Interaction Between China`s Carbon Markets Under The Impact Of COVID-19

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***Abstract*—Due to the COVID-19, most of China's economic activity slowed to a halt in 2020. China's pilot carbon market has also been affected by the COVID-19, and its activity has declined. Based on the quantile regression method, this paper compares whether each carbon market has an impact on the Hubei carbon market before and after the epidemic. First, the carbon emission allowance price series of each pilot carbon market in China is processed smoothly, and seven quantiles of lower quantile, middle quantile and upper quantile are selected to represent three different market environments. The influence relationship between each carbon market and Hubei carbon market is analyzed respectively. Then, the VAR model is used to compare the impact of each carbon market before and after the epidemic. Firstly, the optimal lag order is selected according to the majority principle, and then the stability of the model is checked. Finally, the variance decomposition is performed to obtain the effect size.**

Keywords—Carbon market; COVID-19; Quantile regression;VAR

I. INTRODUCTION

In recent years, the natural environment on which human beings depend has been severely damaged after continuous development over the years. The current climate issue and the new crown epidemic have become two major problems that plague the international community. Global warming is one of the major environmental problems facing human beings today. In recent years, the warming of the global climate system has accelerated [1], the glaciers have melted, the phenological period has advanced, and the sea level has risen. A number of historical records have been refreshed, and the extremes of the climate have increased significantly. The massive use of fossil fuels by humans is the main cause of global warming and emits a large amount of carbon dioxide and other greenhouse gases. Uncertainty about climate and extreme weather will only further increase the social cost of carbon emissions [2].

Since 2005, China has participated in the global carbon market by developing clean development mechanism projects [3]. At that time, China played the role of seller and seller in the world carbon trading market, which allowed China to obtain substantial benefits from it. In 2009, my country promised for the first time at the Copenhagen World Climate Conference that by 2020, the national carbon intensity will be reduced by 40% to 45% compared with 2005. In 2011, my country first proposed the goal of carbon dioxide emissions per unit of GDP in the “Twelfth Five-Year Plan” (2011-2015). The National Development and Reform Commission selected Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen to carry out pilot carbon emission trading market construction. In 2013, Shenzhen took the lead in launching a pilot carbon market, followed by Shanghai, Beijing, Guangdong, Hubei, Guangdong, and Chongqing. In 2015, my country submitted its Nationally Determined Contribution to Climate Change to the Secretariat of the United Nations Framework Convention on Climate Change. It is proposed that by 2030, carbon dioxide emissions per unit of GDP will be reduced by 60% to 65% compared with 2005, and actions to deal with climate change will be included in the “Thirteenth Five-Year” development plan. In 2020, my country announced at the United Nations General Assembly that China will strive to reach the peak by 2030 and strive to achieve carbon neutrality by 2060 [4].

With the outbreak of the new crown epidemic in early 2020, countries have entered a state of emergency and adopted a series of measures to curb the spread of the epidemic. These measures will undoubtedly cause a huge blow to the world economy [5]. After years of trials and preparations, the national carbon market will be officially launched in 2020, which happens to be the first year of my country's launch of the national carbon trading market. Although the domestic epidemic has stabilized under strong control and epidemic prevention measures, due to the continuous deepening of globalization, the overseas epidemic is still expanding. The global economic recession caused by the new crown epidemic will inevitably be transmitted to my country's carbon trading market, indirectly affecting the The construction of the national carbon market brings challenges [6].

II. LITERATURE REVIEV

In recent years, with the rapid development of the domestic carbon market, articles on the domestic carbon market have increased rapidly. The research mainly focuses on the fluctuation of carbon price and the influencing factors of carbon price.

To the first branch, Chen Min [7] described the fluctuation of carbon price by means of mean regression, and proved the validity of mean regression method to describe the fluctuation of carbon price. After decomposing carbon price, Feng Zhenhua [8] explored the change of carbon price from three perspectives: market mechanism, heterogeneous environment and temperature. The study found that the carbon price is affected by the market with a high frequency and a short duration, while the heterogeneous environment affects the carbon price with a low frequency, a long duration and a large amplitude. Julien Chevallieret [9] used the GARCH model to test the impact of option introduction on volatility by using dummy variables in the volatility equation, and completed the endogenous structure breakpoint test and window estimation. The study found that the introduction of option trading to EU-ETS Volatility on futures prices did not have a significant effect.

