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Retraction

Retracted: High-Order Moment Contagion of the Carbon Market: A Heterogeneity Analysis of Market Volatility Trend

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Ni, P. Yun, and J. Sun, "High-Order Moment Contagion of the Carbon Market: A Heterogeneity Analysis of Market Volatility Trend," *Security and Communication Networks*, vol. 2022, Article ID 1608871, 14 pages, 2022.

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Research Article

High-Order Moment Contagion of the Carbon Market: A Heterogeneity Analysis of Market Volatility Trend

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Information asymmetry and extreme events shocks can lead to the phenomenon of significant carbon market contagion. However, the existing studies mainly focus on the low-order moment of carbon price, making it difficult to reveal the risk contagion characteristic caused by irrational behaviors and policy shocks. This article takes market skewness and kurtosis into the research framework and constructs the FR, CS, and CK statistical model to detect the contagion in correlation channel, coskewness channel, and cokurtosis channel, respectively. The contribution of this article is to reveal the significant high-order moment contagion channel and strength of carbon market to its infected market under different market volatility trends. The results show significant contagion is widespread from the carbon market to its infected markets through the channels of coskewness and cokurtosis in different volatility trends. Additionally, the contagion strength in volatility rapid and slowly rise trend is generally higher than in the volatility rapid and slowly decline trend. That is to say, the shock of market irrationality and external events in the carbon market measured by the high-order moment contagion channels are essential risk factors that affect its infected markets. Those results convince that the acceptance of significant contagion sourced from the carbon market varies for different infected markets.

1. Introduction

As a financial tool to achieve carbon dioxide emission reduction, the carbon market was formally established in 2005, with the signing of the Kyoto protocol. The market realizes the target of resources allocation and emission reduction through market transaction among various reduction entities. The signing of the Paris Agreement in December 2015 further highlights the carbon market's capital allocation mechanism for emission reductions. The carbon market is characterized by strong sensitivity to policy shocks, and the price is vulnerable to external event shocks compared with other markets. For example, the COVID-19 caused an abnormal global economic downturn, and led to a significant drop in carbon futures and spot prices, especially as of March 23, 2020, the carbon futures prices have fallen by as much as 35% for 13 continuous trading days. Consequently, the carbon price implies more complex risk, and is prone to transmit crisis to the other closely market through the global financial network, that forms risk contagion and exhibits different contagion performance according to different market volatility. It is found that the spillover of carbon market to crude oil and natural gas market is much larger than the spillover accepted by the carbon market [1]. Therefore, it is of theoretical and practical significance to examine the risk contagion between carbon market and its infected markets and investigate the contagion of high-order moment channels characterized by market skewness and kurtosis reflected the asymmetry and extreme shocks.

The theoretical basis of this article is the asset pricing theory under market irrationality. That is, contagion is the irrational comovement after eliminating the fundamentals and rational behaviors [2]. Based on market correlation analysis, Forbes and Rigobon [3] and Renée et al. [4] put that the contagion exists if the correlation between markets increases significantly after financial shocks.

As for the research of contagion, we find previous contagion studies only focus on the low-order moment channel (market mean and variance) to examine the price information linkage and volatility spillover between carbon market and its infected markets [5] that cannot fully reveal the carbon market characteristics of peak thick tail and heterogeneity of volatility trend [6]. Actually, the aggregated excess returns can be predicted by the skewness risk premium, which is constructed to be the difference between the physical and risk-neutral skewness [7].

Therefore, the motivation of this article is focusing on the contagion caused by high-order moment attributes rather than the manner of previous low-order moment manners. That is, we take the market skewness and kurtosis reflected the asymmetry and extreme shocks into the research framework, analyze the risk contagion of high-order moment channels in the carbon market caused by irrational behaviors and external event shocks, and explore the difference of contagion under different market volatility trends and its corresponding explanations.

The remainder of this paper is organized as follows: Section 2 reviews the related literature. Section 3 introduces the methodology and data descriptions. Section 4 presents the empirical results and robustness discussions. Finally, Section 5 is the conclusion.

2. Related Literature

Although the literature related to risk contagion of carbon market is scarce, the studies on information linkage and volatility spillover between carbon market and its homogeneous market, capital market, and energy market have provided a foundation for this article.

2.1. Research on Information Spillover between Carbon Market and Its Homogeneous Market. The products of carbon market and its homogeneous market are affected by the same supply and demand. Research concluded that there is a long-term equilibrium relationship between EUA (European Union Allowance) future and CER (Certified Emission Reduction) spot in the first phase of the European Union Emissions Trading System (EU ETS); the price discovery of CER spot is more significant than that of EUA futures [8].Conducted the multivariate GARCH model, Mansanet-Bataller et al. [9] detected a significant information spillovers correlation between EUA and CER, and the correlation coefficient floats dynamically between 0.01 and 0.9. Subsequently, Chevallier [10] introduced economic recession factor into the study of spillovers relationship between EUA and CER; the results show that economic recession significantly increases the correlation between the two markets. Employed the multivariate dynamic condition correlation model (MS-DCC-GARCH), the research points a time-varying correlation and volatility spillover relationship between EUA spot and EUA futures [11], furthermore, the spillover strength is stronger than that of EUA and CER, and the EUA market has strong price discovery function compared with other markets [12].

2.2. Research on the Correlation between Carbon Market and Capital Market. The financial nature of carbon market is prominent; the properties such as negative asymmetry and positive correlation with stocks indexes during the trading session, typical of financial assets, are detected in the work of Medina and Pardo [13]. As a reflection of macroeconomics, the capital market affects the capital flow and volatility of carbon market. The carbon price is positive correlated with the stock price; the impact of carbon market on the capital market is stronger than that on the energy market [14]. Conducted the GARCH model, Reboredo [15] pointed that the crude oil prices are closely related to macroeconomy and capital markets; it is possible to transfer the capital market uncertainty to the carbon market. The exchange market also affects carbon price; employed the Copula-ARMA-GARCH model, Zhang et al. [16] depicted the risk factors correlation between carbon and exchange market. The research pointed that the potential carbon market risk is higher than that of exchange market. Researches found that there exists considerable asymmetric risk spillover between European carbon market and financial market, and the weak bidirectional causality relation between China carbon prices and energy-intensive stock indexes has also been examined [17–19].

2.3. Research on Spillover Effect between Carbon Market and Energy Market. Energy prices are the most important drivers of carbon prices due to the ability of power generators to switch between their fuel inputs [20]. According to Nazifi and Milunovich [21], the EUA futures have a causal effect on gas prices, and the electricity prices drive carbon prices. Used the GARCH model, Aatola et al. [22] argued that the short-term dynamic carbon future return is closely to natural gas return. The price of coal market has two-way causal relationship with electricity price [23]. Hammoudeh et al. [14] described that the impact of coal price on carbon market price in falling trend is stronger than that of rising trend. Furthermore, conducted the EMD decomposition model, Cao et al. [24] hold that the relationship between carbon price and electricity price has changed from bidirectional linear causality to one-way causality with nonlinear characteristics. It is found that there exists an obvious positive relationship between the EUA and oil markets and such dynamic spillover effect varies with time [25]. Employed the canonical vine copula model, Uddin et al. [26] investigated a stronger one-way and two-way risk spillover relationship between carbon market and energy market. The time-varying and directional spillover between carbon and energy markets have detected the electricity market is the main net information receiver affected by the carbon market [27]. Additionally, the complex time-frequency and neural network mechanism between carbon and oil markets has been explored by the model of novelty partial wavelet and deep learning models [28–30].

2.4. The Comment on the Previous Studies. The common perspective of above literature, however, is based on the view of low-order moment attribute (mean-variance) of carbon asset, focusing on studying the information transmission and risk contagion effect between carbon market and its infected markets. The foundation of these studies may ignore the impact of high-order moment attribute (market skewness and kurtosis) of carbon price on the contagion process; it is difficult to capture and explain the contagion behavior of carbon market caused by external policy and irrational investment.

