Analysis of Guangdong Carbon Emissions Trading Market: New Evidence Using Quantile-on-Quantile Regression Approach

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ABSTRACT: The relationship between the China carbon trading market and stock markets remains unsettled in the previous literature. This article proposes two quantitative methods (the quantile regression and the quantile-on-quantile regression models) to quantify the impact among them by taking the carbon-emissions trading market of Guangdong Province as an empirical example. First, the quantile regression is applied to evaluate the impacts of the Shanghai and Shenzhen stock market and the European carbon trading futures market on the China carbon-trading market under different quantiles points, respectively. The result reveals that no matter the European carbon trading futures market and Shanghai and Shenzhen stock markets under bearish conditions and bullish conditions market states, they always have a positive impact on the China carbon trading market. Second, the novel model quantile-on-quantile regression is used to provide more detailed information to uncover the elaborate features of the impact, accounting for extreme observations. The findings indicate that the China carbon trading market is insensitive to the European carbon trading futures market across all the quantiles combination of them. However, the China carbon trading market is sensitive to the Shanghai and Shenzhen stock market changes, especially while the Shanghai and Shenzhen stock markets under bullish market condition positively affect the China carbon trading market in the upper quantiles. Further, when the Shanghai and Shenzhen stock markets are in the bearish state and the China carbon trading market is recovering from the bearish state, the impact of the Shanghai and Shenzhen stock market will become slighter. Finally, this paper hopes to show that the investors should take the different quantiles condition of the markets into account when they adjust their investment plans and asset portfolios.

1 INTRODUCTION

As a developing country, China must establish a long-term carbon-constraint mechanism in accord with its current economic development and potentially huge energy use. Ever since the *Kyoto Protocol,* China has clearly listed its carbon-emission-reduction targets under the United Nations 2014 Framework Convention on Climate Change. China has promised that by 2030, carbon emissions per unit of GDP will fall by 60-65% compared with 2005 (Li *et al.*, 2021). Aiming to mitigate the excessive carbon emissions issue, emissions trading systems (ETS) are adopted as effective market mechanisms, from which the carbon price is formed by the supply and demand of carbon emission allowances. The National Development and Reform Commission of China has embarked on one of the largest endeavors in climate economics ever, having established since 2011 seven carbon-trading pilots in Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei, and Shenzhen to explore the establishment of a carbon-trading mechanism.

Moreover, carbon emissions in the trading schemes are characterized by the ability to be capped, priced and traded. These allowances indicate a cost of emissions reduction and can be traded between companies, so they have market value (Wen *et al.*, 2020). Furthermore, the carbon price depends on marginal abatement costs and marginal revenues, especially when the latter is related to the forecasts of production growth, which is associated to the economic activity. According to the previous study, there is a positive relationship between economic growth and energy needs. Additionally, the rise of energy needs will lead to higher carbon emissions, resulting in higher carbon prices. But, on the flip side, high carbon prices will cause an increase of enterprise's production costs, thereby suppressing the economic growth. Due to the intricate relationship of carbon emissions and economic growth, the stock market seems to be a suitable indicator because stock prices are sensitive to the performance of both economy and enterprise (Jiang *et al.*, 2022). Although study related to the topic of the relationship between the carbon trading market and the stock markets is increasing, yet studies related to China's carbon trading market are few, let alone any applying the non-linear models of quantile regression (QR) and the novel quantile-on-quantile regression (QQ) to shed light on the relationship of stock markets and China's carbon trading market.

Following the introduction, this article will organize as follows: The second section conducts a review of relevant study. The description of data applied in the study and the quantitative methodology, namely, quantile-on-quantile regression model are placed in the third section. The fourth section provides a series of tests, especially the quantile-on-quantile regression (QQ) estimates, and analyzes the results of them in detail. The last section will propose corresponding conclusions based on the analysis above. We hope that the findings of this paper will be of interest to policymakers and stakeholders.

2 LITERATURE REVIEW

The necessity of applying non-linear models to test the relationship between variables has been addressed in much previous research (Su *et al.*, 2019). Classical econometric methods, such as ordinary least squares (OLS) and quantile regressions (QR), cannot solve the complexity and might hide some interesting characteristics of the relationship. Instead, the quantile-on-quantile regression (QQ) researchers do not need to sort different regimes, such as Markov-switching approaches, but can present the nonlinear link in an ad-hoc fashion (Han *et al.*, 2019).

