

The Relationship Between Carbon Market And Energy Market In China: Evidence From A Quan-Tile Regression Approach

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Abstract—Carbon trading was a new type of international trading mechanism designed by the United Nations to respond to climate change and reduce greenhouse gas emissions represented by carbon dioxide. In response to the urgent need for energy saving and emission reduction, China has also gradually started exploring the carbon market. Li Gao who is director of the Department of Climate Change said that the fourth quarter of 2021 will show a series of achievements in the construction of the carbon market. The carbon market has once again entered peoples field of vision, and discussions on carbon futures have heated up again. Carbon price is an information carrier and a concentrated manifestation of the development of the carbon market, and energy prices are a very important external factor. There is still a lack of research on the impact of energy prices on the carbon price of China in different positions. This paper uses the quantile regression method to investigate the impact of energy prices (natural gas prices, No. 0 diesel prices, coal prices, and electricity prices) on carbon prices in the Shenzhen pilot and the virtual domestic carbon market in different intervals. According to the results of different quantiles are used to analyze the impact of energy price changes on the trend and intensity of carbon prices in the Shenzhen pilot and the virtual domestic carbon market. Under this, related policy implications are put forward for constructing and improving carbon emission right market and scheme.

Keywords—Carbon market; Quantile Regression; Energy market; Shenzhen; Carbon price

I. INTRODUCTION

At the regular press conference of the Ministry of Ecology and Environment held on August 30, 2019, Li Gao who is director of the Department of Climate Change said that the fourth quarter of this year will show a series of achievements in the construction of the carbon market. The carbon market has once again entered people's field of vision, and discussions

During the "14th Five-Year Plan" period, China will continue to promote the green transformation of production and lifestyle. The first is to promote the

reduction of carbon emission intensity and achieve green and low-carbon development. In order to achieve the long-term goal of "carbon emissions will be stable after peaking", we will support green technology innovation, promote the development of clean production and environmental protection industries, promote the green transformation of key industries and important fields, and vigorously develop clean energy. The second is to further reduce the discharge of major pollutants and continuously improve the environmental quality. Will continue to increase pollution prevention and control efforts, fully implement the pollution permit system, and strengthen the governance of energy conservation and emission reduction through the establishment of market-based trading mechanisms such as pollution rights, energy use rights, water rights, and carbon emission rights. Continue to use binding indicators such as environmental protection, energy conservation and emission reduction to guide the reduction of pollution emissions and improve environmental quality (Liang Jing 2021). [4]

Green development is the only way. As far as China is concerned, the main source of current carbon emissions is the process of using fossil energy. Energy use is the main source of China's greenhouse gas emissions. Therefore, studying the dependence of the carbon market and energy market on China's The green development path is of great significance.

II. LITERATURE REVIEW

Through consulting a large number of relevant documents, it is found that the current research on the carbon market mainly focuses on carbon price prediction, carbon price dynamic driving factors, carbon market effectiveness and policy formulation. At the same time, because of EU carbon The maturity of the emission system development and the success of the market practice test, most domestic and foreign literatures use EU ETS transaction data as the basis to explore the dynamic relationship between the carbon market and the energy market. But there are few studies on the domestic carbon market, especially the research on the linkage relationship between the carbon market and the energy market.

A. Application of quantile regression in carbon market

Zhu et al. (2018) used the quantile regression method to study the impact of EU Emission Allowance

