sustainability

MDPI

Article

The Asymmetric Effects of Extreme Climate Risk Perception on Coal Futures Return Dynamics: Evidence from Nonparametric Causality-In-Quantiles Tests

Wang Gao [1,2], Jiajia Wei [3,*] and Shixiong Yang [4,*]

1 Research Center for Finance and Enterprise Innovation, Hebei University of Economics and Business, Shijiazhuang 050062, China; gaowang@hueb.edu.cn
2 School of Finance, Hebei University of Economics and Business, Shijiazhuang 050062, China
3 School of Mathematics and Statistics, Beijing Technology and Business University, Beijing 102488, China
4 School of Statistics, Renmin University of China, Beijing 100872, China
* Correspondence: 20190756@btbu.edu.cn (J.W.); sy1800@ruc.edu.cn (S.Y.)

Abstract: This paper uses nonparametric causality-in-quantiles tests to examine the asymmetric effects of climate risk perception (CRP) on the thermal and coking coal futures high-frequency returns and volatilities. The results show that CRP significantly impacts the dynamic high-frequency returns of the coal futures market, with volatility indicators exhibiting asymmetry at different percentiles and being more pronounced in a downward market. The influence of CRP on dynamic coal futures mainly transmits through continuous components, while its impact on coking coal futures primarily transmits through jump parts. Additionally, the positive and negative volatilities of coal futures are asymmetrically affected by CRP. By incorporating the climate risk perception factor, investors can better predict price fluctuations in the coal market. This study provides an important supplement to the theory of pricing climate risks, and it is beneficial for formulating financial policies related to climate risk management and promoting the sustainable development of the coal industry.

Keywords: climate risk perception; coal; high frequency; nonparametric causality-in-quantiles tests

check for updates

Citation: Gao, W.; Wei, J.; Yang, S. The Asymmetric Effects of Extreme Climate Risk Perception on Coal Futures Return Dynamics: Evidence from Nonparametric Causality-In-Quantiles Tests. *Sustainability* **2023**, *15*, 8156. https://doi.org/10.3390/su15108156

Academic Editors: Michael C S Wong and Kaiguo Zhou

Received: 29 March 2023
Revised: 14 May 2023
Accepted: 15 May 2023
Published: 17 May 2023

1. Introduction

With the acceleration of global warming, climate risks have become a big concern for investors and policymakers [1–3]. Due to human-made greenhouse gas emissions, extreme climate events occur more frequently, last longer, and become more fierce, resulting in drought, extreme cold, rising sea levels, and drastic changes in precipitation [4]. According to observations from NASA's Gravity Recovery and Climate Experiment (GRACE), the impacts of extreme climate events on economies and societies around the world are increasingly deepening, forcing many countries and organizations to take emergent actions and response measures [5]. The crux of the matter is to restrain the combustion and utilization of fossil fuels, such as coal, oil, and natural gas, so that greenhouse gas emissions can be minimized as much as possible [6–10]. In particular, coal has been the largest engine driving climate change, accounting for almost one-third of the average temperature rise since the Industrial Revolution. The growing concerns of both the public and governments regarding climate risks have accelerated the establishment of climate production targets and policies in various countries, such as the Paris Agreement, the European Climate Law, and "Fit For 55" [11–13]. These legislative measures have gradually altered the conditions and structure of traditional energy markets, which is important for high-carbon-dependent countries to undergo a transformation. China is one of the world's top consumers of high-carbon energy, with coal being the largest proportion of its energy consumption—accounting for about 59% [14]. Meanwhile, China is actively playing a leading role in responding to climate change and energy transformation, concentrating all efforts to achieve the carbon peak and carbon neutrality goals. Thus, China's coal market structure is undergoing deep adjustments accordingly [15]. At least for the foreseeable future, the role of coal in production still cannot be completely replaced by new energy. Therefore, the Chinese coal market faces significant challenges in addressing climate change under the context of sustainable development, and managers and investors must consider climate risks when pricing assets and constructing investment portfolios.

The potential influence of climate risk might affect coal markets through various pathways. Climate risks generally involve physical and transition risks [16,17]. On the one hand, climate-related physical risks, such as frozen soil, rising sea levels, and typhoons, could damage infrastructure and the equipment used for coal mining and transportation, leading to increased operating costs and suspensions. Typhoons can cause extensive damage to high-value equipment; rising temperatures can reduce thermal efficiency, thereby increasing the demand for cooling water; abnormal precipitation patterns can pose challenges for coal exploration in inland areas [18]. In addition, extreme weather conditions reduce the visibility and safety of roads, leading to temporary interruptions in coal supply, the severity of which depends on the duration of the interruption and emergency stock levels. The frequency and variability of extreme events, such as heat and cold waves, have significant impacts on the peak load of coal-fired power [19]. On the other hand, the transition risks confronted by the coal industry include changes in climate policies, technological innovations, and low-carbon preferences among consumers and investors [20,21]. For example, coal enterprises are gradually losing their profitability due to carbon taxes, and there is a risk of stranded capital for earlier investments [22]. The rapid expansion of clean energy has brought default risks and operational pressure on the coal industry to transform [23]. Changes in coal demand caused by low-carbon preferences among consumers and investors can also lead to imbalances in coal markets, which exacerbates price fluctuations. It can be seen that the impact mechanism of climate risk on the coal market is complex, and there is still a lack of empirical research due to the difficulty in obtaining data. Fortunately, research has shown that these impact pathways are driven by public awareness and attention to these climate risks [24]. Therefore, in this article, we select people's perception of climate risks as a proxy variable to study the impact of climate risks on coal prices.

The fundamental transformation of economic activities and resource allocation caused by climate risks poses a challenge to the adaptability of the coal industry's low-carbon transition [25,26]. Some studies have already discussed the relationship between the climate-related factor and coal prices, focusing on the effects of climate policies [27–31]. For example, Walk and Stognief (2022) found that the coal phase-out was primarily driven by climate policies [28]. Ren et al. (2022) examined the causal relationship between climate policy uncertainty and traditional energy, including coal, using time-varying Granger tests, and they suggested that governments should pay attention to the role of climate implementation in the energy transition [31]. However, there is currently no relevant research from the perspective of market participants. As pointed out by Fahmy (2022), the views of investors and the public on climate risks are the main driving factors of market fluctuations, consistent with the behavioral finance theory [24]. On the one hand, when climate risks arise, investors and traders may be driven by extreme emotions and make more impulsive and short-sighted investment decisions. This exacerbates the herd effect and amplifies coal market volatility, leading to the possibility of extreme tail risks. On the other hand, as the awareness of climate risks in society rises, the public's voice will gain more influential power, so the government would formulate policies to regulate the impact of climate risks on the coal market. Favorable/unfavorable policies will impact investors' interests, leading to increases/decreases in price volatility. Furthermore, the notion that climate risk is a new source of risk for the financial system has been validated [32]. With the gradual deepening of the marketization of China's coal industry, financial derivatives, such as index pricing and futures, are gradually being recognized, and the financial attributes of coal are constantly emerging. As one of the most actively traded futures contracts in China, coal futures prices are inevitably subject to the systemic contagion of climate risk. Therefore, this paper delves into the effects of climate risk perception (CRP) on the returns and volatility of the coal price. The use of climate risk perception data has another advantage: they can be matched with high-frequency data in the coal market. High-frequency data are more suitable for our research for several reasons [33,34]. Firstly, high-frequency return and volatility data for coal futures can be more detailed and accurately reflect market behavior and conditions, thus providing a better understanding of short-time price trends and patterns that are in coordination with the outbreak cycle of extreme climate risks. Secondly, in financial risk management, using high-frequency data in the coal market for risk monitoring and management allows coal futures traders and investors to respond to sudden climate risks quickly. Thirdly, high-frequency data are commonly used in algorithmic trading, and the results of this study could be helpful for computer programs to engage in real-time trading. Finally, the data used in this study are all dynamic data, which can more clearly test the causal relationship between CRP and the return dynamics of coal futures, especially under different market conditions (bull or bear). In summary, the 5 min high-frequency coal futures return and volatility data used in this study are effective.

Some scholars have utilized OLS, VAR, and GARCH-type models to examine causality between variables [35–37]. However, these methods rely on estimating the conditional mean and cannot capture the causal relationship between market returns and volatility across the entire conditional distribution. Therefore, this paper draws non-causality-in-quantiles tests to explore the asymmetric effects of climate risk perception on coal futures return and volatility under different market conditions (bull, bear, or normal), which is crucial for differentiating market participants [38,39]. Within this framework, we further differentiate the asymmetry between positive and negative volatilities, which is essential for arbitrage or constructing hedging portfolios to reduce risks. Further, we decompose realized volatility into continuous and jump components [40]. This helps to explore the multiple pathways through which climate risk affects coal prices. Based on the above discussion, our paper has three main contributions. Firstly, it is the first to verify a new causal relationship between climate risk perception and coal futures price returns and volatility, expanding the research areas of climate economics and finance. Secondly, we use nonparametric quantile causality tests to examine the asymmetric and nonlinear impact mechanisms of climate risk perception on high-frequency coal indicators, including continuous and jump components and positive and negative fluctuations. Finally, we explore the heterogeneity of the impact of climate risk perception on two different coal futures markets, i.e., coking coal and thermal coal. The above contributions not only help investors to formulate diversified investment portfolio strategies, but they also have significant predictive value for the coal industry to formulate climate risk management policies. The remainder of the paper is as follows: Section 2 presents a literature review, Section 3 presents the methodology and data, Section 4 presents the empirical analysis and discussion, and Section 5 presents the conclusions and policy implications.