In the context of a deteriorating environment, domestic and foreign scholars are increasingly researching carbon-emission issues from three main aspects. First, some focus on renewable energy. Zheng *et al.* (2021) measure the influence of renewable-energy generation in China on its carbon emissions through a quantile-regression model to identify how encouraging the use of renewable energy can help China improve its emissions reductions. Yu *et al.* (2020) construct a panel quantile-regression model to examine whether China's renewable energy development has effectively promoted a reduction in carbon emissions. Khan *et al.* (2020) applied panel quantile-regression to examine the heterogeneity of renewable-energy consumption, carbon dioxide emission and financial development in 192 countries. They pointed out that the impact of renewable energy consumption on carbon emission is negative, while financial development has an increasing influence on carbon emission. Second, some research focuses on the issue of the relationship between China's carbon-emissions trading and stock markets. Wen *et al.* (2020) chose the Shenzhen pilot as an example and applied the difference-in-differences (DID) method to analyze quantitatively the impact of carbon emissions regulation on the stock returns of companies; in their findings, the coefficient of carbon risk factor is significantly positive and can be explained by the fact that companies participating in the carbon market have higher carbon exposures. Jiang et al. (2022) examine the nonlinear dependence between the carbon market and the stock market in China under normal and extreme market conditions by employing two novel nonlinear approaches. Ren *et al.* (2022) employ the quantile Granger causality test and the quantile-on-quantile regression methods to quantify the crude oil price impact on carbon price across the carbon-oil distribution, aiming to detect the short-, medium-, and long-term impacts of the crude oil price on carbon price. Thirdly, some focus on the drivers of carbon emission. Dong *et al.* (2018) employed structural decomposition analysis (SDA) and quantile regression to investigate the factors that drive changes in CEI in China. Xu and Lin (2020) used the quantile regression model to investigate drivers of CO_2 emission in China's heavy industry. The empirical results of their study show that the influence of economic growth exerted on the heavy industry's CO_2 emissions is quite various in different quantiles.

In short, based on the aforementioned discussion, literature on carbon issue is relatively abundant. Furthermore, one can easily see that the QR method is popular among their studies. However, studies that apply the QQ approach to analyze carbon issue are still scarce. Aiming to enrich the previous literature, this paper uses the comprehensive QQ approach to analyze the relationship between the China carbon trading market and stock markets.

3 DATA AND METHODOLOGY

3.1 *Data source*

The article takes the carbon trading price represented by the closing price in Guangdong province as explained variable, while the foreign carbon trading price and the stock market index as explanatory variables. The variables mentioned above are daily data, from August 6, 2018, to December 14, 2021. Definitions of them are provided in Table 1.

Table 1. Variables' definition.

Variable	Symbol	Definition	Source
Carbon trading price	GDEA	Guangdong carbon trading market's closing price and logarithmic	Wind
Foreign carbon trading price	EUA	European carbon trading futures market's closing price and logarithmic	
Stock market index	CSI300	Shanghai and Shenzhen stock markets index and logarithmic	Investing.com

3.2 *Methodology*

Due to the complicated relationship between the carbon trading market and the stock markets, this article introduces a non-linear method, the quantile-on-quantile approach (QQ) proposed by Sim and Zhou to estimate the effect different quantiles of foreign carbon-trading price (EUA) and the China stock market index (CSI300) respectively have on the different quantiles of the Guangdong carbon-trading market (GDEA).

The conventional quantile regression (QR) can merely capture the influence of X variable on the different quantiles of Y variable but is unable to uncover the elaborate features of the impact that account for extreme observations, which are ignored by conventional OLS methods (Han, Liu and Yin, 2019). The QQ approach is modified on conventional quantile regression (Adebayo *et al.*, 2021) and is able to capture the dependence between the distributions of Y variable and X variable as well as uncover two nuanced features in the Y–X relationship (Sim and Zhou, 2015). In short, the QQ approach could provide a lens for the complicated relationship in the Y–X relationship. In the context of this study, the QQ model can start by incorporating the following non-parametric quantile regression model:

$$E_t = \beta^{\theta}(X_t) + u_t^{\theta} \tag{1}$$

where E_t is defined as the GDEA, X_t represents the independent variables, here referring to EUA and CSI300, θ is the θ^{th} quantile of the conditional distribution of the X_t and u_t^{θ} denotes an error term with a zero θ-quantile. Since there is no prior information about how X_t and E_t are related, the function $\beta^{\theta}(X_t)$ is allowed to be unknown. Then, to analyze the relation between the θ^{th} quantile of E_t and the τ^{th} quantile of X_t, denoted by X^{τ}, Eq. (1) is examined in the neighborhood of X^{τ} employing local linear regression. Because $\beta^{\theta}(X_t)$ is unknown, this function can be linearized by a first-order Taylor expansion around a quantile X^{τ}, as follows:

$$\beta^{\theta}\left(X_t\right) = \beta^{\theta}\left(X^{\tau}\right) + \beta^{\theta'}\left(X^{\tau}\right)\left(X_t - X^{\tau}\right) \tag{2}$$

In Eq. (2) where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}\left(X_t\right)$ with respect to X_t, also called marginal effect, meanwhile, is similar in interpretation to the slope coefficient in a linear regression model. A prominent feature of Eq. (2) is that the parameters $\beta^{\theta}\left(X^{\tau}\right)$ and $\beta^{\theta'}\left(X^{\tau}\right)$ are doubly indexed in θ and τ. Given that $\beta^{\theta}\left(X^{\tau}\right)$ and $\beta^{\theta'}\left(X^{\tau}\right)$ are functions of θ and X_t while the X_t is a function of τ, that means $\beta^{\theta}\left(X^{\tau}\right)$ and $\beta^{\theta'}\left(X^{\tau}\right)$ are both functions of θ and τ. Eq. Therefore, Eq. (2) can be rewritten by redefining $\beta^{\theta}\left(X^{\tau}\right)$ and $\beta^{\theta'}\left(X^{\tau}\right)$ as $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$:

$$\beta^{\theta}\left(X_t\right) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(X_t - X^{\tau}\right) \tag{3}$$

By substituting Eq. (3) in Eq. (1), we can obtain the following equation:

$$E_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(X_t - X^{\tau}\right) + u_t^{\theta} \tag{4}$$

Notice that the independent variable X in this paper refers to EUA and CSI300; thus the notations X in Eq. (4) should be distinguished as follow.

$$E_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(EUA_t - EUA^{\tau}\right) + u_t^{\theta}$$
$$E_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(CSI300_t - CSI300^{\tau}\right) + u_t^{\theta} \quad (5)$$

4 EMPIRICAL RESULT AND ANALYSIS

The statistical descriptions of the variables in this paper are shown in Table 2. The numerical value of median and mean of the GDEA and EUA are about 3, while the CSI300 is slightly larger than 3. As for the skewness and kurtosis, the former descriptors reflect the asymmetry of the distribution, whereas the latter describes its steepness. The numerical value of them is about 0 and 2, respectively.

Table 2. Summary statistics.

	GDEA	EUA	CSI300
Mean	3.305	3.394	8.345
Median	3.325	3.260	8.309
Max	3.964	4.487	8.667
Min	2.485	2.724	7.995
Std. Dev.	0.303	0.389	0.168
Skewness	-0.256	0.860	-0.179
Kurtosis	2.617	2.639	1.856
Obs	758	758	758

4.1 *Pre-estimation tests*

Before undertaking further analyses, it is critical to confirm the relevant features of the series. This study applied the ADF test suggested by (Fuller, 1979) to test the stationary of the variables. The outcomes are presented in Table 3 and the outcomes revealed that all the series are non-stationary at level, while their first-order differences are significantly stationary.

Nelson and Plosser (1982) argue that many economic variables are not stationary and that treating the data purely by differencing to a stationary series would deprive the data of important information embedded in their economic theory, but if the original unstable series could be tested for cointegration, rather than being treated by differencing to a stationary series, it would have the advantage of avoiding the loss of economic significance while taking into account the underlying conditions of the regression. Thus, prior to statistical analysis, the Johansen cointegration test was used to test for the presence of cointegration between series and the results presented in Table 4 shown that series have a long-run equilibrium, which means the following statistical analysis will be carried out using the original order data.