To the second branch, Wu Sitong [10] used a fixed effect regression model to explore the influencing factors of carbon price in China, and found that the price of non-clean energy is negatively correlated with carbon price, but positively correlated. And there are individual and time effects in the carbon markets of the six pilot cities in the sample. At the same time, through the panel vector autoregressive model, it is found that the stable growth of the macro economy will increase the carbon price, and the energy conversion cost has a small contribution to the change of the carbon price. Xu Shuai [11] used a linear regression model to analyze variables such as EU carbon prices and end product prices, production factor prices, and market indexes. The results found that electricity prices, natural gas prices, and market indexes had a significant impact on EUA futures prices, and electricity prices Zhang Peng [12] selected factors such as energy prices, financial markets, macroeconomics, foreign carbon market prices, government policies, extreme temperatures, etc, and analyzed the carbon prices in the carbon markets of Beijing, Hubei, Guangdong and Shenzhen influencing factors. The results show that the same influencing factor will have different effects on different carbon market prices in the same time period. In general, the four pilot carbon markets are all positively affected by their own historical transaction prices, and this effect is long-term; EUA prices are mainly affected by Beijing and Hubei pilot markets have a positive impact on carbon prices, while the impact on Guangdong and Shenzhen pilot markets is not significant; extreme temperatures have a significant positive impact on carbon prices in the pilot markets in the short and medium term, while the impact is no longer significant in the long term; compared For other pilot markets, Beijing pilot market is affected by more influencing factors, and its marketization degree is higher. In general, the carbon price is more affected by the demand side than the supply side. Compared with the EU emission trading market, the carbon price marketization degree of my country's pilot carbon market is relatively low, and the connection with the relevant market is weak. Chen Xuan [13] showed that the impact of the severe situation of the epidemic abroad on the domestic carbon price was mainly reflected in the following aspects: on the one hand, since the outbreak of the global epidemic, the international carbon market suffered serious setbacks, and the carbon price fluctuated greatly. The carbon price in the secondary market of the European Union and California in the United States dropped significantly, and the carbon price in the European Union fell by more than 30% at the beginning of the outbreak of the epidemic.

III. METHOD

A. ADF test

The ADF test is the unit root test. Define a random sequence $\{x_t\}$, t = 1, 2 · · · to be a unit root process, if $x_t = \rho x_{t-1+\varepsilon}, (|\rho|<1)$, $\{\varepsilon\}$ is a stationary sequence (white noise), and $E(\varepsilon)=0$, $V(\varepsilon)=\sigma<\infty$, $Cov(\varepsilon,\varepsilon)=\mu<\infty$. In particular, if $\rho=1$, the above formula becomes a random walk sequence, so the random walk sequence is the simplest unit root process.

$(1-\rho L)x_t=\varepsilon$, where L is the lag operator, $1-\rho L$ is a lag operatoryou polynomial, and its characteristic equation is $1-\rho z=0$, with root $z=\frac{1}{\rho}$. When $\rho=1$, there is a unit root in the time series, and $\{x_t\}$ is a unit root process at this time. When $\rho<1$, $\{x_t\}$ is a stationary sequence.

B. Quantile regression model

Multiple regression analysis can study the statistical dependence of the dependent variable on two or more explanatory variables. A multiple regression model is a regression model with two or more explanatory variables. Let the dependent variable be Y, and the k independent variables be $x_1, x_2, \cdots x_k$ respectively. The equation describing how the dependent variable Y depends on the independent variable and the error term ε is called a multiple regression model. Its general form can be expressed as

$$Y_i = B_0 + B_1x_1 + B_2x_2 + \cdots + B_kx_k + \varepsilon \tag{1}$$

Regression analysis is a statistical method in which the least squares method (OLS) is the most commonly used model used to describe the effect of independent variables on the conditional mean of dependent variables. Describe the effect of the conditional mean by establishing the shortest distance between the equation and the sample. OLS has good validity and unbiasedness when the random distractor has a normal distribution with zero mean and the same variance and at the same time does not satisfy the correlation with the explanatory variables. The principle of the least squares method is to make the residual as small as possible, that is,

$$\min \sum \varepsilon_i^2 = \min \sum (y_i - \hat{y}_i)^2 \quad (2)$$

where $\hat{y}_i$ is an estimate.

OLS regression mainly focuses on the mean value and only describes the influence of the independent variable on the local change of the dependent variable, but OLS regression cannot see the trend of the influence, and OLS regression requires the dependent variable Y to be normally distributed, and OLS regression is more sensitive to outliers, and OLS regression is also more sensitive to heteroscedasticity problems.