(EUA) prices on the stock returns of European carbon intensive Industries. The results showed that EUA prices had a significant negative impact on the stock market in the first and third phases of high-income markets, while in the second phase, this impact was positive. In addition, the first and third stages did not show the asymmetric characteristics of the carbon market effect, but in the second stage, it showed a strong asymmetric effect across quantiles. Wang et al. (2019) studied the dependence and influence path between EU quotas (EUA) and its driving factors (energy prices and macroeconomic risk factors) based on quantile regression, and the results showed that: carbon price fluctuations are different throughout the period, and the two effects of the occurrence of financial and energy shortage risks are both Changes in the unstable dependence on commodity price indexes, coal and natural gas prices have the driving factors in the conditional distribution of the phases is highly heterogeneous. Cheng et al. (2018) used the panel quantile regression method to investigate some determinants of carbon intensity in 28 European Union (EU) countries. The empirical results show that there is an inverse U-shaped relationship between crude oil prices and carbon intensity. Shawkat Hammoudeh et al. (2014) used a quantile regression framework to study the impact of changes in crude oil prices, natural gas prices, coal prices, and electricity prices on the distribution of US carbon allowance prices. The results showed that when crude oil prices are high, the increase in crude oil prices will lead to a substantial drop in carbon prices; changes in natural gas prices will have a negative impact on carbon prices when they are very low, but will have a positive impact when they are high; the impact of changes in electricity prices on carbon prices may be positive at the right end of the allocation. The price of coal has a negative impact on the price of carbon.

B. Application of quantile regression model in carbon market and energy market

Duan et al. (2019) studied the dependence of energy and carbon markets by using the method of quantile to quantile regression. The results show that the impact of energy prices (such as oil, natural gas and coal) on carbon prices largely depends on market conditions and price shocks. In the bull market with high carbon price level, the impact of energy price on carbon price is negative, but not so strong; When the market is bearish due to the low-carbon price level, the negative impact of energy prices tends to become greater. Specifically, in the oil and coal markets, with the rise of carbon market price level, the intensity of price impact often shows a monotonous growth trend. In the natural gas market, the impact of its price level tends to ease, and it also shows an upward trend with the increase of carbon price level. Su et al. (2019) analyzed the carbon trading market in Guangdong through quantile regression and found that the energy futures market had a negative impact on the carbon trading market, which became more and more intense.

However, the carbon trading market was positively affected by the European energy market and gradually weakened along the quantile. Nie Yuqi (2015) studied the relationship between EU carbon emission quota price and energy price based on quantile regression method. The results showed that EU carbon emission quota price was quite sensitive to the change of natural gas price, as reflected by the large (Quantitative) correlation coefficient of the valuation from Quantile regression. Secondly, the magnitude of the response of EU carbon emission quota prices to changes in oil prices, coal prices and electricity prices is larger at the left end of the distribution (in absolute terms), making these energy prices particularly relevant when capturing very low EU carbon emission quota prices.

III. METHODOLOGY

Quantile regression was first proposed by Koenker and Basset in 1978(Koenker and Hallock 2001). Different from OLS, quantile regression is not only less restrictive in application but also can reflect more comprehensive information of the data, especially in specific areas, such as data at extreme locations. It can measure the influence of the independent variable on the tail of the dependent variable, so as to describe the influence of the independent variable on the variation range of the dependent variable more accurately. Quantile regression has been widely used in various fields such as economy, finance, society and medicine. Generally speaking, quantile regression is to estimate the data of a specific distribution by estimating the different quantile values of the dependent variable between 0 and 1.

Specifically, assuming that the probability distribution function of the random variable Y is

$$F(y) = P(Y \leq y), \tag{1}$$

For arbitrary $0 < \tau < 1$ define the quantile τ of Y as the smallest y that satisfies $F(y) \geq \tau$, expressed as:

$$F^{-1}(\tau) = \inf\{y: F(y) \geq \tau\}, \tag{2}$$

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

$$\min_{\xi \in R} \sum_{i=1}^n |y_i - \xi|, \tag{3}$$

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

$$\min_{\xi \in R} \sum_{i: Y_i \geq \xi} \tau |y_i - \xi| + \sum_{i: Y_i < \xi} (1 - \tau) |y_i - \xi|, \tag{4}$$

The check function of quantile regression for general problems can be expressed as:

$$\rho_{\tau}(u) = u(\tau - I(u < 0)), \tag{5}$$

The indicator function is:

$$I(u < 0) = \begin{cases} 1, & u < 0 \\ 0, & u \geq 0 \end{cases} \tag{6}$$

Then the check function can be expressed as:

$$\rho_{\tau}(u) = \begin{cases} (\tau - 1)u, & u < 0 \\ \tau u, & u \geq 0 \end{cases} \tag{7}$$