To overcome these shortcomings, Renée et al. [31] and Chan et al. [32] introduce the coskewness, covolatility, and cokurtosis statistics into the high-order moment CAPM framework; the contribution of the above studies is constructing a new nonparametric high-order moment contagion statistics with the assumption of chi-square distribution to measure the risk contagion. However, the research of Renée et al. [31] only consider the contagion caused by the financial crisis and other political events that may have ignored the contagion pattern caused by different market volatility states and trends. As we know, the rapid volatility of carbon market may lead to greater risk contagion compared with the slow volatility trend. Therefore, it is very necessary to provide new convinced evidence of contagion from the high-order moment perspective.

The innovation of this paper is as follows: firstly, this paper investigates the risk contagion sourced from the carbon market from the perspective of high-order moment contagion channels, which is different from the manner of low-order moment. Secondly, we judge the statistical significance of high-order moment contagion channel before investigating the contagion strength. Thirdly, we explore the structural differences of risk contagion under different market volatility trends and its corresponding explanations.

The research is based on the following steps for achieving the research objectives: firstly, the market volatility is divided into three states: stable, high-volatility and low-volatility. Secondly, the volatility further divides into rapid volatility trend (rapid rise and rapid decline) and slow volatility trend (slow rise and slow decline) and thirdly investigates the risk contagion from high-order moment channels under different market volatility trends. The logic frame of this paper is shown in Figure 1.

3. Methodology and Data Descriptions

3.1. Dividing the Volatility State. The volatility state of carbon market is uncertain; the transformation between different states is unobserved according to the complexity of carbon market volatility. Therefore, this paper extends the states of Markov State Transition model to M regimes and establishes the MS(M)-AR(P) model, which overcome the defect of same variance assumption. The model of MS(M)-AR(P) is expressed as follows:

$$R_t = \nu(M_t) + \sum_{i=1}^{p} \phi_a(M_t) R_{t-a} + \varepsilon_t, \tag{1}$$

where R_t denotes the carbon market return; ε_t represents the model residual, $\varepsilon_t \sim N(0, \sigma(M_t)^2)$; t describes the state number of carbon market volatility, $t \in \{1, 2, \ldots, k\}$; M_t obeys the first-order Markov chain; the conversion probability of M_t is expressed as follows: $P_{\text{ab}} = \text{pr}(M_t = b \mid M_{t-1} = a, M_{t-2} = \alpha, \ldots) = \text{pr}(M_t = b \mid M_{t-1} = a)$; a and b represents two random state variables and $\{a, b\} \in t$; $\nu(M_t)$, $\phi_a(M_t)$, and $\sigma(M_t)$ represents the intercept term, autoregressive coefficient, and standard deviation of carbon returns under the state of M_t, respectively.

Under the assumption of normal distribution of residual series, the conditional probability density of return R_t in regime M_t is as follows:

$$f(R_t \mid M_t = b, I_{t-1}; \theta) = \frac{1}{\sqrt{2\pi}\sigma(b)} \exp\left[\frac{-(R_t - \nu(b))^2}{2\sigma^2(b)}\right]. \tag{2}$$

When the probability of $f(M_t = b|I_{t-1}; \theta)$ is known, the probability density of R_t under the complete information condition I_{t-1} is expressed as follows:

$$\begin{aligned} f(R_t \mid I_{t-1}; \theta) = {} & p(M_t = 1 \mid I_{t-1}; \theta) f(R_t \mid M_t = 1, I_{t-1}; \theta) \\ & + p(M_t = 2 \mid I_{t-1}; \theta) f(R_t \mid M_t = 2, I_{t-1}; \theta) \\ & + \cdots + p(M_t = k \mid I_{t-1}; \theta) f(R_t \mid M_t = k, I_{t-1}; \theta), \end{aligned} \tag{3}$$

where I_{t-1} represents the value of all variables R_t in state M_t up to time $t-1$, that is, all the information contents that can be obtained up to time $t-1$, and $\theta = \{p_{\text{ab}}, \nu_i(M_t), \phi_a(M_t), \sigma_a(M_t)\}$ represents the set of model parameters, which can be estimated by the logarithmic likelihood function of the MS(M)-AR(P) model.

To identify the return series of carbon market corresponding to the certain state presented by the maximum smoothing probability, this paper takes 0.5 as the critical value of smoothing probability of each state. The sample selection is based on $p(M_t = b \mid I_T; \theta) > 0.5 \Rightarrow R(\text{state}_t)$.

3.2. Designing the Risk Contagion Model. According to the connotation of risk contagion proposed by Andrew [2], Forbes and Rigobon [3] and Renée et al. [4] put a significant method for detecting contagion; that is, the contagion exists if the correlation between markets increases significantly after financial shocks.

Therefore, the methodology of this paper adopts this idea of risk detection and conducts the statistics model of high-order moment contagion proposed by Zhang et al. [29] to solve the problem of risk contagion in the carbon market. That is, we employed the FR, CS, and CK statistical model to detect the contagion in correlation channel, coskewness channel, and cokurtosis channel, respectively. The difference between this paper and Renée et al. [31] is to detect the risk contagion caused by market volatility heterogeneity, rather than just considering the financial crisis.

3.2.1. Risk Contagion Model of the Correlation Channel. The risk contagion model of correlation channel measures the low-order moment correlation of return between carbon market and its infected markets; the model tests for a significant increase in this correlation coefficient after a shock. The cross-market correlation coefficients show as follows:

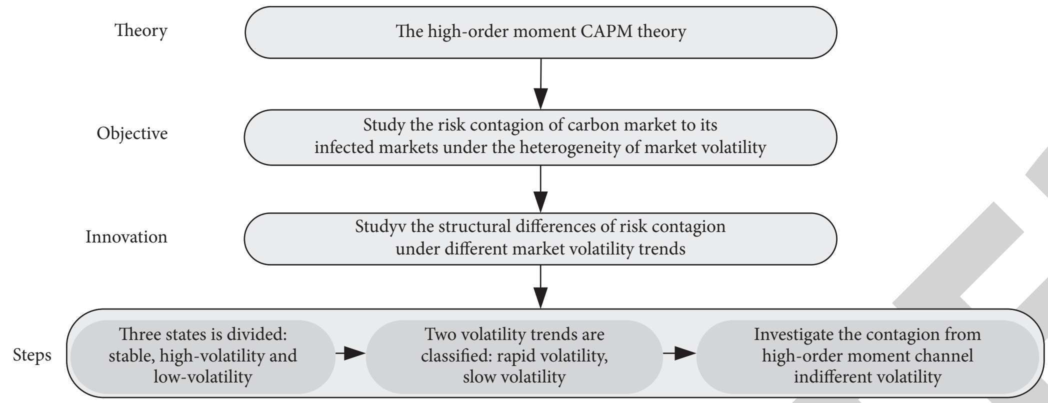

Figure 1: The logic frame of this article.

$$\mathrm{FR}(i \longrightarrow j) = \left(\frac{\hat{v}_{y/x_i} - \hat{\rho}_x}{\sqrt{\mathrm{Var}\left(\hat{v}_{y/x_i} - \hat{\rho}_x\right)}} \right)^2, \qquad \hat{v}_{y/x_i} = \frac{\hat{\rho}_y}{\sqrt{1 + \left(s_{y,i}^2 - s_{x,i}^2/s_{x,i}^2\right)\left(1 - \hat{\rho}_y^2\right)}}, \tag{4}$$

where i and j represents the sourced market (carbon market) and infected market (carbon homogeneous market, capital market, and energy market); x and y represents the volatility state of carbon market; and $\hat{v}_{y/x_i}$ indicates the market correlation coefficient after the transition of volatility state. $\hat{\rho}_x$ and $\hat{\rho}_y$ denotes the unconditional correlation coefficient of the two markets under different market volatility while $s_{x,i}^2$ and $s_{y,i}^2$ denotes the variance of the sourced markets. If the correlation coefficient increases significantly, this suggests that the transmission mechanism between the two markets strengthened after the shock and contagion occurred.