Table 3. Summary statistics.

Variable	GDEA	EUA	CSI300
	Level		
ADF t-Statistic	-1.019	-0.113	-1.336
	First difference		
ADF t-Statistic	-34.039***	-28.599***	-27.195***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Johansen cointegration Test.

		Johansen MLE estimates (GDEA ~EUA)			
NULL:		Trace Statistic	Crit 90%	Crit 95%	Crit 99%
r <= 0	GDEA	17.573	16.162	18.398	23.148
r <= 1	EUA	3.572	2.705	3.841	6.635
		Johansen MLE estimates (GDEA ~CSI300)			
NULL:		Trace Statistic	Crit 90%	Crit 95%	Crit 99%
r <= 0	GDEA	16.668	16.162	18.398	23.148
r <= 1	CSI300	6.052	2.705	3.841	6.635

4.2 *Quantiles regression approach result*

Following most existing studies, this paper uses the 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 95^{th} quantiles as representative to conduct empirical analysis. As the quantile regression uses several quantile functions to estimate the overall model, that gives us a lens to look into the influence of the explanatory variables on the explained variables at different quantile points (Xu and Lin, 2020). The results of QR and OLS (ordinary least squares) are summarized in Table 5. All the results of the two models have passed the significant test with a p-value less than 0.01. Both of the EUA and CSI300 positively impact GDEA, according to the estimations results of QR; the former becomes weakened across quantiles, while the latter has its most significant positive impact on GDEA at the 90^{th} quantile.

Moreover, the results of quantile regression are graphically displayed in figure 1, quantiles regression estimation is in the black line while the 95% confidence interval is denoted by the grey area. The coefficient estimates of variables appears in the vertical axis. The quantile levels are illustrated in the horizontal axis. The OLS estimation is signified by the parallel continuous red line and the 95% confidence interval in the dash red line. Furthermore, the quantile regression (fit) results at different quantile points are depicted in figure 2. The blue continuous line refers to the OLS linear; the dash lines refer to different quantile points from low to high quantiles, respectively.

Table 5. Empirical result of quantiles regression.

variables	OLS	Quantiles levels						
		Q0.05	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9	Q 0.95
EUA	0.65 ***	0.85 ***	0.81 ***	0.77 ***	0.62 ***	0.51 ***	0.41 ***	0.39 ***
CSI300	1.53 ***	1.55 ***	1.36 ***	1.22 ***	1.61 ***	1.74 ***	1.82 ***	1.77 ***

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

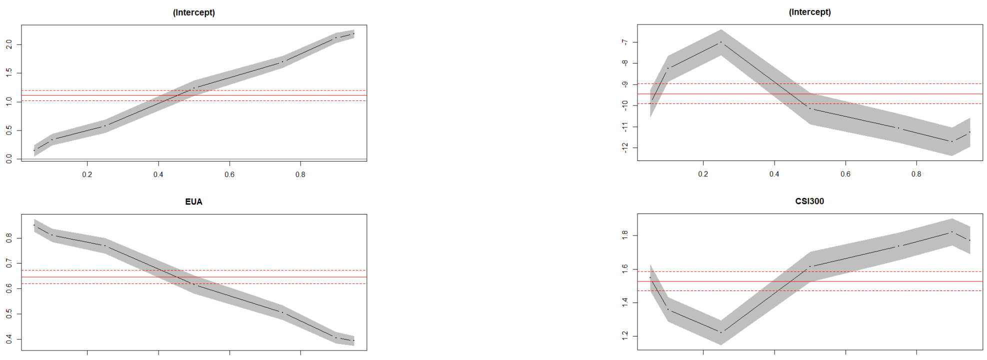

Figure 1. Quantile regression coefficients with 95% confidence intervals.