Then, quantile regression also means that the expected loss is the smallest (that is, the sum of the absolute value of the weighted error is the smallest):

$$\min_{\xi \in \mathbb{R}} \sum_{i=1}^n \rho_{\tau}(y_i - \xi), \quad (8)$$

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

$$Q_{\tau}(Y|X) = \inf\{y: F_{Y|X}(y) \geq \tau\}, \quad (9)$$

Then, conditional quantile function for general form can be expressed as :

$$Q_{\tau}(Y|X) = x' \beta(\tau), \quad (10)$$

The estimated parameter value is

$$\hat{\beta} = \arg \min_{\beta \in \mathbb{R}^p} \sum_{i=1}^n (y_i - x_i' \beta) \quad (11)$$

In order to describe the relationship between the price of carbon emissions and the prices of four energy sources (No. 0 diesel oil, natural gas, coal, and electricity), this article relies on a quantile regression framework to describe the effects under different market conditions. The rationale for choosing this method can be explained as using different quantiles can capture the distribution of carbon price best. Quantile regression can reveal the asymmetric and nonlinear effects of conditional variables on dependent variables. It can capture the impact of sudden changes in energy prices around different quantiles on the signs and intensity of carbon prices.

Hence, the quantile regression model can be expressed as in equation

$$Q_{\tau}(CO_{2t}|I_t) = \beta_1 GAS_t + \beta_2 OIL_t + \beta_3 COAL_t + \beta_4 ELECTRICITY_t + e_t, \quad (12)$$

where $\tau \in (0,1)$, $Q_{\tau}(CO_{2t}|I_t)$ is the conditional quantile of the price of carbon, $\beta_i, i = 1, \dots, 4$ is the slope that measures the effect of energy prices on the price of carbon at quantile τ . $GAS_t, OIL_t, COAL_t$ and $ELECTRICITY_t$ mean the energy prices at time t . I_t is the information set at time t , e_t is the error term.

We use quantile regression and OLS regression to study the relationship between the energy price series and carbon price. Following the quantile regression literature, seven quantiles were chosen, from the lowest (0.05th) to the highest (0.95th), and divide them into the lower (0.05th, 0.10th and 0.25th), middle (0.50th) and upper (0.75th, 0.90th and 0.95th) quantiles to represent three different market circumstances. OLS regression estimates the average effects of the regression on response variables. Compared with the OLS, quantile regression provides a richer description.

IV. DATA AND RESULTS

A. Data

This article mainly adopts the quantile regression methodology to This article mainly uses the method of quantile regression to empirically analyze the impact of changes in energy prices (No. 0 diesel oil prices, natural gas price, coal prices, and electricity prices) on China's carbon prices under different quantiles. Shenzhen is the first pilot area to start carbon trading in China. As the first pilot area for carbon trading in China, Shenzhen has a relatively mature carbon market. For this reason, we have studied the

dependence of the energy market in Shenzhen on the carbon market at first. And the carbon price data of Shenzhen adopts the daily carbon transaction price in Shenzhen from January 1, 2014 to January 1, 2021 obtained from the carbon emissions trading network. The carbon price in China is based on the average price (yuan) of the sum of the carbon transaction prices of various exchanges (Shenzhen, Beijing, Shanghai, Guangdong, Tianjin, Hubei, Chongqing and Fujian) obtained from the carbon emissions trading network. The prices of No. 0 diesel oil and natural gas are subject to the market prices announced by the National Bureau of Statistics. The prices of No. 0 diesel oil and natural gas are based on the market prices issued by the National Bureau of Statistics. The coal price uses the daily closing price of CZCE thermal coal futures in the Wind database, expressed in Coal. The electricity price adopts the daily closing price of the stock China Power 02380, expressed in Electricity