To test a significant change in correlation coefficients of *FR* between carbon market and its infected markets under different volatility trends, the null and alternative hypotheses of *FR* are as follows:

$$H(\mathrm{FR})_0\colon \hat{v}_{y/x_i} = \hat{\rho}_x, \qquad H(\mathrm{FR})_1\colon \hat{v}_{y/x_i} \neq \hat{\rho}_x. \tag{5}$$

Under the null hypothesis of no contagion, tests of contagion based on changes in the channel of FR are asymptotically distributed as follows:

$$\mathrm{FR}(i \longrightarrow j) \xrightarrow{\mathrm{df}} \chi_1^2. \tag{6}$$

3.2.2. Risk Contagion Model of the Coskewness Channel. The coskewness contagion model is a measure of whether the asymmetry of portfolio return between carbon market and its infected markets has changed significantly during different market volatility trend [31]. According to the difference between the market horizontal return and square return in calculating the coskewness coefficient, the test of coskewness is divided into two categories: CS_{12} and CS_{21}, where CS_{12} represents the transmission from the return of carbon market to the variance of infected markets and CS_{21} represents the transmission of carbon market variance to the return of infected markets. The smaller contagion coefficient indicates the joint distribution of portfolio is close to the standard distribution and faces less asymmetric risk.

$$\mathrm{CS}_{12}\left(i \longrightarrow j; r_i^1, r_j^2\right) = \left(\frac{\hat{\psi}_y\left(r_i^1, r_j^2\right) - \hat{\psi}_x\left(r_i^1, r_j^2\right)}{\sqrt{\left(4\hat{v}_{y/x_i}^2 + 2\right)/T_y + \left(4\hat{\rho}_x^2 + 2\right)/T_x}} \right)^2,$$
$$\mathrm{CS}_{21}\left(i \longrightarrow j; r_i^2, r_j^1\right) = \left(\frac{\hat{\psi}_y\left(r_i^2, r_j^1\right) - \hat{\psi}_x\left(r_i^2, r_j^1\right)}{\sqrt{\left(4\hat{v}_{y/x_i}^2 + 2\right)/T_y + \left(4\hat{\rho}_x^2 + 2\right)/T_x}} \right)^2, \tag{7}$$

where

$$\hat{\psi}_y\left(r_i^1, r_j^2\right) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{\mathrm{yi}}}{\hat{\sigma}_{\mathrm{yi}}} \right)^1 \left(\frac{y_{j,t} - \hat{\mu}_{\mathrm{yj}}}{\hat{\sigma}_{\mathrm{yi}}} \right)^2,$$
$$\hat{\psi}_y\left(r_i^2, r_j^1\right) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{y_{i,t} - \hat{\mu}_{\mathrm{yi}}}{\hat{\sigma}_{\mathrm{yi}}} \right)^2 \left(\frac{y_{j,t} - \hat{\mu}_{\mathrm{yj}}}{\hat{\sigma}_{\mathrm{yi}}} \right)^1,$$
$$\hat{\psi}_x\left(r_i^1, r_j^2\right) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{\mathrm{xi}}}{\hat{\sigma}_{\mathrm{xi}}} \right)^1 \left(\frac{x_{j,t} - \hat{\mu}_{\mathrm{xj}}}{\hat{\sigma}_{\mathrm{xi}}} \right)^2,$$
$$\hat{\psi}_x\left(r_i^2, r_j^1\right) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{x_{i,t} - \hat{\mu}_{\mathrm{xi}}}{\hat{\sigma}_{\mathrm{xi}}} \right)^2 \left(\frac{x_{j,t} - \hat{\mu}_{\mathrm{xj}}}{\hat{\sigma}_{\mathrm{xi}}} \right)^1. \tag{8}$$

In the above model, $\hat{\psi}_x$ and $\hat{\psi}_y$ represents the market skewness correlation coefficient between market i and j in volatility state x and y. r_i^1 and r_j^2 denotes the first and second order moment of market i and j, while r_i^2 and r_j^1 denotes the second and first order moment of market i and j, respectively. T_x and T_y means the market capacity under different volatility; $x_{i,t}$, $x_{j,t}$, $y_{i,t}$, and $y_{j,t}$ represents the return of sourced market and infected market under the state of x and y, respectively; $\hat{\mu}_{\mathrm{xi}}$, $\hat{\mu}_{\mathrm{xj}}$, $\hat{\mu}_{\mathrm{yi}}$, and $\hat{\mu}_{\mathrm{yj}}$ represents the mean corresponding to the above returns, respectively; $\hat{\sigma}_{\mathrm{xi}}$, $\hat{\sigma}_{\mathrm{xj}}$, $\hat{\sigma}_{\mathrm{yi}}$, and $\hat{\sigma}_{\mathrm{yj}}$ means the standard deviation of the above returns, respectively; $\hat{v}_{y/x_i}$ indicates the market correlation coefficient after the transition of volatility state.

To test for a significant change in coskewness between carbon market and its infected markets under different volatility trends, the null and alternative hypotheses of CS_{12} are as follows:

$$\begin{aligned} &H\left(CS_{12}\right)_0\text{: } \widehat{\psi}_y\left(r_i^1, r_j^2\right) = \widehat{\psi}_x\left(r_i^1, r_j^2\right),\\ &H\left(CS_{12}\right)_1\text{: } \widehat{\psi}_y\left(r_i^1, r_j^2\right) \neq \widehat{\psi}_x\left(r_i^1, r_j^2\right). \end{aligned} \tag{9}$$

The null and alternative hypotheses of CS_{21} are as follows:

$$\begin{aligned} &H\left(CS_{21}\right)_0\text{: } \widehat{\psi}_y\left(r_i^2, r_j^1\right) = \widehat{\psi}_x\left(r_i^2, r_j^1\right),\\ &H\left(CS_{21}\right)_1\text{: } \widehat{\psi}_y\left(r_i^2, r_j^1\right) \neq \widehat{\psi}_x\left(r_i^2, r_j^1\right). \end{aligned} \tag{10}$$

Under the null hypothesis of no contagion, tests of contagion based on changes in coskewness are asymptotically distributed as follows:

$$CS_{12}(i \longrightarrow j) \xrightarrow{\text{df}} \chi_1^2, CS_{21}(i \longrightarrow j) \xrightarrow{\text{df}} \chi_1^2. \tag{11}$$

3.2.3. Risk Contagion Model of the Cokurtosis Channel. The cokurtosis contagion model is a measure of whether the portfolio between carbon market and its infected markets is affected by policy shocks or external events. Similar to the coskewness contagion model, this study divides the cokurtosis contagion test into two categories: CK_{13} and CK_{31}, where CK_{13} represents the contagion of carbon return to the skewness of infected markets, and CK_{31} means the contagion of carbon market skewness to infected market return. The higher contagion coefficient indicates that portfolio returns face greater impact of systematic risk, while the smaller coefficient indicates lower systemic risk.

$$\begin{aligned} CK_{13}\left(i \longrightarrow j; r_i^1, r_j^3\right) &= \left(\frac{\widehat{\xi}_y\left(r_i^1, r_j^3\right) - \widehat{\xi}_x\left(r_i^1, r_j^3\right)}{\sqrt{\left(18\widehat{\upsilon}_{y/x_i}^2 + 6\right)/T_y + \left(18\widehat{\rho}_x^2 + 2\right)/T_x}}\right)^2,\\ CK_{31}\left(i \longrightarrow j; r_i^3, r_j^1\right) &= \left(\frac{\widehat{\xi}_y\left(r_i^3, r_j^1\right) - \widehat{\xi}_x\left(r_i^3, r_j^1\right)}{\sqrt{\left(18\widehat{\upsilon}_{y/x_i}^2 + 6\right)/T_y + \left(18\widehat{\rho}_x^2 + 2\right)/T_x}}\right)^2, \end{aligned} \tag{12}$$

where

$$\begin{aligned} \widehat{\xi}_y\left(r_i^1, r_j^3\right) &= \frac{1}{T_y}\sum_{t=1}^{T_y}\left(\frac{y_{i,t} - \widehat{\mu}_{yi}}{\widehat{\sigma}_{yi}}\right)^1\left(\frac{y_{j,t} - \widehat{\mu}_{yj}}{\widehat{\sigma}_{yi}}\right)^3 - \left(3\widehat{\upsilon}_{y/x_i}\right),\\ \widehat{\xi}_y\left(r_i^3, r_j^1\right) &= \frac{1}{T_y}\sum_{t=1}^{T_y}\left(\frac{y_{i,t} - \widehat{\mu}_{yi}}{\widehat{\sigma}_{yi}}\right)^3\left(\frac{y_{j,t} - \widehat{\mu}_{yj}}{\widehat{\sigma}_{yi}}\right)^1 - \left(3\widehat{\upsilon}_{y/x_i}\right),\\ \widehat{\xi}_x\left(r_i^1, r_j^3\right) &= \frac{1}{T_x}\sum_{t=1}^{T_x}\left(\frac{x_{i,t} - \widehat{\mu}_{xi}}{\widehat{\sigma}_{xi}}\right)^1\left(\frac{x_{j,t} - \widehat{\mu}_{xj}}{\widehat{\sigma}_{xi}}\right)^3 - \left(3\widehat{\rho}_x\right),\\ \widehat{\xi}_x\left(r_i^3, r_j^1\right) &= \frac{1}{T_x}\sum_{t=1}^{T_x}\left(\frac{x_{i,t} - \widehat{\mu}_{xi}}{\widehat{\sigma}_{xi}}\right)^3\left(\frac{x_{j,t} - \widehat{\mu}_{xj}}{\widehat{\sigma}_{xi}}\right)^1 - \left(3\widehat{\rho}_x\right). \end{aligned} \tag{13}$$

