Carbon Emission Price and Stock Price of Energy-Chemical Industry in China

Jingye Lyu[1)]
Ming Cao[1),*]
Xiao Dong[1)]

Abstract:

As global warming continues to intensify, how to prevent climate deterioration has become a serious concern for all countries. In recent years, although China's GDP has leap to the second place in the world after the United States, it is accompanied by serious problems of environmental pollution and energy consumption with the rapid development of the economy. Under the common goal of global energy conservation and emission reduction, China has established seven carbon trading markets. Because the energy-chemical industry is a major concern for emission reduction and the carbon trading market has market regulation functions, examining the relationship between them is of great significance and can help the emission reduction effort. This study investigates the relationship between the carbon emission price of China's carbon trading market and the stock price of 30 listed companies in the energy-chemical industry. We use daily data to establish a panel model and var model, and then compare it with European Emissions Trading Scheme (EU-ETS). The result indicates that there is an asymmetric one-way relationship between the carbon emission price and the stock price of the energy-chemical industry in China. The main reason is that the internal endogenous mechanism and external response mechanism of the carbon trading market are not perfect. Then the government should improve relevant legal system and trading system, and furthermore, introduce third-party institutions and strengthen talent pools.

Keywords: energy conservation, carbon trading market, energy-chemical industry, panel model, var model

---

We would like to express our sincere gratitude to Professor Haifeng Li for her advice during ACFEA in 2018, which greatly inspired our study.

1) School of Management, Xi'an University of Science and Technology, Xi'an 710054, China
*Correspondence: 17202099026@stu.xust.edu.cn

1. Introduction

Global warming and other climate change problems caused by CO_2 and other greenhouse gases from burning fossil fuels and other energy sources have attracted increasing attention. It is no longer a purely environmental, ethical or technical issue. Like nuclear issues, terrorism and territorial security issues, it has become a problem of how various social contradictions are balanced and a strategic game between various political forces (Chang et al., 2019). With the rapid economic development of developing countries, the greenhouse gas emissions have grown rapidly and developing countries are required to undertake more emission reduction tasks. China is the world's largest energy consumer and the largest emitter of carbon dioxide (Yin et al., 2019). China's CO_2 emissions from energy, accounting for 28% of the global total in 2018 (Zhang & P. Andrews-Speed, 2020). In recent years, many important countries and regions, such as the EU, the U.S., Australia, New Zealand, and Korea, have established carbon trading schemes (Deng & Zhang, 2019). As the world's largest developing country and the largest carbon dioxide emitter, China has actively demonstrated the responsibility. Carbon trading is to regard the emission right of greenhouse gases as a commodity (Fang et al., 2020). It is expected to be adjusted through market mechanisms to achieve voluntary emission reductions in high-emission industries (Fang et al., 2018). Furthermore, it will reach the goal that carbon dioxide emissions will not exceed the expected total emissions which provides new ideas and solutions for reducing global warming.

The European Union Emission Trading Scheme (EU ETS) was the first, and it is the largest GHG emission trading scheme in place. The EU ETS was built under the Kyoto Protocol mechanism that considers regional trading schemes. A test phase, EU ETS Phase I, lasted from 2005 to 2008. Phase II, 2008-2012, was the first binding phase in which European countries had to fulfill Kyoto obligations. We are now in phase III 20132020. Although some market aspects have changed, the market principles remain the same (Sousa & Aguiar-Conraria, 2015).

Since the EU carbon trading market entered the third stage, countries around the world have successively established and improved their domestic carbon trading markets, such as the Chicago Climate Exchange and the Japanese carbon trading market (Borghesi & Flori, 2019; Lee et al., 2020). The Chinese government beware of great importance of environmental issues and actively learns advanced experience from developed countries. In 2013, Chinese policymakers of National Development and Reform Commission (NDRC) established carbon trading pilot markets in seven regions including Beijing and Shenzhen (Jiang et al., 2018). Then the “National carbon trading market Construction Plan” was issued in 2017 and China's carbon trading market were planned and launched.