2. Literature Review

There are some studies on the impact of climate risk on financial assets, such as stocks, bonds, and commodities [41–45]. Because the economic effects of climate change are difficult to predict, climate change is likely to increase the uncertainties facing capital markets. For example, increased risks of wildfires, floods, and droughts will increase potential losses for insurers and investors. These uncertainties are likely to result in higher long-term costs for the financial sector. Existing research generally suggests that climate risks affect market returns. For example, Hong et al. (2020) found that longer durations of drought significantly harmed industry profits, leading to higher equity capital and a significant decrease in investor returns [46]. Zhu et al. (2020) found that climate risks have time-varying effects on the returns of fuel stocks [45]. Painter (2020) found that climate change increases the issuance costs of long-term bonds and makes capital adjustment more difficult in extreme weather [47]. In addition, there is some evidence to suggest that climate risks significantly increase market volatility. Bansal et al. (2016) found that stock prices have a significant negative elasticity with temperature risk [48]. Krueger et al. (2020) showed that disaster uncertainty leads to an implied volatility increase of 5–10% in companies' ROE [45]. Xu et al. (2023) indicated that both low and high climate policy uncertainty could increase the correlation between the volatilities of the Chinese and US stock markets. However, the impact of climate risks on the coal market is yet to be examined, and ignoring this relationship could lead to a mispricing of assets [41], or lower accuracy in price forecasts [49,50].

Moreover, there is evidence that climate factors have nonlinear effects on financial markets. For example, Ren et al. (2022) found significant nonlinear effects of climate policy uncertainty on the energy market, which varied under different market conditions [31]. Mosquera-López and Uribe argued that weather variables are the determining factors in changing market conditions [51]. Therefore, throughout this study, we use nonparametric causality-in-quantiles methods to explore the causal relationship between CRP and the coal market. Since the introduction of the Granger method, the primary causality test is constantly improving and playing a significant role in widespread application, among which the nonparametric causality-in-quantiles approach proposed by Balcilar et al. (2017) is one of the latest achievements [52]. Within the framework of coupling the k-th order nonparametric of Nishiyama et al. (2011) and the nonparametric quantile causality of Jeong et al. (2012), the hybrid method is utilized to capture nonlinear dynamic dependencies, and it is robust to misspecification errors, structural breaks, and frequent outliers, which are commonly found in price series [35,53]. This fact makes it very suitable for detecting nonlinear causality from extreme climate risk perception to coal futures returns and volatility. In addition, this article further distinguishes between coking coal and thermal coal, which have certain differences in trading volume, trading price, and trading mode [15,54,55]. The demand for thermal coal accounts for more than half of China's total coal consumption, and it is usually used for power generation and heating [15,54]. Coking coal is an important raw material for China's chemical and basic steel products, connecting the coal carbonization, coking, and steel industries and playing an important role in the industrial chain [55]. However, its consumption accounts for a relatively low proportion. China has relatively abundant thermal coal resources, and the domestic market mainly dominates its price. However, China's high-quality coking coal is relatively scarce and needs to rely to some extent on imports, so the price of coking coal is to some extent subject to importing countries such as Australia and exhibits different fluctuations from thermal coal. The combustion of both coking coal and thermal coal generates greenhouse gases, such as carbon dioxide and carbon monoxide, as well as air pollutants, such as sulfur dioxide, nitrogen oxides, and particulate matter. The emission of these gases and particles aggravates environmental problems, such as air pollution, acid rain, and smog, and it increases the probability and intensity of extreme weather events [56]. However, the chemical composition of the two types of coal differs slightly. Coking coal has a low ash content, fewer harmful substances, and less alkali metal content, while thermal coal has a higher calorific value and more pollution [57,58]. Therefore, the two have many differences in response to climate risk changes.

3. Methodology

3.1. Nonparametric Causality-In-Quantiles Tests

Based on the previous discussion, we adopt a novel nonparametric causality-in-quantiles approach proposed by Balcilar et al. (2017) to check the causality of CRP to the coal market [52]. To simplify the exposition, let y_t and x_t represent coal futures returns or volatility and climate risk perception (CRP), respectively, and the causality-in-quantiles hypotheses can be indicated as follows: x_t does not cause y_t in the θ-quantile with regards to the lag-vector of $y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}$ if

$$Q_\theta(y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}) = Q_\theta(y_t, y_{t-1}, \ldots, y_{t-p}) \quad (1)$$

x_t is a prima facie cause of y_t in the θ-th quantile with regards to $y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}$ if

$$Q_\theta(y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p}) \neq Q_\theta(y_t, y_{t-1}, \ldots, y_{t-p}) \tag{2}$$

Here, $Q_\theta(y_t \cdot)$ is the θ-th quantile of y_t, representing different market conditions (bull or bear). The conditional quantiles of y_t depend on t, and the quantiles are restricted between zero and one, $0 < \theta < 1$.

For a compact presentation of the causality-in-quantiles tests, we define the following vectors: $y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p}), x_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p}), z_t = (X_t, Y_t)$. Let us also define the conditional distribution functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$, which signify the distribution functions of y_t for nearly all Z_{t-1} and Y_{t-1}. If we define $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1} = \theta\}$ with probable on. As an end, the hypotheses to be tested based on definitions Equations (1) and (2) are as follows:

$$H_0 : P\Big\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\Big\} = 1 \tag{3}$$

$$H_1 : P\Big\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\Big\} < 1 \tag{4}$$

In order to define a measurable metric for the useful implementation of the causality-in-quantiles tests, Jeong et al. [41] use the distance measure $J = \{\varepsilon_t\{E(\varepsilon_t)|Z_{t-1}\}f_Z(Z_{t-1})\}$, where ε_t is the regression error team, and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1}. In our case, the estimator of the unknown regression error is defined as

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \le \hat{Q}_\theta(Y_{t-1})\} - \theta \tag{5}$$

In Equation (5), $\hat{Q}_\theta(Y_{t-1})$ is the estimate of the θ-th conditional quartile of y_t given Y_{t-1}. In the following, we use the nonparametric kernel method to estimate $\hat{Q}_\theta(Y_{t-1})$ as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}{}_{y_t|Y_{t-1}}(\theta Y_{t-1}) \tag{6}$$

where $\hat{F}^{-1}_{y_t|Y_{t-1}}(y_t Y_{t-1})$ is the Nadarya–Watson kernel estimator given by

$$\hat{F}^{-1}_{y_t|Y_{t-1}}(y_t Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)\mathbf{1}(y_s \le y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1}-Y_{s-1}}{h}\right)} \tag{7}$$

$L(\cdot)$ denotes the kernel function, and h denotes the bandwidth.

Next, we examine the causal relationship in variance (2nd moment) because the rejection of causality in moment m does not indicate non-causality in moment k for $k < m$, from climate risk perception (CRP) to the volatility of coal futures returns. We can indicate this by using the following model:

$$y_t = g(Y_{t-1}) + \sigma(X_{t-1})\varepsilon_t \tag{8}$$

where the higher-order causality-in-quantiles can be tested as

$$H_0 : P\Big\{F_{y_t^K|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\Big\} = 1\, fork = 1, 2, \ldots, K \tag{9}$$

$$H_1 : P\Big\{F_{y_t^K|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\Big\} < 1\, fork = 1, 2, \ldots, K \tag{10}$$

We test that x_t Granger causes y_t in quantile θ up to the k-th moment using Equation (9) to calculate the feasible kernel-based test statistic following Jeong et al. (2012) [53]; for each k, we follow the sequential testing method as in Nishiyama et al. [42]. The lag order of 1 is chosen based on the Schwarz Information Criterion (SIC) in a VAR involving both variables.

The bandwidth value is selected by using the least squares cross-validation techniques. Finally, for $K(\cdot)$ and $L(\cdot)$, we employ Gaussian-type kernels.

3.2. Coal Futures Return Dynamics

3.2.1. Price Return

The basis measure we consider is the coal futures returns. This paper uses logarithmic returns, which are the first-order difference of logarithmic prices. There are two advantages of using logarithmic returns. First, logarithmic difference processing can to some extent eliminate the correlation between price sequences. Second, logarithmic returns have convenient mathematical properties. The expression is as follows:

$$R_t = log(P_t) - log(P_{t-1}) \tag{11}$$

where P_t is the closing price at time t. In fact, it calculates the changes between the current and previous periods' prices, representing the rise and fall of futures prices.

3.2.2. Realized Volatility

The second measure in our study is realized volatility (RV), proposed by Andersen and Bollerslev (1998), which represents the risk of market volatility and is robust to microstructure effects, and They hold that no other high-frequency indicators is likely to outperform five-minute realized volatility [59]. The realized volatility is defined as shown below.

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{12}$$

where $r_{t,i}^2$ is the intraday log return of $i(i = 1, \ldots, M)$ on day t. In the data description that follows, we use the 5 min frequency of coal futures closing prices in all estimates.

3.2.3. Jump and Continuous Variations

For the purpose of inferring the different impact patterns of CRP on coal futures volatility, we decompose realized volatility (RV) into continuous variations (C) and jump components (J). Several studies, including Benth (2011) [60], Huang and Tauchen (2005) [61], and Bradley et al. (2022) [62], have documented the presence of volatility jumps in higher-frequency time series. Dunham and Friesen (2007) further show that jump risk accounts for a large proportion of the variation in total volatility [63]. When $M \to \infty$, which means that the intraday sampling frequency becomes higher, RV can be decomposed as the following expression:

$$\lim_{M\to\infty} RV_t = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{t-1<s\le t} \kappa_s^2 t \tag{13}$$

where $\int_{t-1}^{t} \sigma_s^2 ds$ is the continuous sample path variation, and $\sum_{t-1<s\le t} \kappa_s^2$ denotes the discontinuous jump change in $[t-1, t]$.