In the above model, $\widehat{\xi}_x$ and $\widehat{\xi}_y$ represents the market kurtosis coefficient between market i and j in volatility state x and y. r_i^1 and r_j^3 denotes the first and third order moment of market i and j while r_i^3 and r_j^1 denotes the third and first order moment of market i and j, respectively. Other definition of parameters is consistent with the coskewness contagion model defined above. To test the risk contagion of cokurtosis channel between carbon market and its infected markets under different volatility trends, the null and alternative hypotheses of CK13 are as follows:

$$\begin{aligned} &H\left(CK_{13}\right)_0\text{: } \widehat{\xi}_y\left(r_i^1, r_j^3\right) = \widehat{\xi}_x\left(r_i^1, r_j^3\right),\\ &H\left(CK_{13}\right)_1\text{: } \widehat{\xi}_y\left(r_i^1, r_j^3\right) \neq \widehat{\xi}_x\left(r_i^1, r_j^3\right). \end{aligned} \tag{14}$$

The null and alternative hypotheses of CK_{31} are as follows:

$$\begin{aligned} &H\left(CK_{31}\right)_0\text{: } \widehat{\xi}_y\left(r_i^3, r_j^1\right) = \widehat{\xi}_x\left(r_i^3, r_j^1\right),\\ &H\left(CK_{31}\right)_1\text{: } \widehat{\xi}_y\left(r_i^3, r_j^1\right) \neq \widehat{\xi}_x\left(r_i^3, r_j^1\right). \end{aligned} \tag{15}$$

Under the null hypothesis of no contagion, tests of contagion based on changes in cokurtosis are asymptotically distributed as follows:

$$CK_{13}(i \longrightarrow j) \xrightarrow{\text{df}} \chi_1^2, CK_{31}(i \longrightarrow j) \xrightarrow{\text{df}} \chi_1^2. \tag{16}$$

3.3. Samples and Data Preprocessing. The carbon market is not only closely related to carbon homogeneous market and capital market but also related to the energy market [33]. Furthermore, this article chooses the EUAs (European Union Allowance spot) as the representation of the carbon homogeneous market. The others infected market of capital market and energy market are shown in Table 1. We choose the traded products of coal, oil, natural gas, and electricity markets as the energy market variables, and the data sourced from the Wind Database. The research samples with the period from June 2, 2009, to March 23, 2020, and there are total of 2768 samples by

Table 1: The designing of research samples.

Specific market	Typical market products	Abbreviation	Meaning of market products
Panel A: sourced market and data from intercontinental exchange (ICE)			
Carbon market	EUA future market	EUAf	Settlement price of continuous futures contract of EUA
Panel B: infected market and data from Wind Database			
Carbon homogeneous market	EUA spot market	EUAs	Settlement price of continuous spots contract of EUA
Capital market	Dow jones industrial average	DJIA	Closing price of DJIA from the US
	EURUSD	EURUSD	Closing price of EURUSD
	USD-index	USDX	Closing price of USDX
Energy market	Coal market	Coal	Futures settlement price of British thermal coal
	Brent oil market	Oil	Futures settlement price of Brent crude oil
	Natural gas market	Gas	UK natural gas continuous futures prices
	Electricity market	Electricity	US electricity retail prices

eliminating the sample missing and time inconsistency. The return is expressed as R_t, and $R_t = 100\times(\ln P_t\text{-}\ln P_{t-1})$, where P_t denotes the price of market products.

This article defines the contagion of high-order moment channel in the carbon market as a change caused by irrational behavior and policy shocks; this definition makes the sample's return contain more transaction noise, for example, the trading psychology and behavior information. To solve this problem, this research uses the VAR model to fit the original return series according to the suggestion of Forbes and Rigobon [3] and takes the residual as the substitution for measuring the contagion to control the influence of market fundamentals; the improved model of VAR is expressed as follows:

$$Z_t = \omega(L)Z_t + \varepsilon_t, \tag{17}$$

where $Z_t = \left\{R_{\text{it}}, R_{\text{jt}}\right\}$ is the combined return sequence of the source and infected market during the state transformation; ε_t is the residual sequence for computing the contagion statistics; $\omega(L)$ is a vector of lags; the VAR lag order is determined according to the Akaike information criterion (AIC) and Bayesian information criterion (BIC).

4. Empirical Results and Discussion

The empirical test of methodology is carried out (as showed in Figure 2) according to the following steps:

Step 1: dividing the volatility state of carbon market into stable volatility (S1), high volatility (S2), and low volatility (S3) and then clarifying the volatility trend into the rapid volatility trend (S1–S2) and slow volatility trend (S1–S3)

Step 2: examining whether there is high-order moment contagion relationship between carbon market and its infected market from the channels FR, CS, and CK, respectively

Step 3: summarizing the contagion direction and strength in the carbon market and testing the robustness of above conclusion

4.1. Identifying the Volatility Trend of Carbon Market

4.1.1. Selecting the State Transformation Model. To divide the market state accord with the characteristics of carbon price volatility and avoid the errors caused by setting the state parameter in subjectively, the performance of alternative models under different volatility states is compared according to the AIC and BIC minimization principle. As shown in Table 2, it is found that the model of MS (3)-AR (3) is more suitable for the state division of the carbon market than other models.

4.1.2. Clarifying the Volatility State and Trend. Research result shown in Table 3 reveals that the standard deviations of the three states are 1.17%, 6.94%, and 2.39%, respectively, which can define as the state of market stability, high volatility, and low volatility according to the estimation results of MS (3)-AR (3) model. Furthermore, the standard deviation of high volatility is equal to three times of the low volatility state and six times of stable volatility state, and the value of low volatility state is two times of stable volatility state. As a result, the volatility in different states of carbon market varies greatly and makes the impact of systemic risk on market returns vary fiercely.

Based on the volatility states divided above, the difference of volatility coefficient between state1 and state 2 is 5.77%, 1.22% for S1 and S3, and 4.55% for S2 and S3. Therefore, the state transformation difference of 5.77% and 1.22% is highly representative in denoting the maximum and minimum market volatility state differences. Based on this, we consider the volatility difference of the three states; this article defines the transformation between S1 and S2 and S1 and S3 as the representative transmission channel for measuring the risk contagion. Correspondingly, those two channels further divide into two trends: rapid volatility and slow volatility. Among them, the rapid change of volatility is divided into two kinds of trends: volatility rise rapidly (contagion from stable state to high volatility state, S1–S2) and volatility decline rapidly (contagion from high volatility state to stable state, S2–S1); and slow volatility is divided into volatility rise slowly (contagion from stable state to slow volatility state, S1–S3) and volatility decline slowly (contagion from slow volatility state to stable state, S3–S1).