Quantile regression effectively makes up for these deficiencies. If you want to see the influence relationship and influence trend of X on Y, you can use quantile regression; quantile regression can check the influence trend and change of X on Y, and quantile regression can be used for outliers and dependent variables. Both normality and heteroscedasticity problems have strong robustness. Typically, quantile regression estimates data for a specific distribution by estimating different quantile values of the dependent variable between 0 and 1. Suppose the probability distribution function of the random variable Y is:

$$F(y) = P(Y \le y) \quad (3)$$

For any $0 < \tau < 1$, the quantile τ of Y is defined as the smallest Y satisfying $FY \ge \tau$, expressed as:

$$F^{(-1)}(\tau) = \inf \{y : F(y) \ge \tau\} \quad (4)$$

where $F^{(-1)}(0.5)$ is the median. The regression of the sample median is to minimize the sum of the absolute values of the errors:

$$\min_{\delta \in R} \sum_{i=1}^{n} |y_i - \delta| \quad (5)$$

While quantile regression is to minimize the weighted sum of absolute errors, it can be expressed as:

$$\min_{\delta \in R} \left\{ \sum_{i:Y_i \ge \delta} \tau |y_i - \delta| + \sum_{i:Y_i \ge \delta} (1-\tau) |y_i - \delta| \right\} \quad (6)$$

The test function for quantile regression is expressed as:

$$\rho_\tau(\alpha) = \alpha(\tau - I), (\alpha < 0) \quad (7)$$

For a given X, the quantile Y can be expressed as:

$$Q_\tau(Y \mid X) = \inf \{y : F_{Y|X}(y) \ge \tau\} \quad (8)$$

The estimated parameter values are:

$$\hat{\beta} = \arg\min_{\beta \in R_\rho} \sum_{i=1}^{n} (y_i - x_i'\beta) \quad (9)$$

C. VAR model

The VAR model, also known as the vector autoregressive model, is a commonly used econometric model, which was proposed by Christopher Sims in 1980. VAR model is to use all current variables in the model to regress several lagged variables of all variables to study the interaction between different variables. The mathematical expression of the general VAR(p) model is:

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots + b_p Y_{t-p} + \varepsilon_t \quad (10)$$

Y_t is a k-dimensional vector, b_0 is a constant vector, $b_i (i = 1, 2, \cdots, p)$ is a $k \times k$ coefficient matrix, and ε_t is a residual vector.

IV. EXPERIMEATAL RESULTS

Table.1 reports the descriptive statistical analysis of the variables involved in the model with the dependent variable Hubei carbon market price and the remaining seven carbon market prices as independent variables as research samples. The daily sampling period used in the analysis was from January1, 2017 to January 1, 2021.

TABLE I. DESCRIPTIVE STATISTICS TABLE OF RETURN SERIES OF EACH VARIABLE IN CARBON MARKET BEFORE THE EPIDEMIC

Variables	mean	sd	min	median	max	skewness	kurtosis
Beijing	62.10	13.75	30.32	57.71	87.50	0.47	-0.87
Chongqing	10.92	9.76	1.00	6.80	38.94	1.21	0.39
Fujian	22.55	8.24	7.19	20.54	42.28	0.23	-0.71
Guangdong	17.34	4.66	9.80	15.19	28.03	0.79	-0.74
Hubei	23.11	8.55	11.26	19.07	53.85	0.53	-0.65
Shanghai	36.39	4.89	24.75	37.03	49.98	-0.30	-0.56
Shenzhen	28.99	9.16	7.35	31.42	44.69	-0.84	-0.14
Tianjin	11.83	2.20	8.50	12.50	15.80	-0.56	-1.09

Table.1 shows that all variables have positive mean values. Kurtosis coefficient determines whether the data distribution is steeper or smoother than normal distribution. Intuitively, kurtosis reflects the cuspness of the peak. If the kurtosis is less than zero, the peak is flattened. If the kurtosis is greater than three, the peak is sharper and steeper than the normal distribution peak. By measuring the skewness coefficient, we can judge the degree of asymmetry and direction of data distribution. It can be seen from the data that all variables have a certain degree of skewness, and most of them are skewed to the right. This indicates that the unconditional distribution of these variables is asymmetric, so using quantile regression methods can solve these problems by providing a more flexible and complete description of the problem.

Before performing quantile regression, we performed a unit root test using the Augmented Dickey-Fuller (ADF) method to test whether the variables used were stationary. If no unit root for stationary time series of the variables, can do further analysis.