According to Barndorff-Nielsen et al. [48], the continuous sample path variation $\int_{t-1}^{t} \sigma_s^2 ds$ can be achieved by the double-power variation (RBV_t), expressed as

$$RBV_t = z_1^{-2} \frac{M}{M-2} \sum_{j=3}^{M} |r_{t,j-2}||r_{t,j}| \tag{14}$$

where $z_1 = E(Z_t) = \sqrt{\pi/2}$, and Z_t is a random variable that drives a standard normal distribution. The Z-statistic can be used to identify discontinuous jump changes.

$$Z_t = \frac{(RV_t - RBV_t)RV_t^{-1}}{\sqrt{\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right)\frac{1}{M\, max\left(1, \frac{RTQ_t}{RBV_t^{-2}}\right)}}} \to N(0,1) \tag{15}$$

where $\mu_t = \sqrt{2/\pi}$, and RTQ_t devotes the realized tri-power quarticity equated as

$$RTQ_t = M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=4}^{M}\left|r_{t,j-4}\right|^{4/3}\left|r_{t,j-2}\right|^{4/3}\left|r_{t,j}\right|^{4/3} \quad (16)$$

However, RBV_t is not a robust estimate for testing discontinuous jump changes because it is strongly influenced by the sampling frequency. Due to factors related to market microstructure, the estimate of RBV_t does not converge to the integrated volatility as the sampling frequency increases. So, to overcome this drawback, Andersen et al. (2012) propose a robust estimation method, $MedRV_t$, as an alternative to RBV_t [64]. Its formulation is

$$MedRV_t = \frac{\pi}{6-4\sqrt{3}+\pi}\left(\frac{M}{M-2}\right)\sum_{j=2}^{M-1} Med\left(\left|r_{t,j-1}\right|\left|r_{t,j}\right|\left|r_{t,j+1}\right|\right)^2 \quad (17)$$

Accordingly, the statistic Z_t for the implementation of the three-weighted quadrature (RTQ_t) of the jump test is modified by $MedRTQ_t$ as

$$MedRTQ_t = \frac{3\pi M}{9\pi+72-52\sqrt{3}}\left(\frac{M}{M-2}\right)\sum_{j=2}^{M-1} Med\left(\left|r_{t,j-1}\right|\left|r_{t,j}\right|\left|r_{t,j+1}\right|\right)^4 \quad (18)$$

Finally, the daily continuous sample path changes C_t, and the jump change in realized volatility J_t is expressed by

$$C_t = I(Z_t \leq \phi_\alpha)\cdot RV_t + I(Z_t > \phi_\alpha)\cdot MedRV_t \quad (19)$$

$$J_t = I(Z_t > \phi_\alpha)\cdot(RV_t - MedRV_t) \quad (20)$$

where $I(\cdot)$ is the indicator function, and ϕ_α is the critical value of the normalized normal distribution. In our estimation, following Andersen et al. (2012), $\alpha = 0.95$ [64].

3.2.4. Realized Semi-Variance

Given that downside (upside) risk cannot be directly observed, we computed the downside (upside) realized semi-variance based on high-frequency data, which provides a relatively more accurate measure to capture volatility risk in different directions. This could be an important consideration for hedging operations involving coal positions when estimating potential losses during market downturns. Following Barndorff-Nielsen et al. (2008) [65], the negative and positive daily realized semi-variance indicators (RSV_t^- and RSV_t^+) are defined as

$$RSV_t^- = \sum_{j=1}^{M} r_{t,j}^2\{r_{t,j} \leq 0\} \text{ and } RSV_t^+ = \sum_{j=1}^{M} r_{t,j}^2\{r_{t,j} > 0\} \quad (21)$$

3.2.5. Signed Realized Jump

The signed realized jump provides a proxy for volatility jump components based on positive and negative market conditions and allows us to evaluate the asymmetric effect at different quantiles that CRP may have on coal price. Following Patton and Sheppard (2015) [66], we express the signed jump as the difference between the positive and negative realized semi-variances as

$$SJ_t = RSV_t^+ - RSV_t^- \quad (22)$$

4. Data and Empirical Findings

4.1. Data

Our dataset comprises intraday coal futures price data at 5 min intervals. The earliest futures contract for coking coal was officially listed on the Dalian Commodity Exchange on

22 March 2013. Thus, the coking coal price sample range that we selected covers all trading periods from 22 March 2013 to 26 September 2022, including 2106 observations. For more details, please refer to http://www.dce.com.cn/dalianshangpin/sspz/487450/index.html (accessed on 26 September 2022). The earliest thermal coal futures contract was officially launched on the Dalian Commodity Exchange on 26 September 2013. Similarly, the sample period covers 26 September 2013 to 26 September 2022, including 1569 observations. For more detailed information, please refer to http://www.czce.com.cn/cn/sspz/dlm/H770212index_1.htm (accessed on 26 September 2022). We compiled the climate risk perception (CRP) index as a weighted average of five extreme climates, including extreme cold, high temperatures, waterlogging, drought, and typhoons, obtained from http://index.baidu.com (accessed on 26 September 2022). The sample period covers 22 March 2013 to 26 September 2022. In order to maximize the use of the sample and increase the persuasiveness of the empirical results, we matched the CRP data with both the coking coal and thermal coal data, and we estimated the models separately. Table 1 presents the descriptive statistics of the variables. Upon examining the skewness and kurtosis values, we observe non-normality in the data, with the coal futures returns (R) and signed jump (SJ) showing left-skewed distributions, while the other variables are right-skewed. All variables exhibit excess kurtosis. The unit root tests, the augmented Dickey and Fuller (ADF) and the Phillips and Perron (PP), in Table 1 confirm that all variables are stationary at the 1% significance level, indicating that the data are suitable for adopting nonparametric causality-in-quantiles methods. Figure 1 shows the time-series data of the variables mentioned above. It is not difficult to find that there is a tendency for co-movement between the coal price series and climate risk perception.

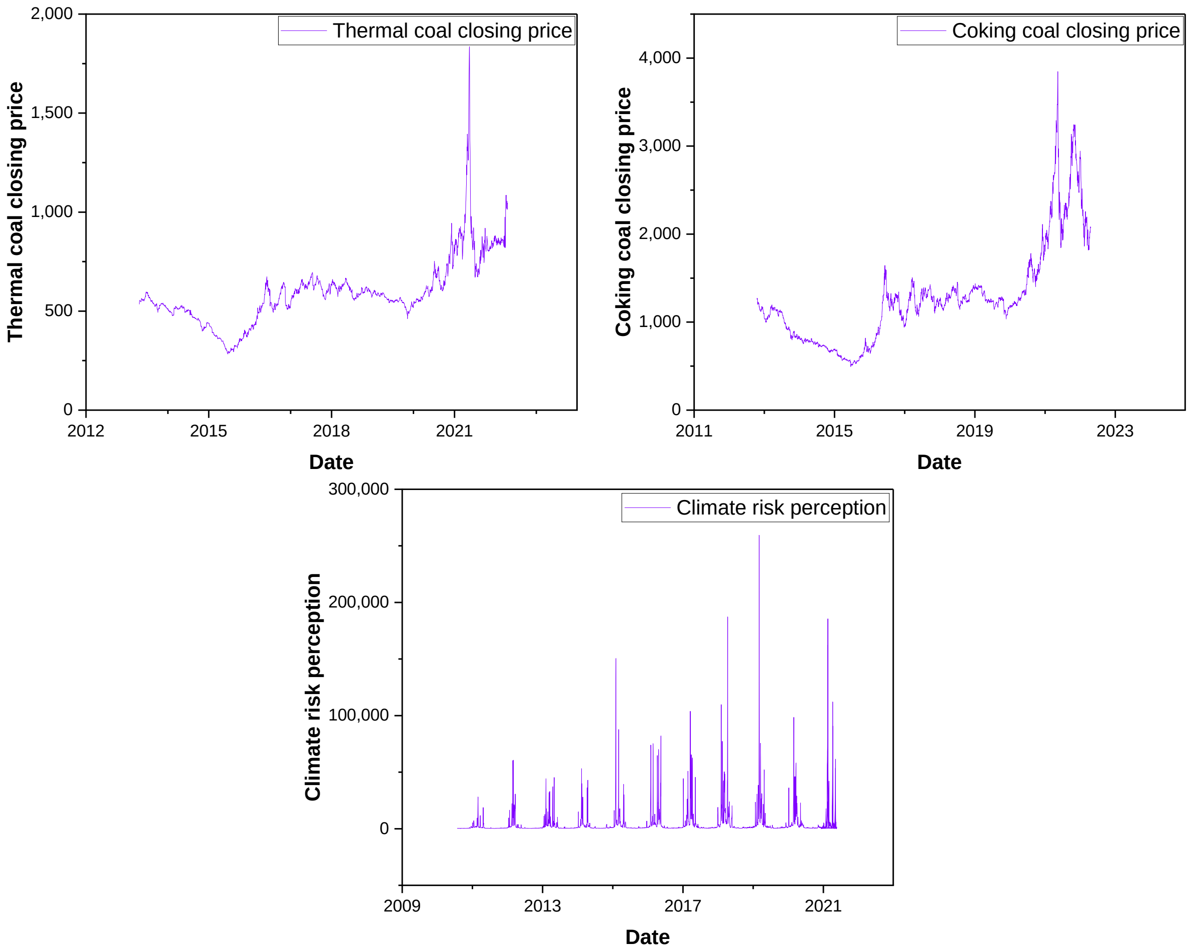

Figure 1. Plot data for the thermal and coking coal closing prices and climate risk perception index.