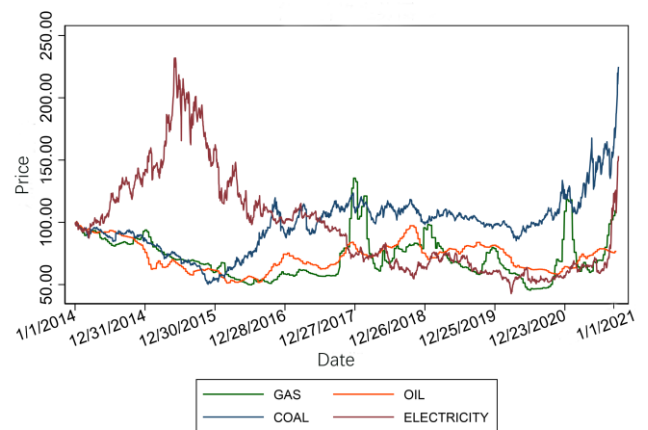


Fig. 1. Daily energy prices from January 1, 2014 to January 1, 2021.

Fig. 1 plots the daily time series of energy (No.0 diesel oil, natural gas, coal and electricity) prices. The prices vary greatly. In order to show the price trend better, we adopt a hundred-point system to standardize the price.

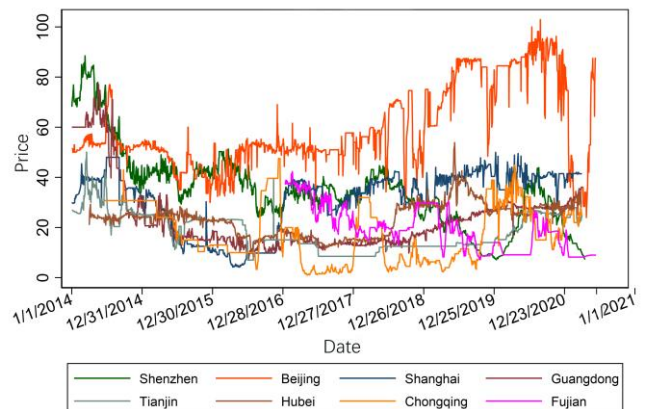


Fig. 2. Daily carbon prices traded on various exchanges in China from January 1, 2014 to January 1, 2021.

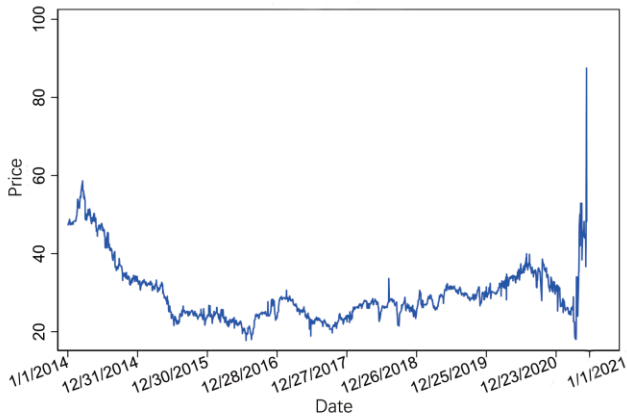


Fig. 3. Daily carbon prices in China from January 1, 2014 to January 1, 2021.

Fig. 2 shows the trend of carbon prices of various cities in China. The vertical axis represents the price, and the horizontal axis represents the date. And Fig. 3 plots the daily time series of carbon price.

Tab. 1 reports the descriptive statistical analysis of the variables involved in the model. Take a full sample of independent variable energy prices and dependent variable carbon prices as research samples. And the daily sample period used in the analysis ranges from January 1, 2014, to January 1, 2021.

TABLE I. STATISTICAL DESCRIPTION OF VARIABLES IN THE MODOL

VB	N	mean	sd	min	max	skewness	kurtosis
GAS	1882	8.249	0.223	7.821	8.911	0.374	2.797
OIL	1882	8.639	0.159	8.359	9.026	-0.00777	2.255
COAL	1887	6.295	0.227	5.646	7.144	-0.391	3.965
ELECTRICITY	1833	0.905	0.380	0.166	1.856	0.426	2.202
SHENZHEN	1763	3.450	0.497	1.967	4.482	-0.830	3.892
China	1803	3.366	0.229	2.77	4.472	0.90	3.626