TABLE II. PANEL UNIT OF ALL VARIABLES(ZEROTH ORDER DIFFERENCES)

Variables	Test Statistic	P
Beijing	-1.539	0.514
Chongqing	-2.532	0.108
Fujian	-2.467	0.124
Guangdong	1.805	0.998
Hubei	-1.109	0.711
Shanghai	-2.237	0.193
Shenzhen	-0.118	0.948
Tianjin	-1.455	0.555

Table.2 shows that in the case of no difference, the P values of the variables are all greater than 0.01 ,so the null hypothesis cannot be rejected,and the series is not stationary. We need to perform first-difference on the sequence and then perform the ADF. The results given in Table.3 show that after the first-order difference of the carbon emission price series, the unit root test P value of the first order difference series is less than 0.01. The null hypothesis is significantly rejected, indicating that the first order difference sequence is a stationary sequence. Therefore, for the dependent variable, all explanatory variables in the model are used for subsequent analytical regression in the form of the first natural log difference.

We use quantile regression to study the impact of the remaining carbon markets on the Hubei carbon market and compare it with the OLS regression results. OLS regression judges whether there is an influence by the significance of the regression coefficients, and what is the direction of the influence. However, OLS regression cannot see the trend of the impact, and OLS regression requires that the dependent variable Y is normally distributed, and OLS regression is more sensitive to outliers, and OLS regression is also more sensitive to heteroscedasticity problems. There are many solutions to normal distribution, outlier problem and heteroscedasticity problem, but the change trend of regression coefficient cannot be viewed. If you want to see the influence relationship and influence trend of other carbon markets on Hubei carbon market, you can use quantile regression. Quantile regression can test the influence trends and changes of other carbon markets on Hubei carbon market. Value, dependent variable normality, or heteroskedasticity problems have strong robustness.

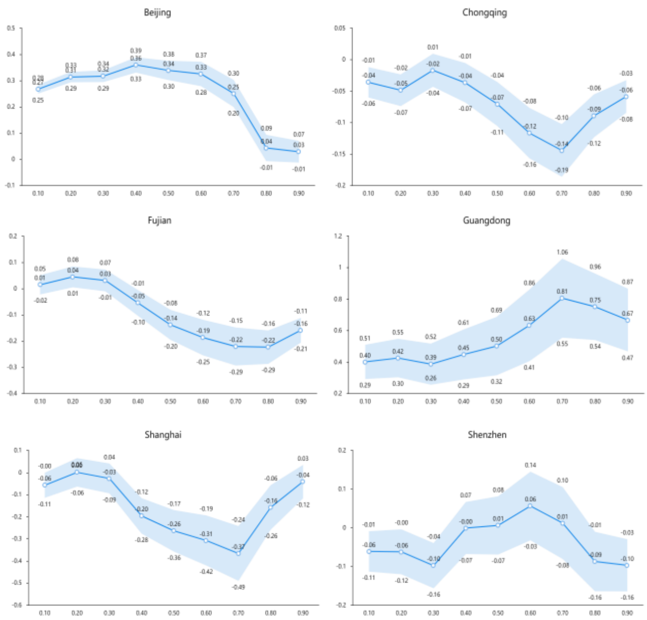
TABLE III. PANEL UNIT OF ALL VARIABLES(FIRST ORDER DIFFERENCES)

Variables	Test Statistic	P
Beijing	-10.086	0.000
Chongqing	-6.370	0.000
Fujian	-24.260	0.000
Guangdong	-12.274	0.000
Hubei	-12.093	0.000
Shanghai	-15.049	0.000
Shenzhen	-7.205	0.000
Tianjin	-8.441	0.000

We selected seven quantiles from the lowest quantile (0.05^{th}) to the highest quantile (0.95^{th}) and divided them into lower quantiles (0.10^{th} and 0.25^{th}), middle quantiles (0.50^{th}) and higher (0.75^{th}, 0.90^{th} and 0.95^{th}) to represent three different market environments. OLS regression estimates the mean effect of the regressors on the response variable. Compared with OLS regression, quantile regression provides a richer description. Table.4 shows the estimation results of quantile regression and OLS regression, and there are differences in the estimated coefficients under different quantiles. This indicates that the remaining carbon market price has an impact on the Hubei carbon market price, and this impact is heterogeneous in different price ranges.