Table 1. Descriptive Statistics.

Panel A: Coking	Mean	Median	Max	Min	Std	Variance	Skewness	Kurtosis	ADF	PP
R_t	0.02	−0.03	8.20	−10.94	1.76	3.09	−0.36	6.77	−45.56 ***	−45.62 ***
RV_t	3.45	1.82	71.80	0.04	4.85	23.53	5.64	57.81	−15.02 ***	−14.97 ***
C_t	2.92	1.52	71.80	0.00	4.23	17.93	5.80	64.70	−23.99 ***	−26.91 ***
J_t	0.53	0.00	70.38	0.00	2.43	5.90	15.05	359.64	−30.56 ***	−33.19 ***
RSV_t^+	1.65	0.88	27.45	0.00	2.07	4.28	3.59	25.58	−19.64 ***	−20.31 ***
RSV_t^-	1.80	0.87	70.43	0.00	3.38	11.46	10.16	170.16	−18.31 ***	−21.16 ***
SJ_t	−1555	−0.02	19.89	−70.43	2.82	7.95	−14.32	334.11	−30.64 ***	−33.54 ***
CRP	7.11	6.72	11.81	5.65	1.09	1.19	1.34	4.23	−8.85 ***	−8.01 ***
Panel B: Thermal	**Mean**	**Median**	**Max**	**Min**	**Std**	**Variance**	**Skewness**	**Kurtosis**	**ADF**	**PP**
R_t	0.04	0.00	9.32	−10.66	1.52	2.31	−0.76	14.00	−34.80 ***	−35.66 ***
RV_t	2.43	1.04	101.68	0.01	6.61	43.74	9.89	123.29	−15.94 ***	−17.58 ***
C_t	1.86	0.75	101.68	0.00	4.95	24.51	10.77	163.25	−15.99 ***	−18.75 ***
J_t	0.57	0.00	100.33	0.00	4.31	18.38	18.38	374.90	−28.87 ***	−28.41 ***
RSV_t^+	1.05	0.48	26.74	0.00	2.03	4.12	6.44	58.65	−18.57 ***	−19.82 ***
RSV_t^-	1.38	0.49	100.65	0.00	5.60	31.41	13.26	205.41	−18.09 ***	−20.54 ***
SJ_t	−0.33	−0.01	24.43	−100.34	5.23	27.33	−14.55	254.02	−21.75 ***	−23.45 ***
CRP	7.24	6.84	11.81	5.84	1.11	1.23	1.28	4.01	−7.64 ***	−7.02 ***

Note: Std represents standard deviation. This table reports descriptive statistics for coking coal futures returns (R), realized volatility (RV), continuous and jump changes (C, J), positive and negative realized semi-volatility (RSV+, RSV−), signed jumps (SJ), and climate risk perception (CRP). The asterisks *** represent significance at the 1% level.

According to Table 2, we adopt the traditional Granger causality test, and the significance is at the 5% level; we do not find a significant causal effect of climate risk perception on coal futures return dynamics. The relationship between climate risk perception and coal futures return dynamics exhibits a nonlinear structure, which can be seen in the Brock–Dechert–Scheinkman (BDS) test results in Table 3 [67]. The results show strong evidence of nonlinearity for the different embedding dimensions (m) of the BDS test. The results suggest that linear models might not be able to capture the true nature of casual flows from climate risk perception to coal futures return dynamics, and, hence, it is legitimate to use nonparametric causality-in-quantiles tests.

Table 2. Results of the linear Granger causality test.

Panel A: Coking	Chi-Sq. Statistic	Prob	Decision
$CRP \nRightarrow R$	5.5889	0.0610	No causality
$CRP \nRightarrow RV_t$	0.7488	0.6880	No causality
$CRP \nRightarrow C_t$	0.4515	0.7980	No causality
$CRP \nRightarrow J_t$	1.0688	0.5860	No causality
$CRP \nRightarrow RSV_t^+$	0.2384	0.8880	No causality
$CRP \nRightarrow RSV_t^-$	1.4337	0.4880	No causality
$CRP \nRightarrow SJ_t$	2.9813	0.2250	No causality
Panel B: Thermal	**Chi-Sq. Statistic**	**Prob**	**Decision**
$CRP \nRightarrow R_t$	1.2948	0.5230	No causality
$CRP \nRightarrow RV_t$	1.5616	0.9170	No causality
$CRP \nRightarrow C_t$	0.1743	0.5230	No causality
$CRP \nRightarrow J_t$	1.2962	0.6310	No causality
$CRP \nRightarrow RSV_t^+$	0.9219	0.2460	No causality
$CRP \nRightarrow RSV_t^-$	2.8084	0.1490	No causality
$CRP \nRightarrow SJ_t$	3.8108	0.8950	No causality

Note: The symbol $\nRightarrow$ indicates the null hypothesis of Granger's non-causal relationship. The item "causality" indicates that the original hypothesis is rejected at the 5% significance level, while the item "no causality" indicates that the original hypothesis of Granger non-causality cannot be rejected at the 5% significance level.

Table 3. The BDS tests with coking and thermal coal.

Panel A: BDS Test with Coking Coal					
Embedding Dimension	**m = 2**	**m = 3**	**m = 4**	**m = 5**	**m = 6**
R_t	12.7426 ***	16.2958 ***	20.2575 ***	25.3950 ***	31.9624 ***
RV_t	49.5603 ***	60.2837 ***	73.7292 ***	91.769 ***	117.3047 ***
C_t	35.2802 ***	44.4288 ***	54.4439 ***	67.0186 ***	84.4758 ***
J_t	4.7613 ***	6.6792 ***	7.5063 ***	8.1157 ***	8.9451 ***
RSV_t^+	47.2427 ***	60.0328 ***	75.8622 ***	98.3250 ***	131.2503 ***
RSV_t^-	33.4811 ***	38.5438 ***	43.6620 ***	49.3561 ***	56.7198 ***
SJ_t	17.4078 ***	20.8513 ***	24.0966 ***	27.5773 ***	31.1949 ***
Panel B: BDS Test with Thermal Coal					
Embedding Dimension	**m = 2**	**m = 3**	**m = 4**	**m = 5**	**m = 6**
R_t	9.0246 ***	11.9894 ***	15.1983 ***	20.0970 ***	26.7040 ***
RV_t	27.8075 ***	28.4370 ***	28.7493 ***	29.1148 ***	29.7465 ***
C_t	23.9704 ***	27.0302 ***	28.6262 ***	30.1882 ***	31.9588 ***
J_t	2.2465 ***	2.9593 ***	3.6069 ***	4.7288 ***	5.5339 ***
RSV_t^+	26.7867 ***	31.1099 ***	34.2424 ***	37.7584 ***	42.0198 ***
RSV_t^-	20.2393 ***	20.6914 ***	20.1458 ***	19.5741 ***	19.4708 ***
SJ_t	17.2931 ***	17.4312 ***	17.2163 ***	16.9062 ***	16.5965 ***

Note: These entries show the BDS tests based on the residuals of climate risk perception and coal futures in different indicators. m is the embedding dimension of the BDS test. The asterisks *** represent significance at the 1% level.

4.2. Empirical Results

4.2.1. The Effects of CRP on Coal Returns and Realized Volatility

Figure 2 presents the results of the quantile causality from climate risk perception (CRP) to the coking and thermal coal futures returns (R) and realized volatility (RV). The horizontal axis shows the quantiles, and the vertical axis shows the nonparametric causality test statistics corresponding to the quantile in the horizontal axis. Specifically, the critical value for a significance level of 5% is 1.96. If the test statistic exceeds this critical value, it indicates a strong causal effect of CRP on coal prices. The findings in Figure 2a,b indicate that the null hypothesis of the no Granger causality of CRP on coking and thermal coal returns cannot be rejected at any of the quantiles; this implies that the impact of CRP on coal returns is insignificant, which is similar to findings in other commodity studies [68,69]. In the case of RV, the null hypothesis of no Granger causality-in-variance is rejected over most of the conditional distribution, particularly at lower and medium quantiles (0.1–0.6), suggesting predictability for coal volatility in bearish and normal markets. There are mainly two reasons for this phenomenon: on the one hand, in normal market conditions, the fluctuation level of coal prices is relatively low, and market investors can make relatively rational asset allocation and investment decisions. However, during periods of extreme market volatility, investors are dominated by extreme emotions, and the impact of climate risk perception is relatively limited. On the other hand, extreme market conditions mean that the market is facing a more unstable environment. As coal has both commodity and financial attributes and is a highly liquid and high-risk asset, it is very sensitive to complex market environments and inevitably subject to strong impacts from other uncertainties, such as economic uncertainty, financial market uncertainty, and geopolitical risk [70]. In conclusion, our results indicate that climate risk perception is a novel predictive factor for coal volatility. This is consistent with the findings of Jost et al. (2019), who suggest that climate risk perception influences the behavior of traders and investors, leading to changes in market volatility [71].

