A1 and A2. Unlike trade wars and the COVID-19 outbreak, it often takes time for policies to be released and to have some effect, which may be one of the main reasons for these results. Moreover, the overall impact of different types of events on risk spillovers in the carbon market and oil sectors was greater than in other sectors.

Table 5. Cumulative anomalies of net spillover between the carbon market and different sectors under different exogenous event shocks.

	A1	**A2**	**B1**	**B2**	**C1**
OPI	−1.73	19.85	23.21	13.54	20.01
PI	0.15	4.57	16.03	6.02	0.72
SI	−5.47	−2.88	0.26	−7.36	10.48
CI	13.89	−10.39	−16.82	14.01	−1.85
NFMI	−2.10	−4.90	−6.25	2.62	7.50
BI	3.05	−0.65	7.32	4.31	24.76

Notes: OPI, PI, SI, CI, NFMI, and BI represent oil, electricity, steel, chemicals, non-ferrous metals, and banking sectors, respectively. A1 and A2 represent the government policies, B1 and B2 represent the events of the Sino–U.S. trade war, and C1 represents the COVID-19 outbreak.

4. Conclusions and Discussion

The carbon emission trading market has now become an important part of the financial market, not only for reducing greenhouse gas emissions, but also for being crucial to the development of a low-carbon economy. Thus, the relationship between the carbon market and other financial markets, e.g., the stock market, has aroused wide interest of scholars, regulators, and investors. To clarify the dynamic risk spillover relationship between the carbon market and the stock market, this paper employs the connectedness method proposed by Diebold and Yilmaz (2012) to study the spillover effects between the carbon and overall market, and between the carbon and sectoral stock markets [37].

To further explore the pattern of the risk spillover effect under complex external market environments, we investigate the impact of three types of exogenous events on the risk spillover relationship. Through empirical research, this paper has the following main findings:

First, the results of static risk spillover effect show that the risk is mainly transmitted from the Chinese carbon market (CT) to the overall stock market (CSI), and the net spillover from CT to CSI is 0.5183. The results of Adekoya et al. (2021) show that the U.S. stock market tends to be the largest transmitter of shocks to other markets, including the EU carbon market [26]. Compared with the Chinese stock market and the EU carbon market, the development of the Chinese carbon market is relatively late and less mature, and the market may fluctuate greatly, which may be the main reason for why our conclusion is contrary to that of Adekoya et al. (2021). From the perspective of the sector level of stock market, we find that risks are mainly transmitted from the high-carbon-emitting sectors to the carbon market, e.g., oil and electricity markets. Compared with the high-carbon-emitting sectors, the connectedness between the carbon market and the bank sector with the low-carbon-emitting sector is relatively weaker. These results are generally consistent with those of Li et al. (2020), which find that the carbon market is a net receiver of the information from the power sector [25]. Banks can influence the production activities and CO_2 emissions of enterprises through financial instruments, e.g., green credits; however, this effect is indirect, and there is a relatively smaller spillover effect between the carbon market and the banks sector.

Second, studies have shown that the shocks from exogenous events can significantly influence the relationship among different markets, e.g., the EU carbon market and the European stock market [21], and the stock and stock indexes of future markets [41]. In this paper, we find that the shocks from different types of exogenous events can both strengthen the risk spillover from the carbon market to the stock market. Specifically, environmentally related policy events can reinforce risk spillovers from the carbon to stock markets in high-carbon-emitting sectors. The Sino–U.S. trade war has increased risk spillovers from the carbon to stock markets in varying sectors and has negatively impacted high-carbon-emitting sectors. A shock from the COVID-19 outbreak could also lead to a spillover of risk from the carbon market to the stock market. Interestingly, the shocks of the Sino–U.S. trade war and the COVID-19 outbreak were more impactful than that of government policies, which may be attributed to the fact that it often takes some time for investors to understand the policy and for it to take effect.

Our results have practical values for market participants and regulators. For hedging and arbitrage, investors can immediately adjust their investment strategies based on the dynamic risk spillover relationships between the carbon and stock market, especially for the patterns after the shocks from different types of exogenous events, to manage their risks. For regulators, our results show that the connectedness relationships between the carbon and stock markets will be reversed after the shocks of different exogenous events, which have implications for regulators to establish a risk warning mechanism for the carbon market.

The limitation of this paper is that it focuses on the dynamic risk spillover relationships between markets but pays less attention to the applications of the patterns of volatility spillover, and the transmission path of spillovers between markets. Future research can focus on the prediction of the return or volatility of carbon and stock markets based on their spillover relationships. In addition, we can further explore the mechanisms behind the risk spillover relationships. In terms of applications, we can also investigate the lead–lag relationships between the carbon and stock market, and combine the above risk spillover relationships to construct investment portfolios, which may achieve higher returns.

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Data Availability Statement: The data presented in this study are openly available in Guangdong's carbon emission trading price data and the CSI300 Index (https://www.wind.com.cn/, accessed on 15 November 2022).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

CT: the Guangdong carbon emission trading market. CSI: the Chinese CSI 300 index; OPI: the oil sector stock market; PI: the electricity sector stock market; SI: the steel sector market; CI: the chemicals sector market; NFMI: the non-ferrous metals sector stock market; BI: the banks sector stock market. A1: the three-year action plan to fight air pollution; A2: the resolution to promote the difficult battle of pollution prevention and control following the law; B1: the U.S. imposes tariffs on USD 60 billion of Chinese imports; B2: the U.S. Department of Commerce puts 11 Chinese companies on the "entity list"; C1: the lockdown imposed in Wuhan.

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