Since the establishment of the carbon trading market in seven pilot areas of China to March 2016, the total turnover of National Certified Emission Reduction (CCER) exceeded $ 1.3 billion (Zeng, 2016), it has played an active role in energy transformation and carbon dioxide emission reduction (Liu et al., 2018). Then, some representative energy-chemical industries such as petrochemical, chemical, coal mining and other industries and eight major carbon emission industries such as building materials, steel, electricity and aviation are included in carbon trading (Wang et al., 2019). From the carbon quota allocation of the eight major industries, the total emissions will reach 5 billion tons, accounting for 50% of the country's full-scale emissions and has reached the world's largest market size. Among them, the energy-chemical industry has many types and large quantities of emissions during the deep processing of products, especially carbon dioxide as a main component of emissions, which has led to an increase in the global warming effect. Therefore, it is extremely important to examine the characteristics of high pollution and high energy consumption in China's energy-chemical industry. Moreover, the coal-based energy resource structure and energy-chemical industry are indispensable components of the national economy and people’s life. As a special financial market, carbon markets play an important role in connecting the stock market and the environment (Zhu et al., 2018), carbon emission rights market also has the functions of regulation, risk aversion and financing. so that it can generate practical implications to encourage the emission reduction behavior of the chemical industry.

The advent of the Industrial Revolution has greatly increased the frequency of the use of traditional energy represented by coal. This has rapidly promoted economic development while also emitting a large amount of carbon dioxide, causing serious ecological problems. Nowadays, as an important part of promoting economic development, the energy industry has a close relationship between its related stock price and carbon emissions and trading prices of carbon emission rights. In Figure 1, we use the energy and chemical market as a link to sort out the relationship between the price of carbon emission rights and the stock price of the energy industry.

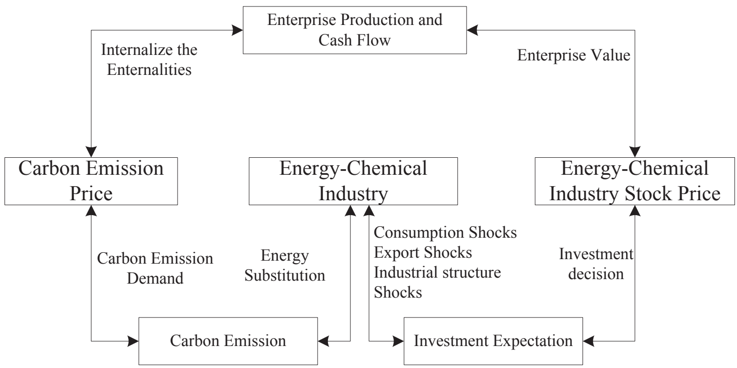

Figure 1. The link between the price of carbon emission rights, the energy market and the stock price of the energy industry

First of all, carbon emissions mainly come from the burning of fossil energy, and the burning of fossil energy is the driving force for the development of the energy industry. This is a direct correlation between the price of carbon emissions and the energy industry. At the same time, new energy represented by wind energy and solar energy The use of carbon dioxide plays an alternative role in fossil energy and ultimately affects the price of carbon emission rights. Second, changes in the price of energy and chemical products will have a direct impact on consumption, exports and industrial structure, affecting investors' investment expectations and leading to investment decisions. Changes will eventually affect the stock price of the energy industry; third, because carbon emissions trading will lead to the internalization of the externalities of enterprises in the energy industry, thereby affecting the stock price of the energy industry by affecting the company's future cash flow.

The energy-chemical industry is an important participating industry to achieve carbon dioxide emission reduction targets. The stock price of listed companies in energy-chemical industry determines the risk of industry development and the stability of economic development. As an emerging global financial market, the carbon emission price of carbon trading market affects the utility while achieving the target of energy conservation. If the interaction between the two markets is not strong, it indicates that the carbon trading market has not yet effectively interfaced with China's mature stock market. The carbon trading market has not effectively reflected the regulation of emission reduction. The national policy has not been effectively implemented, the construction of the carbon trading market is still flawed and there are some financial risks. Therefore, studying the relationship between the carbon emission price of China's carbon trading market and the stock price of the energy-chemical industry is not only beneficial for maintaining the coordination relationship between financial markets, stabilizing economic development, but also beneficial for improving the efficiency of carbon dioxide emission reduction and solving the severe greenhouse problem.

2. Literature Review

At present, the carbon trading market has become a hot topic for scholars in various countries. Scholars have studied the carbon trading market from multiple perspectives in different industries:

(1) Due to different carbon emission characteristics and economic structure in countries, scholars have conducted research based on the characteristics of the specific country.