The average of all variables is positive. The skewness and kurtosis of all variables are represented, so that we can explicate the reason for using the quantile regression approach. The Volatility is measured by the standard deviation, and the sample standard deviation is small, indicating that the sample volatility is small. By measuring the skewness coefficient, we can determine the degree and direction of the asymmetry of the data distribution. Tab. 1 reports that all variables have a certain degree of skewness, but not very serious, and most of the distribution is left-skewed. We can determine whether the data distribution is steeper or gentler than the normal distribution by measuring the kurtosis coefficient. The kurtosis coefficient is greater than 0 for all variables, It is morphologically steeper or thicker than the normal distribution. And the kurtosis coefficient is greater than 3 for some variables, which indicates that the unconditional distribution of these variables are asymmetric. Therefore, the use of

quantile regression methods can solve the problem by providing a more flexible and complete description.

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) approaches are used to test whether the variables used are stationary before estimating the panel quantile regression model. If there is no unit root, the series is a stationary time series. And we can do further analysis.

TABLE II. PANEL UNIT TESTS OF ALL VARIABLE IN THE MODOL.

Variable	ADF	P	PP	P
GAS	-2.687	0.2413	-2.061	0.5677
OIL	-2.246	0.4639	-1.983	0.6106
COAL	-0.877	0.9586	-0.955	0.9498
ELECTRICITY	-1.483	0.8348	-0.677	0.9746
Shenzhen	-1.149	0.9204	-1.609	0.7888
China	-1.832	0.6890	-2.546	0.3055

Tab. 2 indicates that the null hypothesis of the existence of a unit root could not be rejected for most variables in the level. However, the results presented in Tab. 3 shows that the null hypothesis of a unit root for all variables could be rejected at the 1% level in the first difference. Therefore, in correspondence with the dependent variable, all of the explanatory variables in the model take the form of the first natural logarithm difference.

TABLE III. PANEL UNIT TESTS OF ALL VARIABLE IN THE MODOL.

Variable	ADF	P	PP	P
GAS	11.472	0.0000***	42.733	0.0000***
OIL	9.347	0.0000***	43.008	0.0000***
COAL	15.152	0.0000***	43.839	0.0000***
ELECTRICITY	12.61	0.0000***	40.791	0.0000***
Shenzhen	14.64	0.0000***	47.594	0.0000***
China	18.121	0.0000***	57.735	0.0000***

B. Analysis of the Shenzhen Market

As the first city to launch carbon trading in China, Shenzhen's carbon trading is relatively mature. First, we study the relationship between the energy price series and carbon price in Shenzhen. Tab. 4 shows the huge difference between OLS and quantile regression estimates in Shenzhen.

TABLE IV. THE ESTIMATION RESULTS FOR THE QUANTILE REGRESSION AND OLS REGRESSION IN SHENZHEN.

Energy	Q0:05	Q0:1	Q0:25	Q0:5	Q0:75	Q0:9	Q0:95	ols
GAS	0.043	0.002	0.027	0.024	0.114	0.135	0.141	0.017
					***	***	***	
OIL	-0.205	-0.100	0.208	0.252	0.456	0.590	0.643	0.249
	***	*	***	***	***	***	***	***
COAL	0.493	0.545	-0.004	-0.142	-0.395	-0.436	-0.486	-0.045
	***	***		***	***	***	***	
ELECTRICITY	1.060	1.103	0.624	0.278	0.060	0.079	0.038	0.570
	***	***	***	***	*	***		***

In the middle and high quantile stages, natural gas prices and carbon prices have significant negative correlation. This means that when carbon prices are low, there is no significant relationship between natural gas prices and carbon prices. However, high natural

gas prices will lead to a reduction in natural gas consumption, and carbon prices fall consequently, which is in line with the general situation.

The impact of No.0 diesel oil on carbon prices is almost all positive, which is similar to the domestic results. As the quantile increases, the positive correlation of No.1 diesel oil to carbon prices has strengthened. Combined with the results of domestic research, diesel oil, as an important industrial energy source, is one of the indispensable energy sources for economic development. And Shenzhen's industry is developing rapidly. It may not be feasible to reduce diesel oil consumption by raising oil prices.