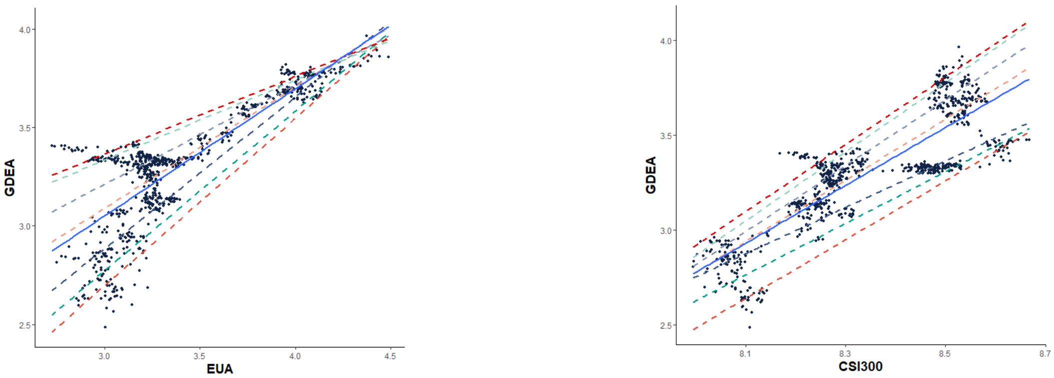

Figure 2. Quantile regression fit results at different quantile points.

4.3 *Quantile-on-Quantile regression approach result*

The QQ outcomes are graphically presented in Figure 3. The figure displays the slope estimates $\hat{\beta}_1(\theta,\tau)$, which catch the influence of the τ^{th} quantile of EUA (CSI300) on the θ^{th} quantile of GDEA for a broad range of combinations. The slope coefficients lie on the z-axis, and the quantiles of EUA (CSI300) and GDEA are depicted on the x and y-axes, respectively. The one on the left is the impact of EUA on GDEA, while the one on the right is CSI300 on GDEA.

In all quantiles (0.01-0.95) of the combination of EUA and GDEA, most of the effect of EUA on GDEA is positive, and it produces a flat-looking figure; more specifically, the obtained slope coefficients take positive and similar values for the majority of quantiles. The influence is more especially strong in the middle tail (0.5–0.75) of GDEA and the lower quantiles of EUA (0.05-0.25), and its sign turns from positive to negative between the lower quantiles of EUA (0.1–0.25) and the lower quantiles of GDEA (0.25-0.5). As for the combination of CSI300 and GDEA, the figure is quite different where the GDEA is sensitive to CSI300's changes. The slope estimates are at the highest between the upper quantiles (0.9-0.95) of GDEA and the upper quantiles of CSI300 (0.9-0.95), which indicates that the CSI300 under bullish market condition positively affects the GDEA while it is in the upper quantiles. A similar impact can also be seen between the upper quantiles of CSI300 (0.9–0.95) and the lower quantiles of GDEA (0.25-0.5). The estimated slope coefficient falls drastically in the area that combines the lower quantiles of CSI300 (0.1–0.25) and the median quantiles of GDEA (0.25–0.5).

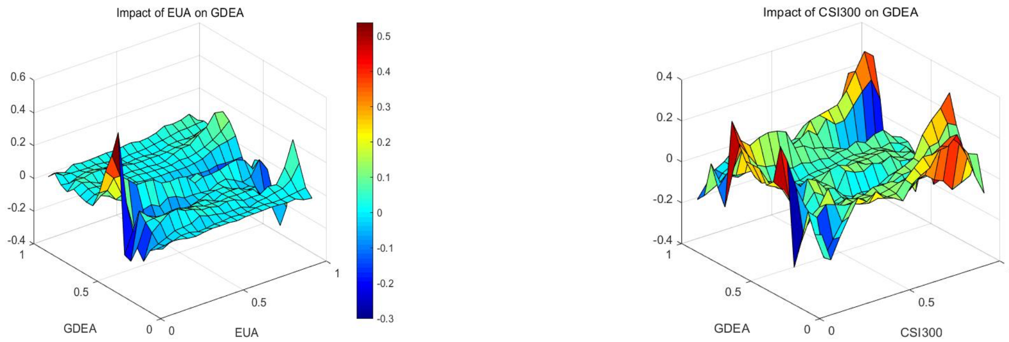

Figure 3. Quantile on Quantile Regression (QQR) estimates.

4.4 *Robustness check*

In this portion, by comparing the results of QQ estimates with the quantile regression (QR), we can recognize the findings of QQ estimates are more or less consistent with the findings of QR.