TABLE IV. THE ESTIMATED RESULTS OF QUANTILE REGRESSION OLS REGRESSION FOR THE CORBON MARKET BEFORE THE EPIDEMIC

Market	Q 0.05	Q 0.1	Q 0.25	Q 0.5	Q 0.75	Q 0.9	Q 0.95	OLS
Beijing	0.232	0.267	0.308	0.339	0.104	0.028	0.033	0.200
Chongqing	-0.017	-0.036	-0.040	-0.071	-0.132	-0.059	-0.067	-0.156
Fujian	-0.001	0.014	0.035	-0.138	-0.265	-0.159	-0.169	-0.145
Guangdong	0.428	0.400	0.447	0.501	0.867	0.666	0.818	0.993
Shanghai	-0.089	-0.058	-0.008	-0.264	-0.284	-0.042	-0.054	-0.316
Shenzhen	-0.056	-0.061	-0.070	0.006	-0.033	-0.097	-0.077	0.090
Tianjin	0.420	0.439	0.400	0.976	1.869	2.737	2.685	1.058



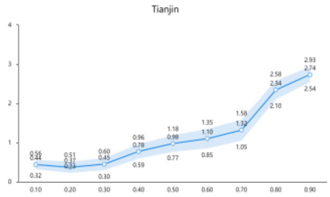


Fig. 1. *The dynamic trajectory of the regression coefficients of various carbon market quantiles in China before the epidemic.*

Table.4 shows that Beijing, Chongqing and Tianjin carbon markets are positively correlated with Hubei carbon markets. It shows that when the price of these three carbon markets increases, the price of Hubei carbon market will increase. And with the increase of quantiles, the positive correlation between Guangdong and Tianjin carbon markets increases. The rest of the carbon market is negatively correlated with the Hubei carbon market.

Fig.1 are the dynamic trajectories of the carbon market quantile regression coefficients, where the vertical axis represents the coefficient estimates of the variables on the distribution, the horizontal axis represents the quantile of the dependent variable, and the quantile regression error corresponds to 0.95 of the bootstrap confidence interval.

Table.5 reports the descriptive statistical analysis of the variables involved in the model with the dependent variable Hubei carbon market price and the remaining seven carbon market prices as independent variables as research samples.

TABLE V. DESCRIPTIVE STATISTICS TABLE OF RETURN SERIES OF EACH VARIABLE IN CARBON MARKET DURING THE EPIDEMIC

Variables	mean	sd	min	median	max	skewness	kurtosis
Beijing	86.26	6.96	62.58	86.61	102.96	-0.99	1.60
Chongqing	25.61	8.33	12.75	26.00	44.86	0.17	-1.11
Fujian	13.53	5.20	8.87	10.95	26.62	0.81	-0.59
Guangdong	28.20	1.12	16.74	28.12	30.84	-4.65	3.30
Hubei	27.11	1.53	22.96	27.51	30.56	-0.25	-0.78
Shanghai	39.73	3.45	28.60	40.10	49.50	-0.39	1.14
Shenzhen	24.80	10.17	7.15	25.06	43.88	-0.03	-1.15
Tianjin	22.19	4.07	15.00	24.00	27.00	-0.47	-1.32

From the data shown in Table.5, it can be seen that, similar to the previous section, using the quantile regression method can provide a more flexible and complete description to study the relationship between domestic carbon markets. Also before performing quantile regression, we perform a unit root test on all variables to test the stationarity of all variables.

TABLE VI. PANEL UNIT OF ALL VARIABLES(ZEROTH ORDER DIFFERENCES)

Variables	Test Statistic	P
Beijing	-6.211	0.000
Chongqing	-1.884	0.340
Fujian	-1.978	0.296
Guangdong	-4.243	0.001
Hubei	-1.659	0.452
Shanghai	-5.917	0.000
Shenzhen	-1.740	0.411
Tianjin	-1.557	0.505

TABLE VII. PANEL UNIT OF ALL VARIABLES(FIRST ORDER DIFFERENCES)

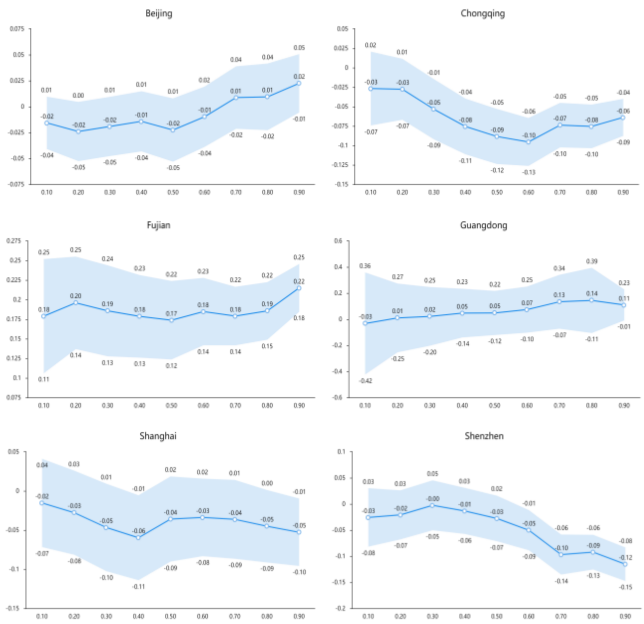
Variables	Test Statistic	P
Beijing	-5.417	0.000
Chongqing	-18.424	0.000
Fujian	-3.162	0.000
Guangdong	-9.643	0.000
Hubei	-12.682	0.000
Shanghai	-8.680	0.000
Shenzhen	-13.422	0.000
Tianjin	-4.542	0.000