Electricity price and carbon price are positively correlated, and the positive correlation coefficient of high electricity price to high carbon price gradually decreases. As one of the special economic zones in China, various industries in Shenzhen are developing rapidly. And rising electricity prices may only reduce part of the electricity use, it lead to a lower growth rate of carbon price.

At the left tail of the carbon price distribution, the increase in low coal prices leads to carbon prices increase. When carbon prices are high, the increase in coal prices has a strong negative effect on carbon prices. This means that when the carbon price is high, the increase in coal prices will produce a large drop in the carbon price, demonstrating the courageous performance of coal prices in the carbon market.

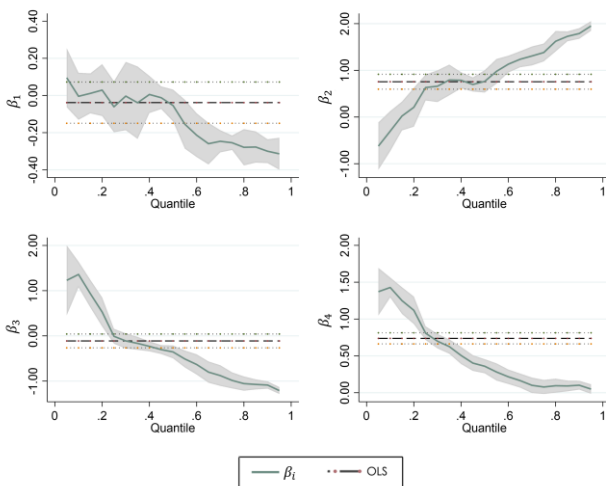


Fig. 4. Dynamic trace of quantile regression coefficients in Shenzhen from January 1, 2014 to January 1, 2021

Fig. 4 is the dynamic trace of quantile regression coefficients in Shenzhen. Where vertical axes shows coefficient estimates of variables over the distribution. And the horizontal axes depict the quantiles of the dependent variable, quantile regression error bars correspond to bootstrapped 95% confidence interval.

C. Analysis of the Chinese Market

Further, let's discuss the domestic situation, and the results are shown in Tab. 5.

TABLE V. THE ESTIMATION RESULTS FOR THE QUANTILE REGRESSION AND OLS REGRESSION IN CHINA.

Energy	Q _{0:05}	Q _{0:1}	Q _{0:25}	Q _{0:5}	Q _{0:75}	Q _{0:9}	Q _{0:95}	ols
GAS	-0.032	-0.079***	-0.062	0.064	0.049	0.014	0.071	-0.051**
OIL	0.457***	0.416***	0.487***	0.600***	0.789***	0.705***	0.673***	0.605***
COAL	-0.238***	-0.219***	-0.148***	-0.168***	-0.329***	0.136**	0.170***	-0.175***
ELEC								
TRICI	-0.068*		-0.084*	-0.023	-0.462***	-0.232***	-0.257***	-0.140***
TY								

We find that Natural gas only shows a significant negative impact at $\tau = 0.1$, and other quantiles are not significant. This means that when carbon prices are low, the increase in natural gas prices has led to a substantial drop in carbon prices. No obvious effect in other cases. This may have a greater relationship with the use of natural gas in each city.

As the quantile increases, the positive correlation of No.0 diesel oil to domestic carbon prices has strengthened. When $\tau = 0.75$, the positive correlation reach the strongest and then weaken. It has a trend of rising first and then falling. But when the carbon price rises to a certain height, the increase in oil prices has a weakened positive impact on carbon prices.

As the quantile increases, coal prices below the 75% quantile are negatively affected, and above 75% quantiles are positively affected, indicating that coal prices and carbon emission allowance prices are below the 75% quantile. The increase in coal prices can bring down the price of carbon emission allowances, and when they are high, the increase in coal prices will increase the price of carbon emission allowances.

Electricity price and carbon price are negatively correlated, When $\tau = 0.75$, the negatively correlation reach the strongest, but the negative correlation coefficient of high electricity prices to high carbon prices gradually decreases. Rising electricity prices will reduce electricity usage and lead to lower carbon prices. However, when the electricity price reaches a certain level, it is not ruled out that the use of coal and other energy sources to replace part of the electricity energy.