Figures 3–5, respectively, show the relationship between carbon assets and standard price changes of the homogeneous market, capital market, and energy market. It can be found that the market price trend of carbon assets and homogeneous products is basically the same regardless of

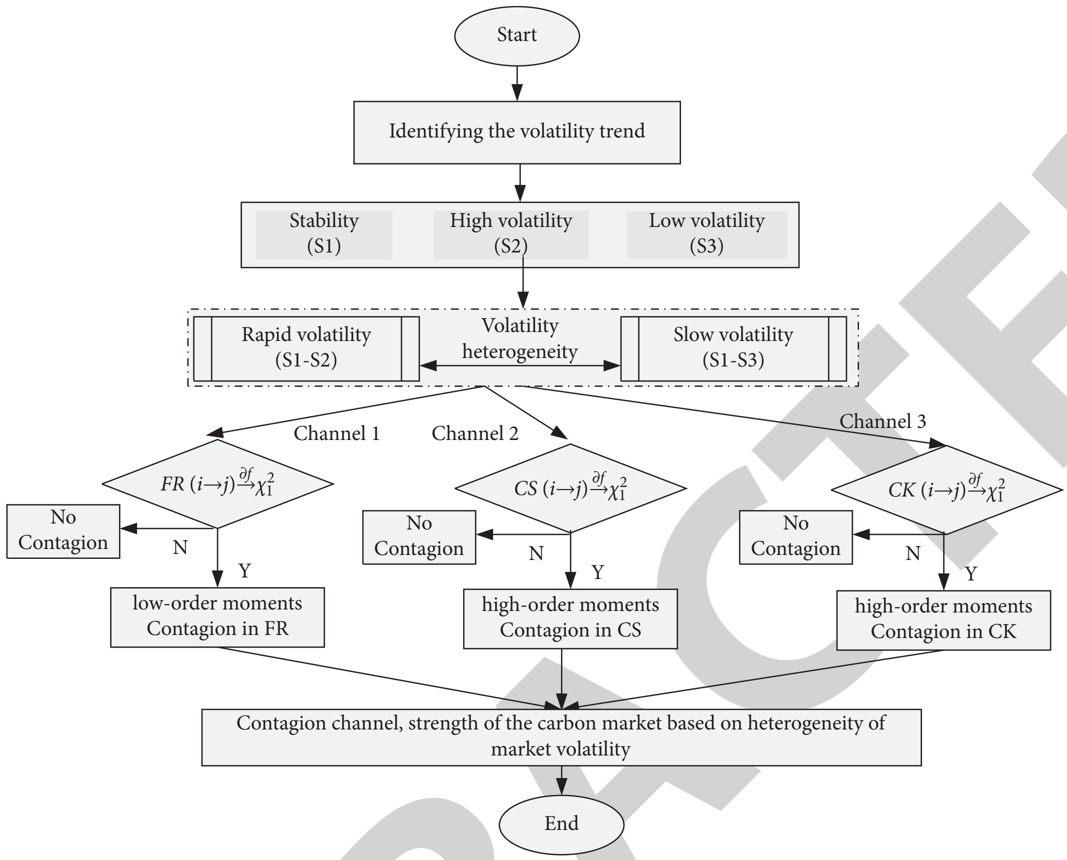

Figure 2: The flowchart of empirical design in this paper.

Table 2: Performance comparison of different state transition models of the carbon market.

Alternative model	Residual distribution	Number of parameters	Likelihood value	AIC	BIC
MS(2)-AR(3)	T	16	6477.4992	−12922.9984	−12899.9263
	N	14	6379.8549	−12731.7098	−12711.5217
MS(2)-AR(4)	T	18	6375.5774	−12715.1548	−12689.1986
	N	16	6380.1796	−12728.3592	−12705.2871
MS(3)-AR(3)	T	27	6487.9839	−12921.9678	−12883.0336
	N	24	6517.1826	−12986.3652	−12951.7569
MS(3)-AR(4)	T	30	6488.3855	−12916.771	−12873.5107
	N	27	6517.7822	−12981.5644	−12942.6302
MS(4)-AR(3)	T	40	6518.2154	−12956.4308	−12898.7504
	N	36	6465.1356	−12858.2712	−12806.3589
MS(4)-AR(4)	T	44	6510.2059	−12932.4118	−12868.9634
	N	40	6526.3629	−12972.7258	−12915.0454

the change of volatility state. This result is basically consistent with the research of Chevallier [10] that the EUA future price guides the spot price. The possible reason is that carbon assets and their homogeneous products have the same trading attributes, their price driving mechanism is relatively similar, and futures products have a strong price discovery function for spot products [27].

4.2. Analyzing High-Order Moments Statistics. Research result shows in Table 4, in term of the portfolio with carbon homogeneous products, as the volatility changes from stable to high volatility (S1–S3–S2), the increasing risk lead the coskewness coefficient of EUAf and EUAs decrease gradually and turn to negative; the result indicates that the return of portfolio composed of EUA futures and spot has significant asymmetry effect; that is, the probability of return decline is greater than that of rise. Additionally, the increasing of cokurtosis coefficient means the return faces increasing external risk shocks.

As for the portfolio with the capital market, Table 4 shows negative coskewness statistic and decreased significantly as the increasing of market volatility. The result proves that the portfolio return has significant asymmetry; the

Table 3: Parameters estimation of state transition of the carbon market based on MS (3)-AR (3) model.

State	Coefficient of volatility (%)	State description	Transition probabilities	Duration	Standard error	P value
S1	1.17***	Stability	0.99	74.98	0.0003	≤0.000
S2	6.94***	High volatility	0.88	8.11	0.0029	≤0.000
S3	2.39***	Low volatility	0.97	39.01	0.0004	≤0.000

Note. ***The statistical significance at the 1% level.

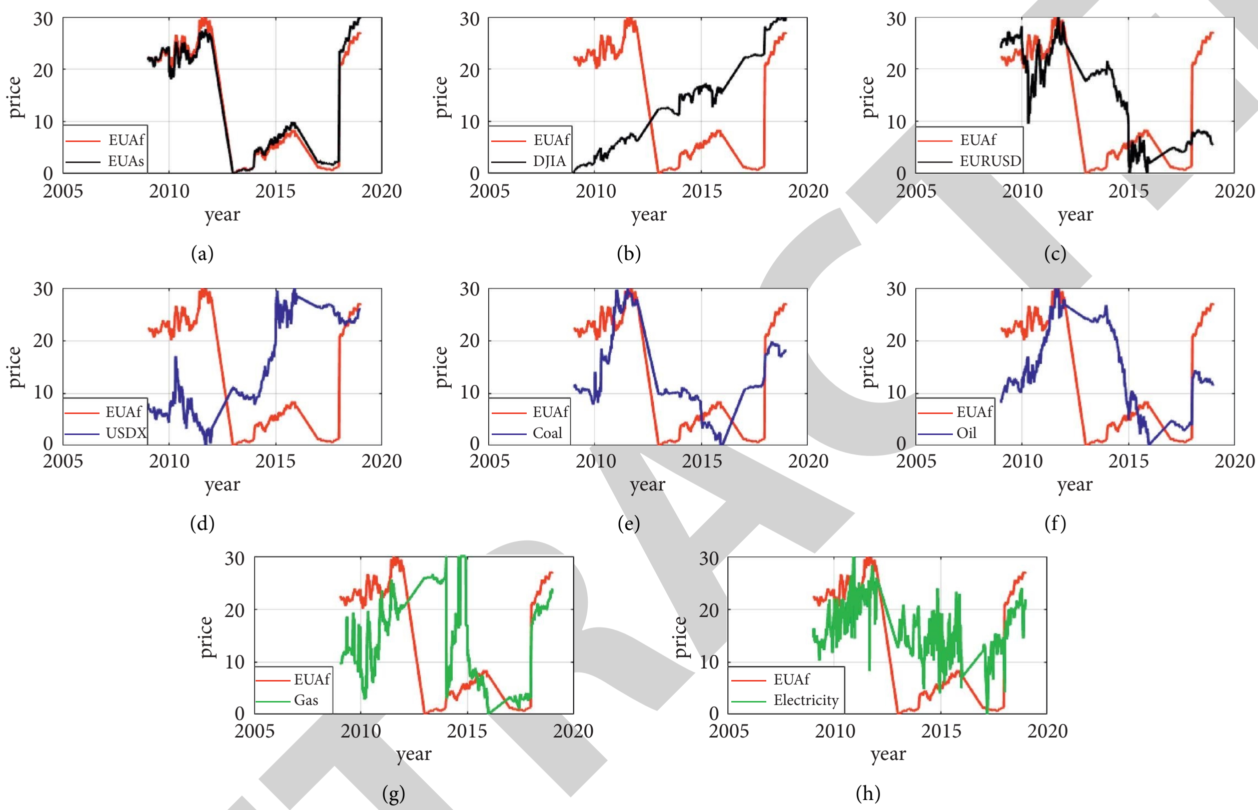

Figure 3: Standardized price change between carbon asset and its pricing factors in stable state (S1). (a) EUAf-EUAs. (b) EUAf-DJIA. (c) EUAf-EURUSD. (d) EUAf-USDX. (e) EUAf-coal. (f) EUAf-oil. (g) EUAf-gas. (h) EUAf-electricity.

probability of return decline and rise is quite different according to the coskewness coefficient. For the coefficient of cokurtosis, however, the portfolio suffers less impact from the external events because the cokurtosis is small in most cases. Therefore, the volatility of the carbon market and capital market is basically stable; the portfolio of those two markets can avoid investment risks effectively.