Table.6 shows that, for most variables, the null hypothesis of the existence of a unit root cannot be rejected. However, the results given in Table.7 show that after the first-order difference of the carbon price series, the unit root test P values of the first-order difference series are all less than 0.01 level, indicating that the first-order difference series is a stationary series. Therefore, similar to the previous section, all variables in the model were subjected to subsequent quantile regression analysis in the form of the first natural log difference.

TABLE VIII. THE ESTIMATED RESULTS OF QUANTILE REGRESSION OLS REGRESSION FOR THE CORBON MARKET DURING THE EPIDEMIC

Market	Q 0.05	Q 0.1	Q 0.25	Q 0.5	Q 0.75	Q 0.9	Q 0.95	OLS
Beijing	-0.005	-0.016	-0.021	-0.023	0.011	0.023	0.015	-0.007
Chongqing	0.000	-0.027	-0.038	-0.088	-0.081	-0.064	-0.075	-0.062
Fujian	0.213	0.179	0.182	0.174	0.170	0.215	0.161	0.185
Guangdong	-0.087	-0.033	0.020	0.048	0.137	0.109	-0.107	0.023
Shanghai	0.021	-0.015	-0.039	-0.036	-0.041	-0.053	0.018	-0.036
Shenzhen	0.010	-0.026	-0.016	-0.028	-0.094	-0.115	-0.091	-0.035
Tianjin	-0.065	0.018	-0.087	-0.114	0.041	0.123	0.065	-0.063

As in the previous section, we choose seven quantiles, which are divided into lower, middle, and upper quantiles to represent three different market environments. OLS regression estimates the mean effects of regressors on response variables, and quantile regression provides a richer description than OLS regression.



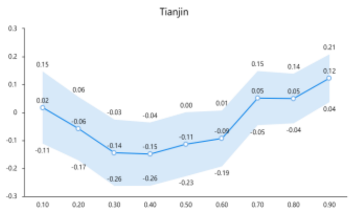


Fig. 2. *The dynamic trajectory of the regression coefficients of various carbon market quantiles in China during the epidemic.*

Table.8 shows the regression results, the Fujian carbon market is positively correlated with the Hubei carbon market. When the carbon market price in Fujian rises, it will lead to an increase in the carbon price in Hubei. The carbon markets of Chongqing, Shanghai and Shenzhen are negatively correlated with the carbon markets of Hubei. The Beijing, Tianjin and Guangdong carbon markets were negatively correlated in the low and middle quantile stages, and positively correlated in the high quantile stage.

TABLE IX. THE CHOICE OF LAG ORDER OF VAR MODEL BEFORE THE EPIDEMIC.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-17031.46	NA	5.67e+10	47.46367	47.51466	47.48336
1	-8158.559	17523.36	1.250249*	22.92635*	23.38527*	23.10354*
2	-8102.721	109.0321	1.279076	22.94908	23.81594	23.28378
3	-8061.016	80.50472	1.361241	23.01119	24.28597	23.50339
4	-8011.544	94.39750	1.417871	23.05165	24.73437	23.70136
5	-7959.842	97.49902	1.467983	23.08591	25.17655	23.89312
6	-7924.940	65.03966	1.593046	23.16696	25.66554	24.13168
7	-7859.345	120.7755*	1.587537	23.16252	26.06903	24.28474
8	-7828.301	56.46796	1.742428	23.25432	26.56875	24.53404

It is known from the previous section that the selected time series is a stationary series. Before fitting the model, we need to determine the optimal lag order. The selection of the optimal lag order is based on the principle of majority. If the lag order is too large, the degree of freedom will be small, and if the lag order is too small, some information of the data will be missed. Table.9 shows the lag tests.

It is seventh order according to LR criterion, and first order according to FPE, AIV, SC and HQ. According to the majority rule, we choose the first order as the optimal lag order. Thereby establishing a VAR(1) model.

Before delving further, we need to check the stability of the model. It can be seen from Fig.3 that all the roots are located in the circle, and the model has passed the stability test, and the variance decomposition can be further studied in the next step.