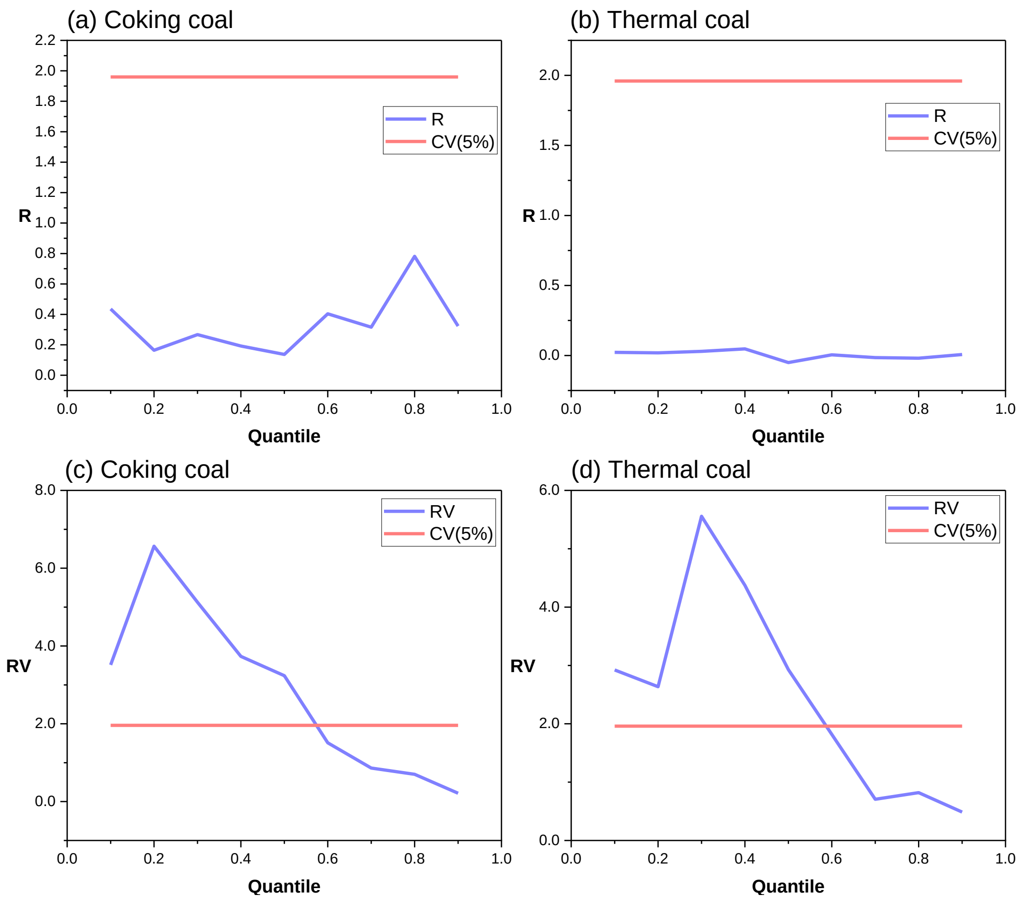

Figure 2. The impact of climate risk perception index on coal futures returns (R) and realized volatility (RV).

Interestingly, the results in Figure 2 also indicate that the effects of climate risk perception on RV are heterogeneous for coking coal and thermal coal. The CRP for coking coal peaks at the 0.2 quantile with a value of around 6.5, while the maximum for thermal coal is only 5.5. This suggests that the causal relationship between climate risk perception and coking coal is stronger than that for thermal coal. This may be due to the fact that coking coal has a more complex production process and a relatively scarce reserve, which makes it more price-elastic than thermal coal [72]. Figure 2 also shows that the volatilities of coking coal and thermal coal futures exhibit similar trends across different quantiles, which is consistent with the findings of Grieb and Terrance (2015), who argue that investors can speculate on one commodity based on the returns and volatility of another commodity [73]. Therefore, investors can exploit the heterogeneity of climate risk perception in different coal futures markets to achieve maximum profits through cross-market arbitrage when trading coal.

4.2.2. The Effects of CRP on Jumps in Coal Volatility

Many studies in the literature suggest that volatility jumps can explain a significant percentage of the total change in variability. Hence, a natural question is whether the impact of climate risk perception on coal market volatility is transmitted through the permanent component or the jump component (or both). If the impact of climate risk perception is limited to the permanent component of volatility, one can assume that its effect is volume driven. If the impact of climate risk perception is limited to the jump component, it would have significant implications for predictive modeling. Inspired by Barndorff-Nielsen and Shephard (2004) [40], we decompose realized volatility (RV) into continuous variations (C) and jump components (J). Figure 3a suggests that the impact of climate risk perception on the coal futures continuous volatility is significant at the [0.4, 0.8] quantile and shows us a saddle-shaped distribution. This means that the causal relationship between the two is significant under most market conditions, except during extreme periods. Comparing Figure 3a,b, we find that the impact of climate risk perception on the coking and thermal coal futures continuous volatilities is heterogeneous. Under normal market conditions, the effects of climate risk perception on continuous variations in thermal coal are more significant than coking coal. One possible explanation for this is the persistent cyclical and seasonal effects of climate risk perception in the thermal coal market, particularly during the peak periods of summer power generation and winter heating [74].

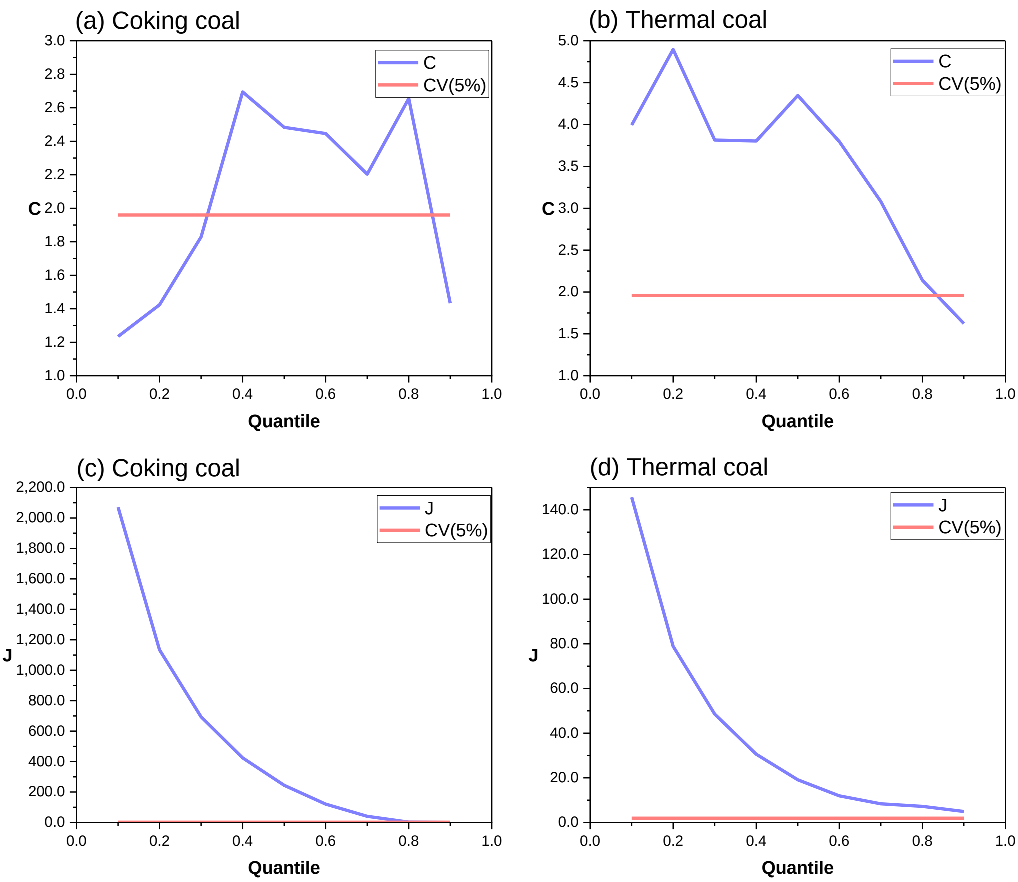

Figure 3. The impact of climate risk perception index on coal futures continuous (C) and jump volatilities (J).

Next, we turn our focus to volatility jumps. Figure 3c,d suggest that the effect of CRP is significant for both coking coal and thermal coal at almost all quantiles of the conditional distribution of the jump values, especially at the low quantiles. This finding suggests that the causal effect of climate risk perception is particularly strong during periods of market downturn captured by the extreme quantiles, implying that climate risks contribute to underlying volatility jumps in coal returns. Comparing the results in Figure 3c,d, it is clear that coking coal is more sensitive than thermal coal. At the extreme low quantile, the statistic value for coking coal exceeds 2000, while the volatility jump caused by climate risk perception in thermal coal is relatively weak, with a statistic value of only 150. This means that, as investors' perceptions of climate risk increases, there is a high likelihood of a sudden surge in coke futures prices. Dao et al. (2021) also mentioned that the severe emission of greenhouse gases can easily lead to unexpected surges in coking coal prices [75]. To that end, our findings provide a new insight into the safe-haven literature regarding the channel through which climate risks impact market volatility [76,77].