And coal as the quantile increases, Below the 0.75 quantile, it is a negative effect. And above 0.75 quantile, it is a positive effect. This shows that in the low and mid-quantile stages, the increase in coal prices can bring down the price of carbon. The increase in high coal prices will increase high-carbon prices. This may be due to differences in policies in different cities, and the market is not fully formed.

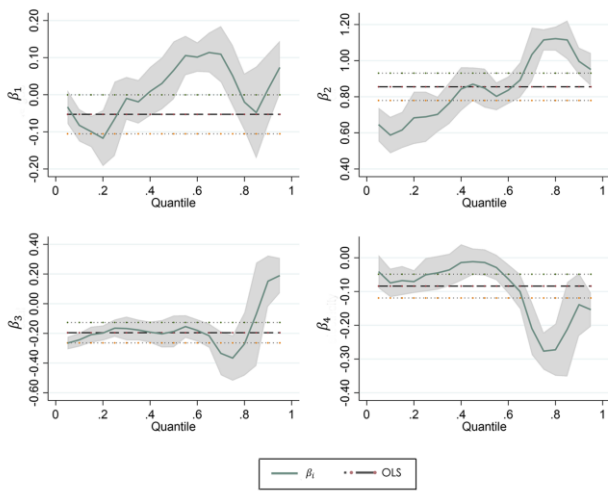


Fig. 5. Dynamic trace of quantile regression coefficients in Chian from January 1, 2014 to January 1, 2021

Fig. 5 plots the dynamic trace of quantile regression coefficients in China. Where vertical axes shows coefficient estimates of variables over the distribution. And the horizontal axes depict the quantiles of the dependent variable, quantile regression error bars correspond to bootstrapped 5% confidence interval.

D. Wald tests

Wald tests following Koenker and Bassett's (1982) method can be used to establish formal parameter heterogeneity across quantiles.

Finally, in order to verify the relationship between the quantile regression model, the Wald test can be used to test the parameter heterogeneity to verify whether the slope of the parameter at different quantiles are different. To save space, we only display the results whether the coefficient in the lower quantiles ($\tau = 0.05$) equate the coefficients in medium ($\tau = 0.50$) and upper quantile ($\tau = 0.95$) in Tab. 6.

TABLE I. WALD TESTS FOR EQUALITY OF SLOPES (0.05 AGAINST 0.5 AND 0.95 QUANTILES)

	Against the 0.50 quantile		Against the 0.95 quantile	
	F statistic	p-Value	F statistic	p-Value
Shenzhen	119.31	0.0000 ***	570.77	0.0000 ***
China	22.66	0.0000 ***	&224.44&	0.0000 ***

The slope equality tests of the coefficients between the quantiles reject the hypothesis of parameter homogeneity across the results of the wald tests can be obtained from the authors upon request. It means that the estimated coefficients are not constant. Changes in the structure of dependence exist because coefficients are not constant.

V. CONCLUSIONS

From the comparison of changes in Shenzhen and China, only No.0 diesel oil has the same influence on carbon prices, and the price of carbon is very sensitive

to No.0 diesel oil prices, and other energy prices have different results. Interestingly, this article confirms two important results. First of all, for the overall situation in China, natural gas prices have a significant impact on carbon prices only at $\tau = 0.1$. As reflected in the large correlation coefficient (in terms of value) of the estimate from the quantile regression, carbon prices are very sensitive to coal, oil and electricity prices at $\tau = 0.75$. For the Shenzhen area, the magnitude of the response of carbon prices to changes in natural gas prices and diesel prices is larger at the right-tail of the distribution (in absolute terms). It makes these energy prices particularly relevant when capturing periods of very high carbon prices. Carbon prices are more sensitive to coal prices at the low and high quantile stages, and electricity prices have a significant positive impact on carbon prices at $\tau = 0.25$. The results of China can only analyze the general situation, and the relationship between carbon prices and energy prices in other cities should be analyzed in detail in conjunction with local policies and economic conditions.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China [No. 71673116] and the Priority Academic Program Development of Jiangsu Higher Education Institutions [No. PAPD-2018-87].

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