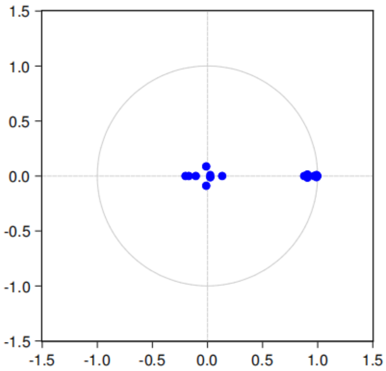


Fig. 3. *VAR model AR root test*

Variance decomposition can determine the degree of influence of influencing factors. This paper obtains the contribution of the remaining seven carbon markets to the Hubei carbon market through variance decomposition, and conducts a comparative analysis. The results of variance decomposition analysis are shown in Table.10 below.

As can be seen from the above table, the first phase of the Hubei carbon market received its own structural impact of 95.993%, and then gradually weakened, and was strengthened by the structural impact of other variables. The impact of the 25th phase itself is still the largest, reaching 86.154%. It can be seen that the impact of other carbon markets on the Hubei carbon market is currently very limited. The second most influential is the Beijing carbon market. The degree of explanation of each influencing factor is ranked from high to low: Hubei > Beijing > Fujian > Shanghai > Chongqing > Shenzhen > Tianjin > Guangdong.

TABLE X. VARIANCE DECOMPOSITION BEFORE THE EPIDEMIC

Period	S.E.	BJ	CQ	FJ	GD	HB	SH	SZ	TJ
1	1.126	0.013	0.043	3.844	0.104	95.993	0.000	0.000	0.000
2	1.445	0.010	0.056	3.615	0.163	95.832	0.274	0.001	0.048
3	1.715	0.039	0.078	3.549	0.145	95.753	0.386	0.003	0.047
4	1.935	0.114	0.099	3.550	0.127	95.564	0.490	0.010	0.046
5	2.127	0.237	0.122	3.580	0.109	95.303	0.582	0.023	0.043
6	2.297	0.401	0.148	3.623	0.095	94.985	0.668	0.040	0.039
7	2.451	0.602	0.175	3.673	0.083	94.622	0.748	0.061	0.036
8	2.592	0.831	0.204	3.726	0.075	94.222	0.823	0.086	0.033
9	2.722	1.086	0.234	3.781	0.069	93.794	0.892	0.114	0.030
10	2.844	1.361	0.266	3.835	0.066	93.343	0.956	0.145	0.027
11	2.959	1.651	0.300	3.890	0.065	92.876	1.015	0.178	0.025
12	3.067	1.954	0.335	3.943	0.067	92.396	1.069	0.213	0.024
13	3.170	2.265	0.372	3.996	0.070	91.908	1.118	0.249	0.023
14	3.268	2.583	0.409	4.047	0.074	91.415	1.163	0.286	0.022
15	3.361	2.905	0.448	4.096	0.080	90.919	1.204	0.325	0.022
16	3.451	3.230	0.488	4.144	0.087	90.423	1.241	0.365	0.022
17	3.537	3.554	0.529	4.191	0.096	89.928	1.274	0.405	0.023
18	3.620	3.878	0.571	4.236	0.105	89.436	1.304	0.446	0.025
19	3.700	4.199	0.613	4.280	0.115	88.949	1.331	0.488	0.027
20	3.778	4.517	0.657	4.321	0.125	88.466	1.354	0.530	0.029
21	3.853	4.832	0.701	4.362	0.137	87.990	1.375	0.572	0.032
22	3.925	5.142	0.745	4.400	0.148	87.520	1.394	0.615	0.036
23	3.996	5.447	0.790	4.437	0.161	87.057	1.410	0.659	0.040
24	4.064	5.746	0.836	4.473	0.173	86.602	1.424	0.702	0.044
25	4.131	6.040	0.882	4.507	0.186	86.154	1.436	0.746	0.049

For the epidemic period, we know from the ADF test that the time series is a stationary series. The optimal lag order is determined by six decision criteria. It can be seen from Table.11 that according to the majority criterion, we choose the second order as the optimal lag order to establish the VAR(2) model.