4.2.3. Asymmetric Effects of CRP

Motivated by the works of Sheppard and Patton (2015), Zhang et al. (2023), and Chen et al. (2019) [78–80], we differentiate between the positive/negative realized semi-variances and signed jumps as described in Sections 3.2.4 and 3.2.5 and explore the possible asymmetries in the effect of CRP on coal volatility. This has important implications for tail risk modeling and cross-asset contagion, as well as for the timing and sizing of hedging strategies [81]. According to Barndorff-Nielsen et al. (2008) [82], we first split realized volatility (RV) into positive/negative realized semi-variance volatility (RSV+/RSV−), where RSV+ (RSV−) measures the upward (downward) volatility of coal futures. In Figure 4, it can be observed that the RSV+ effect of both coking coal and thermal coal caused by extreme climate risk perception shows an increasing-then-decreasing trend, while RSV− follows a similar arch-shaped distribution. It is evident that CRP exhibits significant asymmetry with respect to the positive and negative volatilities of coal. Specifically, for coking coal, we observe that the impact of CRP shocks is usually stronger on RSV− than on RSV+, implying that the volatility of coking coal has a stronger reaction to extreme climate events than to the dissipation of climate risks. Similarly, thermal coal also exhibits a similar asymmetry. In fact, our research findings suggest an asymmetric predictability pattern, indicating that greater predictive profits may be obtained when extreme climate risks occur, which is also mentioned by Mzoughi et al. (2022) [83].

The prediction of positive and negative jumps in coal volatility due to extreme climate events is highly relevant for the pricing of coal options and futures, as volatility jumps are a key parameter in option pricing models. The conditional distribution of coking coal's SJ values reported in Figure 4e shows a significant causal relationship across the entire quantile range, with a stronger effect at lower quantiles, indicating asymmetry. This suggests that extreme climate risk perception can effectively predict negative jumps in coal prices during extreme market conditions, which is an interesting finding, as extreme climate risk may lead to a sudden collapse in the coal market. The impact of CRP on thermal coal is also significant across the entire distribution, but it is more evenly distributed and without a strong asymmetry (see Figure 4f). Given the role of jump risk in pricing commodity returns in the cross-section, climate risk can serve as a systematic risk factor in asset pricing models, and future research can build on our evidence to test its long-term effectiveness.

4.3. Robustness Test

To test the robustness of the above results, we use the kernel-based estimators proposed by Hansen and Lunde (2006) as another measure to calculate volatility [84]. The formula is shown as Equation (23) below. The parameters of realized kernel estimators (q) are set to 6. In the results in Figure 5, it can be observed that the causality pattern is similar to the RV in Figure 2, which indicates that the empirical results are robust to the choice of volatility measures.

$$RK_t = \sum_{j=1}^{M} r_{i,j}^2 + \sum_{i=1}^{q} \left(1 - \frac{i}{q+1}\right) \sum_{j=1}^{M-i} r_{i,j} r_{i,j+i} \tag{23}$$

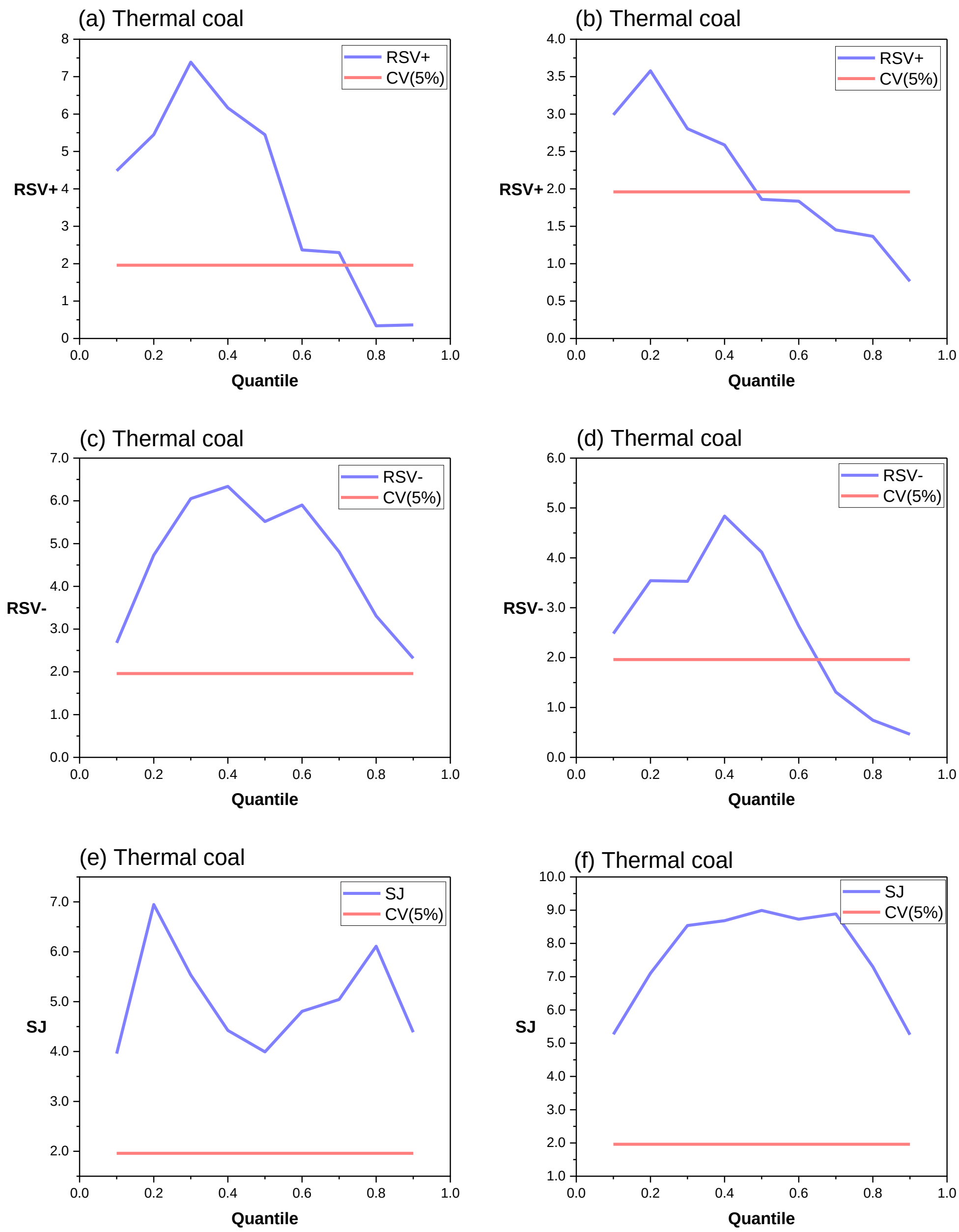

Figure 4. The impact of climate risk perception index on coal futures positive (RSV+) and negative (RSV−) realized semi-variances and signed jumps (SJs).

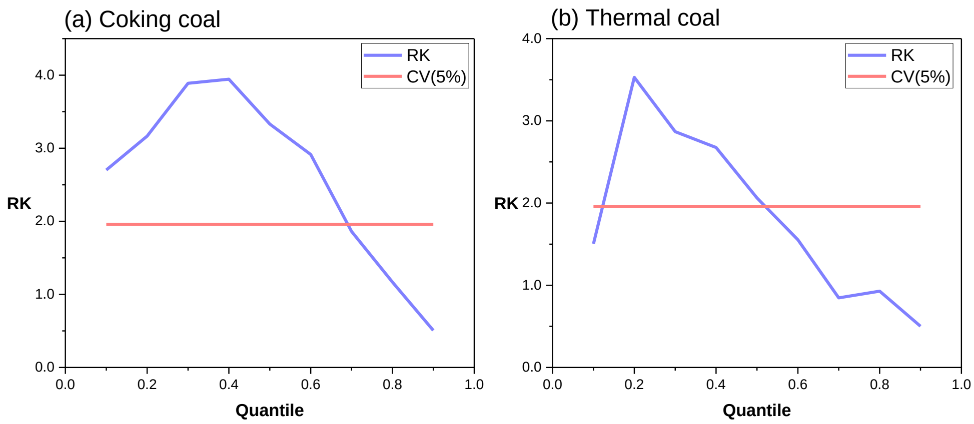

Figure 5. The impact of climate risk perception index on coal futures robustness checks.

5. Conclusions and Policy Implications

This paper uses the nonparametric quantile causal method to examine the influence of climate risk perception (CRP) on the return dynamics of intraday high-frequency indicators of coking coal and thermal coal. The main results are as follows: First, climate risk perception has a significant impact on coal futures continuous (C) and jump (J) volatilities. Second, for coal futures, the positive semi-variance volatility (RSV+) and negative semi-variance volatility (RSV−) indicators are asymmetrically affected by CRP. Third, coal futures are more significantly influenced by CRP in falling markets than in rising markets. Fourth, it is found that the impact of CRP on the two different markets of coking coal and thermal coal is heterogeneous. In detail, coking coal is more susceptible to CRP than thermal coal.

These findings can provide insights for climate risk pricing and government decision making. The main recommendations are as follows: First, investors can improve coal pricing forecasts and reduce trading risks by adding public climate risk perception factors to their investment portfolios. Second, governments can better regulate the coal and other energy futures markets and effectively regulate high-carbon industries by implementing climate improvement policies. Third, enterprises can deepen the integration of "futures + climate" information; identify possible extreme weather events in the futures markets for thermal and coking coal; and dynamically evaluate the likelihood, consequences, and controllability of climate risk outbreaks.

It is important to note the methodological and data limitations of this study. As previously discussed, an important basis of this research program is the reliance of climate risk perception data. Although the data used in this study are more suitable for researching high-frequency financial market volatility than the monthly climate policy uncertainty data used in previous research, real-time physical climate data would be even better. If more fine-grained extreme climate change data (e.g., at the minute or second level) can be obtained in the future, researchers could employ functional data analysis techniques, such as the functional principal component analysis (FPCA), to identify deeper patterns of dynamic evolution in high-dimensional climate risk data. This approach can help to uncover the essential features of complex financial behavior characteristics and provide more rational and intuitive financial interpretations. Future research would benefit from the use of an ultra-high-frequency sample. Our research can also be extended to areas such as green loans, climate bonds, and the pricing of renewable energy assets.