Aguiar Conraria et al. (2018) studied the carbon trading market in California, USA and found that gasoline price was inversely related to local carbon emission price through data analysis, then proposed that the carbon trading market was indeed an important measure to mitigate climate change. Diaz Rainey & Tulloch (2018) focused on the New Zealand carbon trading market and discovered that some restrictions need to be added in the process of small transactions, which can reduce the cost of emission reduction. Through analyzing EU-ETS, Koch et al. (2014) and Calel & Dechezlepretre (2016) found that economic activities and changes in the energy generation of green energy such as wind and solar energy had a dynamic impact on the carbon emission price of EU-ETS, which had a positive impact on technological progress.

Moreno & da Silva (2016) and Song et al. (2018) assessed the impact of carbon trading market in Spain and concluded that a statistically significant positive and negative impact of EU ETS on stock market return was found for Phase II and III respectively. Oestreich & Tsiakas (2015) conducted an empirical analysis of the impact of the German carbon trading market on German stock returns. The results showed that the average performance of companies with free access to carbon emission quotas was significantly better than that of companies that didn't.

(2) Due to different characteristics between industries, scholars have conducted research based on different industry data.

Smale et al. (2006) adopted a model through historical transaction data to analyze the EU's energy-intensive industries. The result showed that the carbon trading market generally brought benefits to these industries. Oberndorfer (2009) and Tian et al. (2016) conducted a large number of panel data analysis and discussed that the carbon emission price changes of EU-ETS were positively correlated with the stock price changes of European electricity company. The changes of them were caused by the impact of the EU-ETS in two periods. Brouwers et al. (2016) explored the impact of verified emissions publications in EU-ETS on the market value of participating companies. The research results showed that when the actual emissions were greater than the quota emissions, the enterprise value would decline and the EU had excessive allocation of carbon emission rights quotas.

(3) Some scholars have conducted research on China's carbon trading market.

Compared with the EU, there have been few studies on China's carbon trading market and the existing research mainly focuses on the operation effect, quotas, legal policies and other aspects of the carbon trading market. Tang et al. (2015) adopted a multi-agent model and found that China's carbon trading market could effectively reduce carbon emissions, but it would have a certain negative impact on the economy. Only by implementing subsidy policies for energy technology improvement could carbon emissions be effectively reduced without any additional negative impact on the economy. Zhang et al. (2014), Yin et al. (2018) and Yu et al. (2018) used the Shapley algorithm and the CEG model to explore the quota allocation among various regions in China. The results showed that regions with higher GDP and carbon emission reductions should allocate more carbon allowances. Yu et al. (2018) analyzed the impact of China's carbon trading market on corporate value. The results showed that China's carbon trading market had increased the market value of energy-related enterprises. Ye et al. (2013) applied the VAR model to decompose the carbon emission price of China's carbon trading market and analyzed the policy reasons that led to the differences of volatility characteristics. Chen & Xiang (2019) analyzed the efficiency and shadow price of carbon trading market in coal-fired power plants, finding that the efficiency performance of power plants remains steady. Wang et al. (2018) constructed spatial econometric models and the results showed that China's carbon dioxide emissions were increasing and there was a stable spatial agglomeration effect. Xie et al. (2018) applied the CGE model to study the carbon tax of Chongqing, a city in southwestern China. The results showed that the implementation of carbon tax policies in China could effectively reduce carbon dioxide emissions and emission intensity, but the carbon tax would have different effects on the macro economy. Liu et al. (2018) explored the impact of China's national carbon trading market on Shanghai and other parts of China through the IMED vertical bar CGE model and predicted China's carbon emission price in 2030.

Scholars from various countries mostly have combined the background of developed countries and already have studied the relationship between carbon trading market construction, rule making, carbon emission price and macro variables from the perspective of industry. Moreover, as a global emerging financial market, the carbon trading market is closely related to other financial markets, especially to companies involved in emission reduction. Some scholars have studied the relationship between the carbon emission price and the stock price of listed companies, but most of them are not specific to the industry and there are heterogeneity among industries, as well as product characteristics and economic characteristics are not the same. Therefore, if we can combine the situation of developing countries, take the most typical country China as an example, conduct in-depth research on energy-chemical industry which has high emissions, it will facilitate the establishment of an effective linkage mechanism between the carbon trading market and the energy-chemical industry in developing countries, improving the carbon trading market mechanism of developing countries and making full use of its regulation as well as improving the efficiency and quality of emission reduction.