As for the portfolio with the energy market, the cokurtosis of joint distribution between EUAf and gas is the largest and negative in the stable stage, the result indicates that the distribution of those two markets is extremely different, and they are not effective substitutions for portfolio.

4.3. Analyzing the Risk Contagion of the High-Order Moment Channel. We find a valuable conclusion from Tables 5 and 6 that there is a significant risk contagion effect from the carbon market to its infected markets in majority of the high-order moment channels rather than the FR contagion in low-order perspective both in rapid and slow volatility trend. This conclusion convinced that the shock of market irrationality and external events measured by the high-order moment contagion channels are essential risk factors that affect its infected markets. An extended finding is that we may get wrong or inaccurate conclusions if only the correlation coefficient in the view of low-order moments is used to judge the existence of risk contagion.

4.3.1. Analyzing the Risk Contagion in the Rapid Volatility Trend. Empirical results showed that, as in Table 5, when the market in trend of rapid volatility, the number of significance in the high-order moment channels is the largest compared with other infected markets as for the homogeneous markets. There is a significant risk contagion from the carbon market to its homogeneous markets in all the high-order moment channels along with the significant FR contagion in the low-order perspective. This conclusion proved that the shock of market irrationality and external

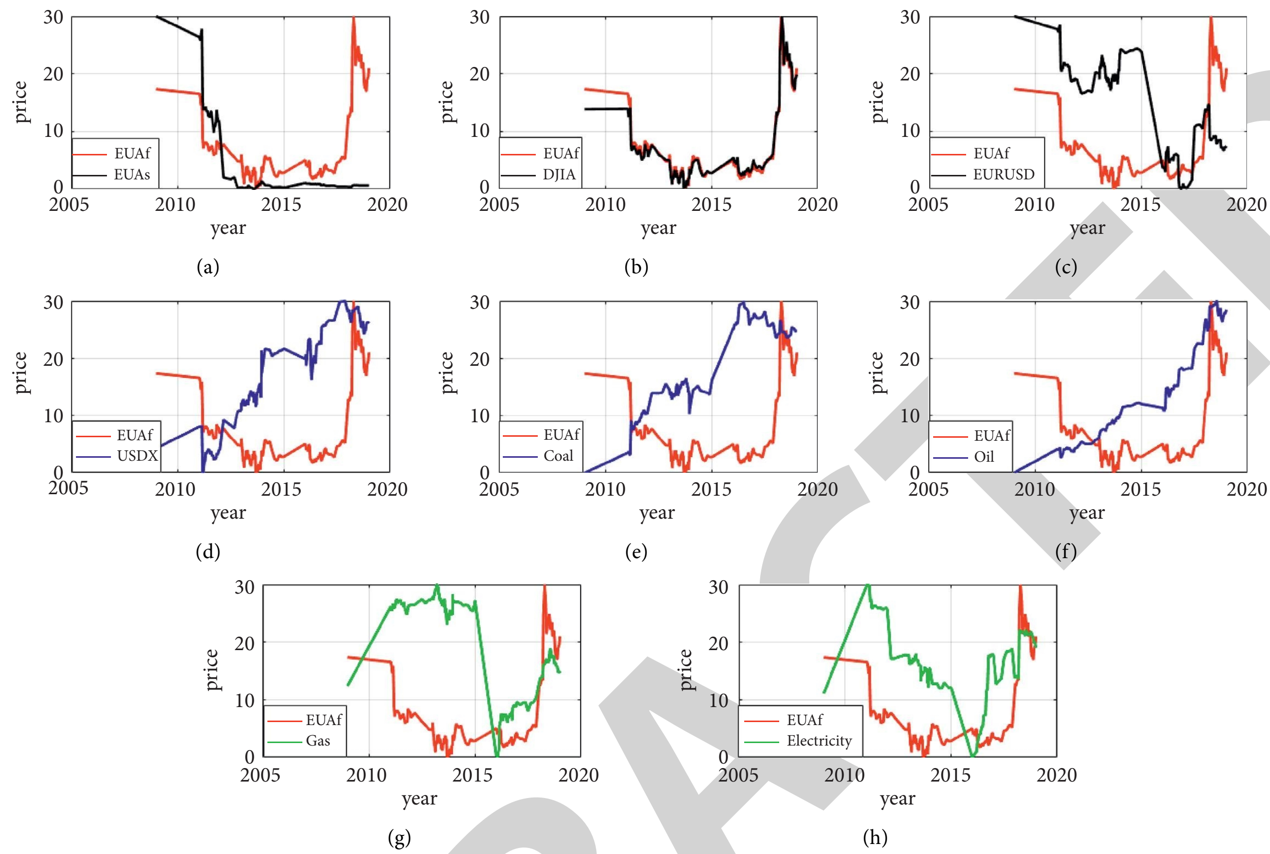

Figure 4: Standardized price change between carbon asset and its pricing factors in high volatility state (S2). (a) EUAf-EUAs. (b) EUAf-DJIA. (c) EUAf-EURUSD. (d) EUAf-USDX. (e) EUAf-coal. (f) EUAf-oil. (g) EUAf-gas. (h) EUAf-electricity.

events sourced from the carbon market are essential risk factors that affect its homogeneous markets. The possible reason is that the price trend and market volatility of EUAf and EUAs are basically the same, the EUAf plays a guidance in the price discovery of the EUAs [8], and as a result, the trading risk and extreme risk of EUAf market can be easily transmitted to the EUAs market; this conclusion have proved in the study of Wang and Guo [1] that the European carbon future market implies more complex systemic risk than other carbon products markets. Additionally, the number of significance for the infected market of DJIA, oil, and electricity market are second only to significance number of EUAs. The number of significance for the EURUSD and coal is the smallest of all the market.

However, the number of significance for the infected market of capital market is generally equal to that of energy market. This shows that the asymmetric and extreme risk of carbon market can easily affect the capital market and energy market in rapid volatility trend although these two kinds of markets have different effects on dispersing carbon risk in the long run.

Further empirical results suggest that the contagion strength transmits from the EUAf to its infected market and is significantly different according to different volatility trend. Table 5 shows that the contagion of EUAf to EUAs in volatility rapid rise trend is higher for all the significant high-order moment channels than in volatility rapid decline trend. The possible reason is that the volatility rapid rise corresponds to more systematic risk (e.g., market asymmetric risk and extreme risk) which leads to a higher contagion coefficient than the volatility rapid decline trend. The conclusion is generally same with the research of risk contagion in the global stock market that was carried out by Forbes et al. and Renée et al. [3, 4]. The coskewness contagion of EUAf to DJIA in CS12 and CS21, EURUSD and electricity in CS21, and USDX in CS12 and CS21; contagion from EUAf to coal and gas in the channel of CS12; and contagion from EUAf to oil in CS12 and CS21 are higher in trend of volatility rapid rise than that of volatility rapid decline. The possible explanation is that the rapid rise of market volatility hides the possibility of continuous increasing of risk as risk averse agents prefer positive skewness to negative skewness [34]; investors will require more coskewness and expect to achieve more returns to offset the systemic risk. While the rapid decline of volatility means the declining of market risk, the lower market skewness can satisfy investors' expectations; therefore, the coskewness contagion coefficient in volatility rise rapidly trend is larger than that of decline trend.