Author Contributions: Conceptualization, W.G.; methodology, W.G.; software, W.G.; formal analysis, W.G.; writing—original draft preparation, W.G.; writing—review and editing, W.G., S.Y. and J.W.; supervision, W.G.; funding acquisition, W.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Foundation of China (No. 22CTJ021).

Institutional Review Board Statement: No ethical approval was required for this study.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data were extracted from http://index.baidu.com (accessed on 26 September 2022), and the coal price data were obtained from the WIND information database, https://www.wind.com.cn (accessed on 26 September 2022).

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

References

1. Burke, M.; Hsiang, S.M.; Miguel, E. Global non-linear effect of temperature on economic production. *Nature* **2015**, *527*, 235–239. [CrossRef] [PubMed]
2. Huang, J.; Mondal, S.K.; Zhai, J.; Fischer, T.; Wang, Y.; Su, B.; Wang, G.; Gao, M.; Jiang, S.; Tao, H.; et al. Intensity-area-duration-based drought analysis under 1.5 °C–4.0 °C warming using CMIP6 over a climate hotspot in South Asia. *J. Clean. Prod.* **2022**, *345*, 131106. [CrossRef]
3. Elkouk, A.; Pokhrel, Y.; Satoh, Y.; Bouchaou, L. Implications of changes in climate and human development on 21st-century global drought risk. *J. Environ. Manag.* **2022**, *317*, 115378. [CrossRef] [PubMed]
4. Rohde, M.M. Floods and droughts are intensifying globally. *Nat. Water* **2023**, *1*, 226–227. [CrossRef]
5. Zhang, J.; Liu, K.; Wang, M. Flood detection using Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage and extreme precipitation data. *Earth Syst. Sci. Data* **2023**, *15*, 521–540. [CrossRef]
6. Liu, W.; McKibbin, W.J.; Morris, A.C.; Wilcoxen, P.J. Global economic and environmental outcomes of the Paris Agreement. *Energy Econ.* **2020**, *90*, 104838. [CrossRef]
7. Huang, M.-T.; Zhai, P.-M. Achieving Paris Agreement temperature goals requires carbon neutrality by middle century with far-reaching transitions in the whole society. *Adv. Clim. Chang. Res.* **2021**, *12*, 281–286. [CrossRef]
8. MMurshed, M.; Ahmed, R.; Kumpamool, C.; Bassim, M.; Elheddad, M. The effects of regional trade integration and renewable energy transition on environmental quality: Evidence from South Asian neighbors. *Bus. Strategy Environ.* **2021**, *30*, 4154–4170. [CrossRef]
9. Liu, J.; Hu, Y.; Yan, L.-Z. Volatility spillover and hedging strategies between the European carbon emissions and energy markets. *Energy Strategy Rev.* **2023**, *46*, 101058. [CrossRef]
10. Alola, A.A.; Adebayo, T.S. Analysing the waste management, industrial and agriculture greenhouse gas emissions of biomass, fossil fuel, and metallic ores utilization in Iceland. *Sci. Total Environ.* **2023**, 164115, *in press*. [CrossRef]
11. McCollum, D.L.; Zhou, W.; Bertram, C. Energy investment needs for fulfilling the Paris Agreement and achieving the Sustainable Development Goals. *Nat. Energy* **2018**, *3*, 589–599. [CrossRef]
12. Ren, X.; Li, Y.; Shahbaz, M. Climate risk and corporate environmental performance: Empirical evidence from China. *Sustain. Prod. Consum.* **2022**, *30*, 467–477. [CrossRef]
13. Ovaere, M.; Proost, S. Cost-effective reduction of fossil energy use in the European transport sector: An assessment of the Fit for 55 Package. *Energy Policy* **2022**, *168*, 113085. [CrossRef]
14. Jie, D.; Xu, X.; Guo, F. The future of coal supply in China based on non-fossil energy development and carbon price strategies. *Energy* **2021**, *220*, 119644. [CrossRef]
15. Gu, F.; Wang, J.; Guo, J. How the supply and demand of steam coal affect the investment in clean energy industry? Evidence from China. *Resour. Policy* **2020**, *69*, 101788. [CrossRef]
16. Zhang, S.Y. Are investors sensitive to climate-related transition and physical risks? Evidence from global stock markets. *Res. Int. Bus. Financ.* **2022**, *62*, 101710. [CrossRef]
17. Salisu, A.A.; Ndako, U.B.; Vo, X.V. Transition risk, physical risk, and the realized volatility of oil and natural gas prices. *Resour. Policy* **2023**, *81*, 103383. [CrossRef]
18. Qi, X.-L.; Xu, H.-J.; Chen, T.; Shan, S.-Y.; Chen, S.-Y. Effects of climate change, coal mining and grazing on vegetation dynamics in the mountain permafrost regions. *Ecol. Inform.* **2022**, *69*, 101684. [CrossRef]
19. Zamanipour, B.; Ghadaksaz, H.; Keppo, I.; Saboohi, Y. Electricity supply and demand dynamics in Iran considering climate change-induced stresses. *Energy* **2023**, *263*, 126118. [CrossRef]
20. Liu, J.; Zhang, D.; Cai, J. Legal systems, national governance and renewable energy investment: Evidence from around the world. *Br. J. Manag.* **2021**, *32*, 579–610. [CrossRef]
21. Ren, X.; Zhang, X.; Yan, C. Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Econ.* **2022**, *113*, 106209. [CrossRef]
22. Wong, J.B.; Zhang, Q. Impact of carbon tax on electricity prices and behaviour. *Financ. Res. Lett.* **2022**, *44*, 102098. [CrossRef]
23. Lorente, D.B.; Mohammed, K.S. Dynamic connectedness among climate change index, green financial assets and renewable energy markets: Novel evidence from sustainable development perspective. *Renew. Energy* **2023**, *204*, 94–105. [CrossRef]
24. Fahmy, H. The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus. *Energy Econ.* **2022**, *106*, 105738. [CrossRef]

25. Kung, C.-C.; Cao, X.; Choi, Y.; Kung, S.-S. A stochastic analysis of cropland utilization and resource allocation under climate change. *Technol. Forecast. Soc. Chang.* **2019**, *148*, 119711. [CrossRef]
26. He, W.; Yang, Y.; Gu, W. A comparative analysis of China's provincial carbon emission allowances allocation schemes by 2030: A resource misallocation perspective. *J. Clean. Prod.* **2022**, *361*, 132192. [CrossRef]
27. Zhao, Y.; Dai, X.; Zhang, D. Do weather conditions drive China's carbon-coal-electricity markets systemic risk? A multi-timescale analysis. *Financ. Res. Lett.* **2023**, *51*, 103432. [CrossRef]
28. Walk, P.; Stognief, N. From coal phase-out to net zero: Driving factors of UK climate policy. *Environ. Sci. Policy* **2022**, *138*, 76–84. [CrossRef]
29. Ding, Q.; Huang, J.; Zhang, H. Time-frequency spillovers among carbon, fossil energy and clean energy markets: The effects of attention to climate change. *Int. Rev. Financ. Anal.* **2022**, *83*, 102222. [CrossRef]
30. Curran, G. Coal, climate and change: The narrative drivers of Australia's coal economy. *Energy Res. Soc. Sci.* **2021**, *74*, 101955. [CrossRef]
31. Ren, X.; Li, J.; He, F. Impact of climate policy uncertainty on traditional energy and green markets: Evidence from time-varying granger tests. *Renew. Sustain. Energy Rev.* **2023**, *173*, 113058. [CrossRef]
32. Battiston, S.; Dafermos, Y.; Monasterolo, I. Climate risks and financial stability. *J. Financ. Stab.* **2021**, *54*, 100867. [CrossRef]
33. Caporin, M.; Naeem, M.A. Asymmetric and time-frequency spillovers among commodities using high-frequency data. *Resour. Policy* **2021**, *70*, 101958. [CrossRef]
34. Alam, M.S.; Shahzad, S.J.H. Causal flows between oil and forex markets using high-frequency data: Asymmetries from good and bad volatility. *Energy Econ.* **2019**, *84*, 104513. [CrossRef]
35. Nishiyama, Y.; Hitomi, K.; Kawasaki, Y. A consistent nonparametric test for nonlinear causality—Specification in time series regression. *J. Econom.* **2011**, *165*, 112–127. [CrossRef]
36. Song, Y.; Fang, Z.; Fu, H.-Z. Influence of interdisciplinarity on scientific impact: The case of climate change field. *J. Informetr.* **2023**, *17*, 101410. [CrossRef]
37. Zhou, D.; Siddik, A.B.; Guo, L.; Li, H. Dynamic relationship among climate policy uncertainty, oil price and renewable energy consumption—Findings from TVP-SV-VAR approach. *Renew. Energy* **2023**, *204*, 722–732. [CrossRef]
38. Kyritsis, E.; Andersson, J. Causality in quantiles and dynamic relations in energy markets: (De) tails matter. *Energy Policy* **2019**, *133*, 110933. [CrossRef]
39. Shahzad, S.J.H.; Raza, N. Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? *Resour. Policy* **2017**, *53*, 208–218. [CrossRef]
40. Barndorff-Nielsen, O.E.; Shephard, N. Power and bipower variation with stochastic volatility and jumps. *J. Financ. Econom.* **2004**, *2*, 1–37. [CrossRef]
41. Barnett, M.; Brock, W.; Hansen, L.P. Pricing uncertainty induced by climate change. *Rev. Financ. Stud.* **2020**, *33*, 1024–1066. [CrossRef]
42. Dafermos, Y.; Nikolaidi, M.; Galanis, G. Climate change, financial stability and monetary policy. *Ecol. Econ.* **2018**, *152*, 219–234. [CrossRef]
43. Choi, D.; Gao, Z.; Jiang, W. Attention to global warming. *Rev. Financ. Stud.* **2020**, *33*, 1112–1145. [CrossRef]
44. Krueger, P.; Sautner, Z.; Starks, L.T. The importance of climate risks for institutional investors. *Rev. Financ. Stud.* **2020**, *33*, 1067–1111. [CrossRef]
45. Zhu, B.; Hu, X.; Deng, Y.; Zhang, B.; Li, X. The differential effects of climate risks on non-fossil and fossil fuel stock markets: Evidence from China. *Financ. Res. Lett.* **2023**, 103962, *in press*. [CrossRef]
46. Huynh, T.D.; Nguyen, T.H.; Truong, C. Climate risk: The price of drought. *J. Corp. Financ.* **2020**, *65*, 101750. [CrossRef]
47. Painter, M. An inconvenient cost: The effects of climate change on municipal bonds. *J. Financ. Econ.* **2020**, *135*, 468–482. [CrossRef]
48. Bansal, R.; Kiku, D.; Ochoa, M. *Price of Long-Run Temperature Shifts in Capital Markets*; National Bureau of Economic Research: Cambridge, MA, USA, 2016.
49. Guo, K.; Liu, F.; Sun, X.; Zhang, D.; Ji, Q. Predicting natural gas futures' volatility using climate risks. *Financ. Res. Lett.* **2023**, 103915, *in press*. [CrossRef]
50. Nguyen, Q.; Diaz-Rainey, I.; Kuruppuarachchi, D. Predicting corporate carbon footprints for climate finance risk analyses: A machine learning approach. *Energy Econ.* **2021**, *95*, 105129. [CrossRef]
51. Mosquera-López, S.; Uribe, J.M. Nonlinear empirical pricing in electricity markets using fundamental weather factors. *Energy* **2017**, *139*, 594–605. [CrossRef]
52. Balcilar, M.; Bonato, M.; Demirer, R. The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. *Resour. Policy* **2017**, *51*, 77–84. [CrossRef]
53. Jeong, K.; Härdle, W.K.; Song, S. A consistent nonparametric test for causality in quantile. *Econom. Theory* **2012**, *28*, 861–887. [CrossRef]
54. Batten, J.A.; Brzeszczynski, J.; Ciner, C. Price and volatility spillovers across the international steam coal market. *Energy Econ.* **2019**, *77*, 119–138. [CrossRef]
55. Safarian, S. To what extent could biochar replace coal and coke in steel industries? *Fuel* **2023**, *339*, 127401. [CrossRef]