The QQ approach regresses the θ^{th} quantile of the EUA (CSI300) on the τ^{th} quantile of GDEA; therefore, its parameters can be explained by θ and τ. Because the QR parameters are only explained by θ, the QQ approach can be referred to as the "decomposition" of the QR estimates (Sim and Zhou, 2015). Based on this principle, approximate estimates of the QR should be recovered from the QQ estimates. Denoting the slope coefficient of QR as $\gamma_1(\theta)$, the impact of EUA (CSI300) on GDEA can be written as follows:

$$\gamma_1(\theta) \equiv \hat{\bar{\beta}}_1(\theta) = \frac{1}{S}\sum \hat{\beta}_1(\theta, \tau) \tag{6}$$

where S = 19 is the number of quantiles θ = [0.05, 0.10, …, 0.95].

The outcome is depicted in the figure 4; estimations of parameters for quantile regression are presented by continuous black lines. Dashed red lines present the averaged quantile regression estimations at various quantiles of GDEA. The one on the left is the estimates of EUA on GDEA, while the one on the right is CSI300 on GDEA.

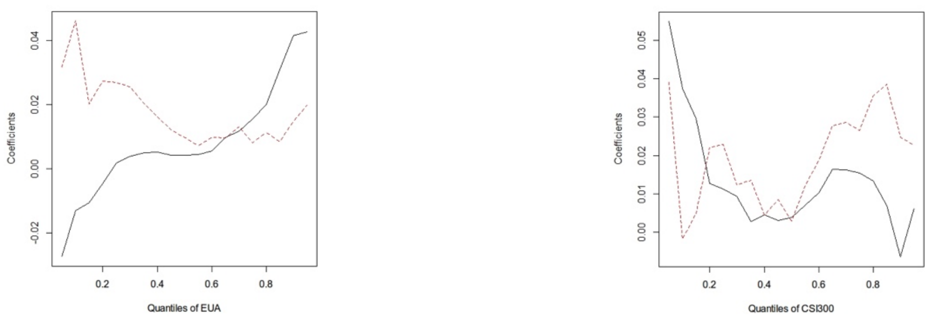

Figure 4. Comparison of quantile-on-quantile regression (QQ) and quantile regression (QR).

5 CONCLUSION

China has made a great effort in low-carbon development since 2011, as the conception of decreasing carbon emissions has become a core issue of human concern. Especially for China, the world's largest energy consumer and carbon emitter, the implementation of measures to reduce carbon emissions will definitely influence carbon-reducing throughout the world. The purpose of this paper is to acquire some new data by applying the novel quantile-on-quantile regression method to discuss the impact of the stock market and the foreign carbon-trading market on the Guangdong carbon-trading market. The array of results from the empirical analysis is outlined as follows:

The QR approach estimation result shows that both of the EUA and CSI300 have a positive impact on GDEA; in other words, no matter the EUA and CSI300 market under bearish and bullish market conditions, they always have a positive impact on the China carbon trading market. The influence of EUA on GDEA becomes weakened across quantiles, while the CSI300 acquires its most significant positive impact on GDEA at the 90^{th} quantile. And the latter indicates that when the Shanghai and Shenzhen stock markets are in the bullish condition, the positive influence on China’s carbon trading will become stronger than the others. As for the QQ approach estimation result, although most of the effect of EUA on GDEA appears to be positive across quantiles, it does provide more detailed information compared to the QR result, showing a flat-looking figure. The result indicates that China’s carbon trading market is insensitive to the European carbon trading futures market across all the quantiles combination of them. On the contrary, the findings show that the GDEA is sensitive to CSI300 changes, while the CSI300 under bullish market condition positively affects the GDEA while it is in the upper quantiles. Moreover, when it comes to the area between the lower quantiles of CSI300 (0.1–0.25) and the median quantiles of GDEA (0.25–0.5), the estimated slope coefficient falls drastically. It can be interpreted as when the Shanghai and Shenzhen stock markets are in the bearish condition and the China carbon trading market recovers from a bearish condition, the impact coming from the CSI will become slighter.

For whomever may be concerned, the investors can refer to the conclusion this paper sets out. When they adjust their investment portfolio or manage risk hedging, we hope that the estimation result, the impact of EUA and CSI300 on GDEA under different quantiles conditions, could provide some useful information.

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