Another evidence that convinces the stronger contagion in volatility rise rapidly trend concludes that the contagion coefficient from the sourced EUAf market to majority of its infected market in the channel of CK13 and CK31 are

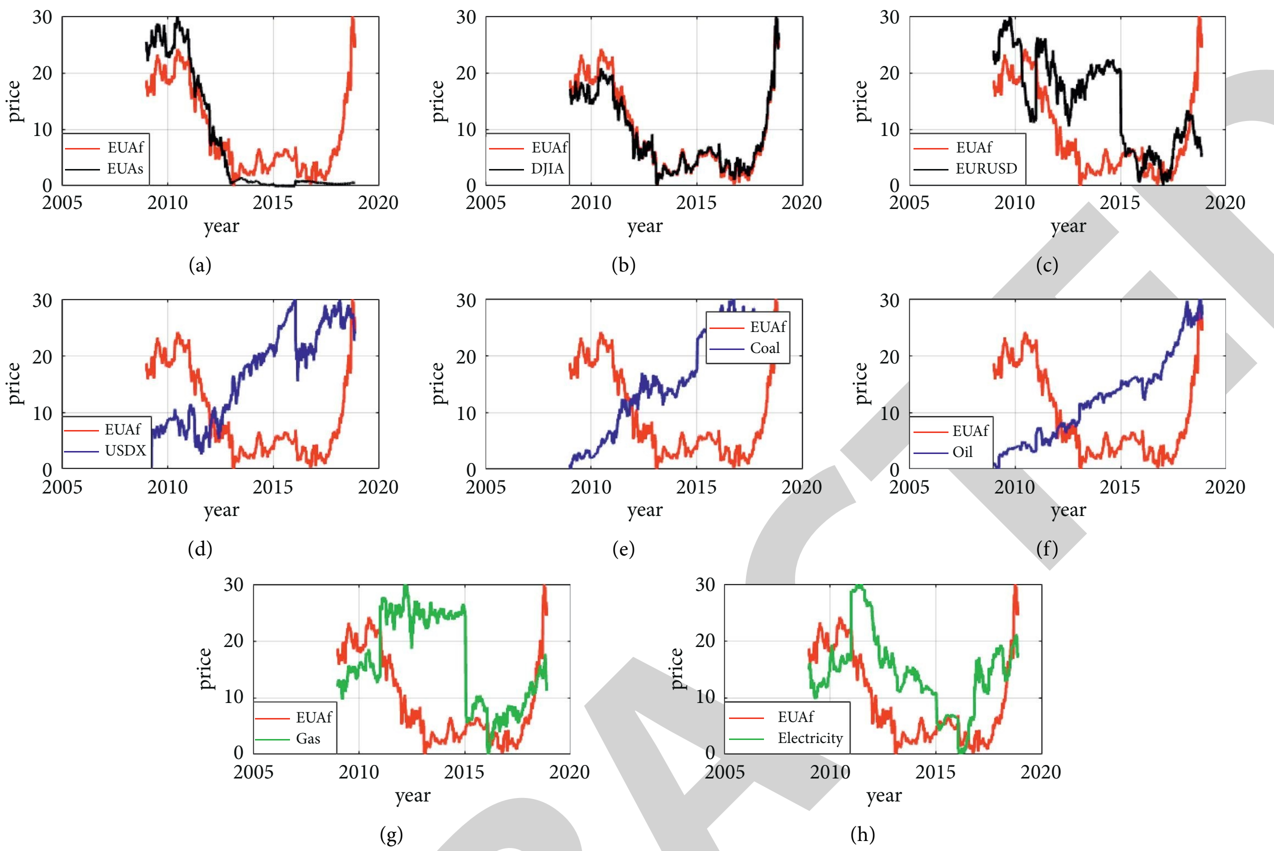

FIGURE 5: Standardized price change between carbon asset and its pricing factors in low volatility state (S3). (a) EUAf-EUAs. (b) EUAf-DJIA. (c) EUAf-EURUSD. (d) EUAf-USDX. (e) EUAf-coal. (f) EUAf-oil. (g) EUAf-gas. (h) EUAf-electricity.

TABLE 4: Descriptive statistics for the high-order moments coefficients of joint distribution between carbon market and its infected markets.

	State	EUAs	DJIX	EURUSD	USDX	Coal	Oil	Gas	Electricity
	S1	0.115	−0.011	−0.004	−0.049	0.124	−0.037	0.513	0.056
Coskewness12	S3	−0.141	0.063	−0.058	−0.061	−0.082	−0.078	−0.141	−0.306
	S2	−0.657	−0.805	−0.165	−0.342	−0.97	−0.439	−0.177	−0.367
	S1	0.111	0.085	−0.021	0.039	0.046	−0.045	0.008	−0.058
Coskewness21	S3	−0.084	−0.052	−0.042	0.047	−0.014	−0.041	−0.036	−0.057
	S2	−0.406	−0.026	−0.158	−0.103	0.014	−0.135	−0.032	−0.014
	S1	1.925	−0.236	0.675	−0.813	0.069	0.601	3.372	0.463
Cokurtosis13	S3	2.010	−1.028	0.298	−0.53	0.491	1.167	0.239	0.521
	S2	4.903	1.810	0.362	−0.011	0.917	3.392	1.276	2.594
	S1	1.604	0.009	0.483	−0.446	0.513	0.319	0.244	0.238
Cokurtosis31	S3	1.784	0.145	0.121	−0.211	0.163	0.285	0.373	0.352
	S2	3.421	0.451	1.188	1.101	0.113	0.578	0.591	0.437

generally higher in trend of volatility rise rapidly than in volatility decline rapidly. This can be explained by the higher systemic risk consistent with the volatility rise rapidly trend.

4.3.2. Analyzing the Risk Contagion in the Slow Volatility Trend. The empirical results showed in Table 6 that the number of significance in high-order moment contagion channels for the infected market of EUAs market is the highest among other infected markets when the market is in slow volatility trend. This conclusion is proved in above analysis. The number of significance for the infected market of DJIA,USDX, oil, gas, and electricity market are second only to significance number of EUAs. This indicates that asymmetric and extreme risks of the carbon market are more easily transmitted to these three markets rather than others during the slow volatility trend. When the carbon market is in slow volatility trend, there is less systemic risk than the rapid volatility trend; investors have enough time to develop portfolio strategies and increase

Table 5: Risk contagion in high-order moment channels from carbon market to its infected markets under the rapid volatility trend.

Carbon homogeneous market		Capital market			Energy market			
	EUAs	DJIA	EURUSD	USDX	Coal	Oil	Gas	Electricity
Panel A: rapid decline in volatility of EUAf (S2-S1)								
FR	2.85***	0.01	3.11	2.25	0.92	1.11	0.08**	0.08*
CS12	22.35***	19.88***	1.21	3.56***	6.1**	11.87***	24.78***	0.62
CS21	7.21***	0.03***	1.92***	2.08***	0.25	0.44***	0.01	0.47***
CK13	163.34***	10.95***	39.12	41.04	198.6***	289.9***	123.29	42.88***
CK31	87.59***	19.22***	21.81***	18.1***	36.9	85.18***	40.68***	44.45***
Panel B: rapid rise in volatility of EUAf (S1–S2)								
FR	15.5***	0.09	0.62	0.59	0.34	1.51	0.27**	0.16*
CS12	37.5***	21.87***	1.48	4.33***	7.05**	14.53***	30.23***	0.69
CS21	12.09***	0.04***	2.34***	2.53***	0.06	0.53***	0.01	0.53***
CK13	387.49***	11.67***	4.86	3.61	0.29***	293.5***	294.11	45.49***
CK31	222.49***	19.53***	26.24***	19.2***	0.44	114.3***	49.03***	46.31***

Note. S1, S2, and S3 denotes the stability, high volatility and low volatility state of the carbon market, respectively. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Risk contagion in high-order moment channels from carbon market to its infected markets under the slow volatility trend.