56. Yu, B.; Liu, J.; Lyu, T.; Li, Z.; Wang, M.; Yang, W. A new detection method to assess the influence of human activities and climate change of CO_2 emissions in coal field. *Ecol. Indic.* **2022**, *143*, 109417. [CrossRef]
57. Cao, X.; Yan, J.; Wang, Z.; Lei, Z.; Ren, S.; Kang, S.; Li, Z.; Shui, H. Comparative study on coal blending and coke-making property of two kinds of thermal dissolution soluble fractions from lignite and coking coal. *J. Anal. Appl. Pyrolysis* **2022**, *166*, 105585. [CrossRef]
58. Nishiyama, Y. Causality between government spending and income: The case of Saudi Arabia. *Appl. Econ. Lett.* **2019**, *26*, 433–435. [CrossRef]
59. Andersen, T.G.; Bollerslev, T. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *Int. Econ. Rev.* **1998**, *39*, 885–905. [CrossRef]
60. Benth, F.E. The stochastic volatility model of Barndorff-Nielsen and Shephard in commodity markets. *Math. Financ. Int. J. Math. Stat. Financ. Econ.* **2011**, *21*, 595–625. [CrossRef]
61. Huang, X.; Tauchen, G. The relative contribution of jumps to total price variance. *J. Financ. Econom.* **2005**, *3*, 456–499.
62. Bradley, E.H.; McGraw, S.A.; Curry, L.; Buckser, A.; King, K.L.; Kasl, S.V.; Andersen, R. Expanding the Andersen model: The role of psychosocial factors in long-term care use. *Health Serv. Res.* **2002**, *37*, 1221–1242. [CrossRef] [PubMed]
63. Dunham, L.M.; Friesen, G.C. An empirical examination of jump risk in US equity and bond markets. *North Am. Actuar. J.* **2007**, *11*, 76–91. [CrossRef]
64. Andersen, T.G.; Dobrev, D.; Schaumburg, E. Jump-robust volatility estimation using nearest neighbor truncation. *J. Econom.* **2012**, *169*, 75–93. [CrossRef]
65. Barndorff-Nielsen, O.E.; Hansen, P.R.; Lunde, A.; Shephard, N. Designing realized kernels to measure the ex post variation of equity prices in the presence of noise. *Econometrica* **2008**, *76*, 1481–1536.
66. Patton, A.J.; Sheppard, K. Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Rev. Econ. Stat.* **2015**, *97*, 683–697. [CrossRef]
67. Broock, W.A.; Scheinkman, J.A.; Dechert, W.D.; LeBaron, B. A test for independence based on the correlation dimension. *Econom. Rev.* **1996**, *15*, 197–235. [CrossRef]
68. Shahzad, S.J.H.; Naeem, M.A.; Peng, Z.; Bouri, E. Asymmetric volatility spillover among Chinese sectors during COVID-19. *Int. Rev. Financ. Anal.* **2021**, *75*, 101754. [CrossRef]
69. Bahloul, W.; Balcilar, M.; Cunado, J.; Gupta, R. The role of economic and financial uncertainties in predicting commodity futures returns and volatility: Evidence from a nonparametric causality-in-quantiles test. *J. Multinatl. Financ. Manag.* **2018**, *45*, 52–71. [CrossRef]
70. Dai, X.; Dai, P.-F.; Wang, Q.; Ouyang, Z.-Y. The impact of energy-exporting countries' EPUs on China's energy futures investors: Risk preference, investment position and investment horizon. *Res. Int. Bus. Financ.* **2023**, *64*, 101806. [CrossRef]
71. Jost, F.; Dale, A.; Schwebel, S. How positive is "change" in climate change? A sentiment analysis. *Environ. Sci. Policy* **2019**, *96*, 27–36. [CrossRef]
72. Liu, F.; Kang, Y.; Guo, K. The relationship between air pollution, investor attention and stock prices: Evidence from new energy and polluting sectors. *Energy Policy* **2021**, *156*, 112430. [CrossRef]
73. Grieb, T. Mean and volatility transmission for commodity futures. *J. Econ. Financ.* **2015**, *39*, 100–118. [CrossRef]
74. Zhao, X.; Lyon, T.P.; Wang, F. Why do electricity utilities cooperate with coal suppliers? A theoretical and empirical analysis from China. *Energy Policy* **2012**, *46*, 520–529. [CrossRef]
75. Dao, X.; Ji, D.; Zhang, X.; He, J.; Meng, X.; Wang, Z.; Liu, Y.; Xu, X.; Tang, G.; Wang, Y. Characteristics, sources and health risk assessment of PM2. 5 in China's coal and coking heartland: Insights gained from the regional observations during the heating season. *Atmos. Pollut. Res.* **2021**, *12*, 101237. [CrossRef]
76. Lei, H.; Xue, M.; Liu, H.; Ye, J. Precious metal as a safe haven for global ESG stocks: Portfolio implications for socially responsible investing. *Resour. Policy* **2023**, *80*, 103170. [CrossRef]
77. Aldieri, L.; Bruno, B.; Lorente, D.B.; Vinci, C.P. Environmental innovation, climate change and knowledge diffusion process: How can spillovers play a role in the goal of sustainable economic performance? *Resour. Policy* **2022**, *79*, 103021. [CrossRef]
78. Chen, Y.; Ma, F.; Zhang, Y. Good, bad cojumps and volatility forecasting: New evidence from crude oil and the U.S. stock markets. *Energy Econ.* **2019**, *81*, 52–62. [CrossRef]
79. Zhang, C.; Ma, H.; Arkorful, G.B.; Peng, Z. The impacts of futures trading on volatility and volatility asymmetry of Bitcoin returns. *Int. Rev. Financ. Anal.* **2023**, *86*, 102497. [CrossRef]
80. Fang, N.; Jiang, W.; Luo, R. Realized semivariances and the variation of signed jumps in China's stock market. *Emerg. Mark. Financ. Trade* **2017**, *53*, 563–586. [CrossRef]
81. Zhang, H.; Demirer, R.; Huang, J.; Huang, W.; Tahir Suleman, M. Economic policy uncertainty and gold return dynamics: Evidence from high-frequency data. *Resour. Policy* **2021**, *72*, 102078. [CrossRef]
82. Barndorff-Nielsen, O.E.; Kinnebrock, S.; Shephard, N. Measuring Downside Risk-Realised Semivariance. CREATES Research Paper No. 2008-42. 2008. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1262194 (accessed on 23 January 2023).

83. Mzoughi, H.; Urom, C.; Guesmi, K. Downside and upside risk spillovers between green finance and energy markets. *Financ. Res. Lett.* **2022**, *47*, 102612. [CrossRef]
84. Hansen, P.R.; Lunde, A. Realized variance and market microstructure noise. *J. Bus. Econ. Stat.* **2006**, *24*, 127–161. [CrossRef]