TABLE XI. THE CHOICE OF LAG ORDER OF VAR MODEL DURING THE EPIDEMIC

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4247.299	NA	99035041	41.11400	41.24280	41.16609
1	-2945.540	24 90.321	634.2231*	29.15498*	30.31418*	29.62375*
2	-2890.864	100.3719*	695.7652	29.24506	31.43467	30.13052
3	-2852.351	67.72386	895.8498	29.49131	32.71133	30.79346
4	-2805.307	79.08807	1068.560	29.65514	33.90556	31.37397
5	-2769.703	57.10349	1435.012	29.92950	35.21033	32.06502
6	-2732.362	57.00446	1914.617	30.18707	36.49831	32.73928
7	-2701.970	44.04541	2766.914	30.51179	37.85343	33.48069
8	-2648.081	73.93583	3236.030	30.60947	38.98152	33.99506

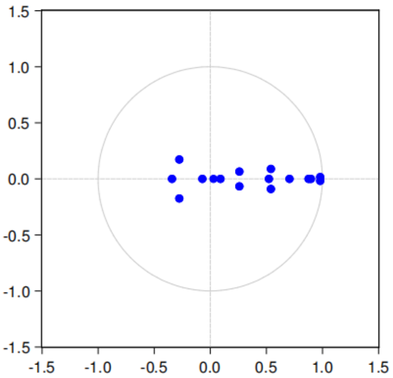


Fig. 4. *VAR model AR root test*

Likewise, we need to check the stability of the model. As can be seen from the fig.4, all the roots are located in the circle, the model has passed the stability test, and the next step can be to further study the variance decomposition.

Similarly, we perform variance decomposition to determine the degree of influence of each influencing factor during the epidemic.

It can be seen from Table.12 that the first phase of the Hubei carbon market suffered the strongest structural impact, and the explanation degrees of each influencing factor are ranked from high to low:Hubei > Fujian > Chongqing > Beijing > Tianjin > Shenzhen > Guangdog > Shanghai.

TABLE XII. VARIANCE DECOMPOSITION DURING THE EPIDEMIC

Period	S.E.	BJ	CQ	FJ	GD	HB	SH	SZ	TJ
1	0.838	0.037	2.443	1.352	0.118	96.051	0.000	0.000	0.000
2	0.915	2.348	3.918	1.531	0.318	91.079	0.010	0.061	0.734
3	0.981	2.433	4.010	1.845	0.297	90.582	0.010	0.105	0.719
4	1.022	2.692	4.850	2.564	0.341	88.650	0.011	0.208	0.684
5	1.057	3.198	5.512	3.536	0.343	86.447	0.022	0.302	0.639
6	1.087	3.609	6.076	4.717	0.342	84.213	0.036	0.400	0.606
7	1.113	3.915	6.500	6.021	0.334	82.103	0.049	0.499	0.579
8	1.137	4.112	6.799	7.389	0.324	80.158	0.058	0.604	0.555
9	1.159	4.232	6.995	8.771	0.314	78.370	0.064	0.717	0.538
10	1.179	4.295	7.109	10.132	0.304	76.720	0.068	0.836	0.535
11	1.198	4.320	7.162	11.446	0.295	75.191	0.070	0.963	0.552
12	1.216	4.321	7.169	12.695	0.287	73.767	0.071	1.095	0.596
13	1.233	4.305	7.144	13.867	0.279	72.435	0.071	1.229	0.671
14	1.249	4.279	7.095	14.956	0.272	71.187	0.072	1.364	0.776
15	1.265	4.246	7.030	15.959	0.265	70.017	0.072	1.497	0.913
16	1.280	4.210	6.955	16.878	0.259	68.919	0.072	1.627	1.080
17	1.294	4.172	6.874	17.715	0.253	67.889	0.073	1.750	1.273
18	1.308	4.133	6.791	18.474	0.248	66.923	0.073	1.867	1.490
19	1.321	4.094	6.706	19.161	0.244	66.018	0.074	1.975	1.727
20	1.333	4.057	6.623	19.782	0.239	65.170	0.075	2.074	1.981
21	1.345	4.020	6.541	20.341	0.235	64.376	0.076	2.164	2.247
22	1.356	3.985	6.462	20.845	0.231	63.634	0.077	2.244	2.523
23	1.366	3.951	6.386	21.298	0.228	62.939	0.079	2.314	2.806
24	1.376	3.919	6.313	21.707	0.225	62.289	0.080	2.374	3.093
25	1.386	3.889	6.244	22.075	0.222	61.682	0.082	2.426	3.382

V. CONCLUSION

Through the above empirical results, it can be seen that the influence of each carbon market is reduced, and compared with before and after the epidemic, the influence of carbon market in Hubei Province, which was the most affected by the epidemic, is also changing. The epidemic has a significant inhibitory effect on China' s carbon emissions in the short term. Regarding this phenomenon, market managers can optimize the formulation of total carbon quotas to improve market efficiency. At the same time, we should draw lessons from the measurement of European carbon market or mature carbon market, and formulate methods that meet the requirements of our carbon market development.

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