Carbon homogeneous market		Capital market			Energy market			
	EUAs	DJIA	EURUSD	USDX	Coal	Oil	Gas	Electricity
Panel A: slowly decline in volatility of EUAf (S3–S1)								
FR	0.59***	0.02**	0.03**	0.41***	0.01***	0.02***	0.04***	0.09***
CS12	7.24***	32.29***	1.01	0.03**	11.13	0.48***	128.44	5.15**
CS21	3.71**	3.46	0.35	0.03	0.67	0.002	0.73	0.12
CK13	14.27***	3.45***	11.34***	11.9***	17.26***	70.1***	1.39***	0.02***
CK31	17.31**	9.07	11.62	14.54	2.54	15.17	8.39*	4.61
Panel B: slowly rise in volatility of EUAf (S1–S3)								
FR	10.72***	0.09**	0.61**	0.61***	0.33***	0.47***	0.27***	0.15***
CS12	10.25***	45.16***	1.12	0.03**	11.96	0.49***	135.63	5.52**
CS21	5.24**	4.26	0.39	0.03	0.73	0.004	0.77	2.11
CK13	30.88***	2.21***	11.21***	11.76***	43.59***	72.5***	1.64***	0.91***
CK31	36.36***	5.43	10.05	0.63	0.36	2.99	8.91*	2.001

Note. S1, S2, and S3 denotes the stability, high volatility, and low volatility state of the carbon market, respectively. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1%, respectively.

the possibility of rational investment behavior. As we know, the DJIA, which reflects the global macroeconomy, has become an important investment tool for carbon investors to diversify risks and obtain excess returns [6]. The global economy affects the trend of carbon price, the price volatility of oil market hides real arbitrage opportunities for the carbon market investors, and therefore, these markets are more likely to be affected by the risk contagion of high-order moment channels from the carbon market. Additionally, the number of significance for the infected market of EURUSD and coal market is the smallest of all the market.

Further empirical results suggest that the contagion strength is significantly different according to different volatility trend. Table 6 shows that the contagion strength in slow rise of market volatility is higher in majority of case than that of slow decline volatility for the high-order moment contagion channel of CS12, CS21, CK13, and CK31. The potential explanation is the slow rise of market volatility promotes the increasing of systemic risk, despite contrasted to the increase of risk in rapid volatility trend analyzed above, the slow rise of market volatility can still increase the portfolio risk impacted by extreme events and thus improves the risk contagion compared with the slow decline volatility. This conclusion is similar to the previous analysis that the contagion is stronger in volatility rise rapidly trend than decline rapidly trend.

4.4. Robustness Test of the Empirical Results. We now perform some simple variations on our basic analysis, with an eye toward checking robustness with respect to the empirical results above. We choose the subperiod of 2013.1.2–2018.11.14 as the sample span for conducting the robustness test following the same research steps and methods mentioned above. The reason is that since 2013, the European carbon emissions trading system (the world's largest carbon trading market) has entered the third development stage. Compared with the previous two stages, the scope of emission reduction entities has gradually

Table 7: Robustness test of risk contagion in high-order moment channels under the trend of volatility rise rapidly and decline rapidly, respectively.

	Carbon homogeneous market	Capital market				Energy market			
	EUAs	DJIA	STOXX	EURUSD	USDX	Coal	Oil	Gas	Electricity
				Panel A: rapid decline in volatility of EUAf (S2-S1)					
FR	1.57***	0.05	0.05	1.92	0.23	0.016	0.12	0.22	0.03
CS12	12.66***	0.72	0.04	0.69	7.02	1.18***	0.72	19.17***	0.25
CS21	6.81***	0.98**	1.25***	0.001**	1.11***	0.37	0.13	0.08	0.51
CK13	254.41***	13.13*	0.02	16.71	8.49	62.2***	0.02	15.34	2.84
CK31	83.59***	16.32***	4.57***	5.47***	2.51***	0.62**	8.8***	2.81***	0.62***
				Panel B: rapid rise in volatility of EUAf (S1-S2)					
FR	5.65***	0.01	0.03	0.32	0.36	0.02	0.05	0.03	0.01
CS12	20.28***	0.75	0.04	0.79	7.96	1.19***	0.76	21.93***	0.26
CS21	10.89***	0.99**	1.25***	0.02**	1.25***	0.37	0.13	0.12	0.52
CK13	453.45***	4.84*	0.59	5.92	13.41	75.91**	6.96	74.13	0.06
CK31	143.43***	6.68***	8.96***	19.05***	26.2***	1.33***	13.2***	5.95***	1.34***

Note. S1, S2, and S3 denotes the stability, high volatility, and low volatility state of the carbon market, respectively. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% respectively.

Table 8: Robustness test of risk contagion in high-order moment channels under the trend of volatility rise slowly and decline slowly, respectively.

	Carbon homogeneous market	Capital market				Energy market			
	EUAs	DJIA	STOXX	EURUSD	USDX	Coal	Oil	Gas	Electricity
				Panel A: slowly decline in volatility of EUAf (S3–S1)					
FR	0.03***	0.04	0.05	0.01	0.08	0.01	0.008	0.01	0.006
CS12	3.59***	1.66	0.09	3.55**	7.56	5.26***	19.3***	79.35	2.17***
CS21	0.52***	0.26*	0.56	0.86*	0.57	0.39	0.46	0.64	0.35
CK13	230.6***	3.53*	1.86***	0.11***	1.93*	24.91***	8.13***	650.72	168.43*
CK31	12.9***	5.11*	0.67*	9.26	6.52	0.21**	2.64***	0.53**	0.87
				Panel B: slowly rise in volatility of EUAf (S1–S3)					
FR	4.61***	0.04	0.006	0.31	0.35	0.01	0.01	0.03	0.01
CS12	5.08***	1.66	0.09	3.55**	7.69	5.45***	19.4***	79.73	2.23***
CS21	0.73***	0.25*	1.87	0.85*	0.59	0.41	0.39	0.67	0.34
CK13	335.4***	4.82***	3.95***	4.99***	16.59*	27.97***	12.8***	725.11	182.19*
CK31	14.7***	7.58*	0.72*	0.41	0.004	0.23***	2.69***	0.36**	2.06

Note: S1, S2, and S3 denotes the stability, high volatility, and low volatility state of the carbon market, respectively. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1%, respectively.

expanded, the trading products have gradually enriched, and especially the proportion of auctions in the process of quota allocation has gradually increased, while the allocation of free quotas is decreasing.

Tables 7 and 8 illustrate the robustness test of risk contagion from the sourced carbon market to its infected markets in high-order moment channels. The main findings are as follows.

Firstly, there is a significant risk contagion effect from the carbon market to its infected markets in majority of the high-order moment channels rather than the FR contagion in the low-order perspective both in rapid and slow volatility trend. Secondly, the number of significance in the high-order moment channels is the largest compared with other infected markets as for the EUAs both in rapid and slow volatility trend. Thirdly, the contagion strength of carbon market to its infected market in majority of high-order moment channel is higher in volatility rapid and slow rise trend than that of decline trend. Generally, the robustness result of risk contagion is essentially consistent with the conclusion. This demonstrates that the conclusions of this article based on the proposed model are reliable.

5. Conclusions

Research on the risk contagion between carbon market and its infected markets can not only reveal the risk contagion direction and strength but also provide reference for investors. However, the existing studies mainly focus on exploring information linkage and volatility spillover from the perspective of low-order moment attributes of returns. For remedying the defects of the existing research, the contribution of this article is to reveal the significant high-order moment contagion channel and strength of carbon market to its infected market under different market volatility trends and explore the contagious difference caused by volatility trends. Based on the empirical results, some main conclusions are obtained as follows.

Firstly, the contagion of the carbon market to its infected markets happens mostly in the high-order moment channel, rather than the view of the low-order moment channel in previous studies. Secondly, the market of EUAs, DJIA, coal, and oil are more likely to trigger risk contagion in the carbon market.

Thirdly, the contagion strength of EUAf to its infected market is higher in the majority of high-order moment channels than in the slow volatility trend. The possible explanation is the rapid volatility of market trends may hide more systemic risks and uncertainties; the contagion power is higher than the slowly volatility trend.

The methodology measured the risk contagion from the view of high-order moment has potential advantage than other models. Moreover, the methodology makes a significant judgment on the existence of risk contagion before determining the risk contagion coefficient; this measure is consistent with the connotation of risk contagion proposed by King and Wadhwani [35]. However, frankly, this methodology is designed to study contagion relationships only between two assets or two markets; it's unsuitable to study contagion relationships among the capital market, the energy market, and the carbon market at the same time. Therefore, the methodology and the risk contagion model can be improved in the future study to be more suitable for the high-order moment channel risk contagion among the multimarkets case.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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