3. Sample selection

Since there are seven pilot markets in China's carbon trading market, the daily trading data of these pilot markets are chosen from July 24, 2017 to July 24, 2018. As for the stock price of the industry, we use proportion of market performance in the carbon trading market (As shown in Table 1).

Table 1. Market performance of carbon markets in China

Pilot market	Market share
Hubei	42.53%
Shanghai	25.13%
Guangdong	11.18%
Shenzhen	8.60%
Beijing	7.71%
Chongqing	3.11%
Tianjin	0.67%

Source: Hubei Carbon Market

In addition, this paper selected the stock prices of 30 listed companies in the energy and chemical industry as research samples based on the location, main business and size of the listed company. Considering that some coal chemical products (such as asphalt, rubber, polyvinyl chloride, etc.) are closely related to the energy-chemical industry, it may affect the model results, thereby adding the trading price of asphalt, rubber and polyvinyl chloride futures markets. The daily trading data from July 24, 2017 to July 24, 2018 is used as a control variable to obtain more realistic empirical results. Variable description as shown in Table 2.

Table 2. Variable description

Variable	Code	Description	Time
Carbon emission rights price	cmp	Dependent variable, the price of China's carbon emission rights weighted according to the market performance in the above table	July 24, 2017 to July 24, 2018
energy-chemical industry stock prices	stp	Explanatory variables, based on the stock prices of the 30 listed companies in the energy industry	July 24, 2017 to July 24, 2018
Asphalt futures prices	lqp	Explanatory variables, traditional coal chemical products, closely linked to the energy industry	July 24, 2017 to July 24, 2018
Rubber futures prices	xjp	Explanatory variables, traditional coal chemical products, closely linked to the energy industry	July 24, 2017 to July 24, 2018
PVC futures prices	jlyxp	Explanatory variables, traditional coal chemical products, closely linked to the energy industry	July 24, 2017 to July 24, 2018

4. Empirical analysis

4.1 Panel model

The panel model can simultaneously obtain two-dimensional data in time and section space, reflecting the change rule and characteristics in two-dimensional space and has the advantages of controlling individual heterogeneity, controlling endogeneity and increasing degree of freedom to improve the estimation efficiency of parameters. Moreover, the daily transaction data of different carbon trading pilot markets is different and the pilot markets corresponding to enterprises in different regions of the industry can be different, so the panel model is more suitable for analyzing such problems. Thus we adopt the panel model for fitting analysis.

In order to avoid the problem of pseudo-regression, the unit root test is first performed on each variable to verify its stationarity. The panel data are analyzed by LLC test, Breitung test, IPS test, ADF and PP test. The unit root and stationarity test results are shown in Table 3 below.

Table 3. Unit root test results

Variable method	LLC	Breitung	Im-Pesaran -Skin	Fisher -ADF	Fisher -PP	conclusion
cmp	-35.656***	-9.277***	-62.656***	1836.200***	1810.560***	steady
stp	-53.654***	-6.453***	-71.993***	2329.900***	2329.140***	steady
lqp	-57.187***	-9.055***	-81.871***	2593.200***	2582.240***	steady
xjp	-59.561***	-35.494***	-76.149***	2475.600***	2475.790***	steady
jlyxp	-94.543***	-38.212***	-93.932***	2738.600***	2728.660***	steady

*** means Prob. is less than 0.01
*** means Prob. is less than 0.05
*** means Prob. is less than 0.1

The panel model contains two-dimensional data of several individual members and periods. The panel model can be divided into many categories according to different assumptions about individual members and timing. First, the carbon emission rights price is used as the dependent variable, the energy industry stock price and the futures prices of asphalt, rubber and polyvinyl chloride are the independent variables to estimate the random model effect on the panel model (the results are shown in Table 4). Then the HAUSMAN test is performed (the results are shown in Table 5) and the fixed effects model or the random effects model is selected according to the test result.

Table 4. Random effect model results

	stp	lqp	xjp	jlyxp	c
Coefficient	-0.013***	0.005***	-0.0002***	-0.001***	20.641***
T-Statistic	-5.25	29.99	-4.51	-11.83	13.43
Std.Error	0.0025	0.0001	0.0004	0.0001	1.5375

*** means Prob. is less than 0.01
*** means Prob. is less than 0.05
*** means Prob. is less than 0.1

Table 5. HAUSMAN test results

	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	145.955	4	0.0001

According to Table 5, the test statistic of the HAUSMAN test is 145.955 and the accompanying probability is less than 0.01, indicating that there is a systematic difference between the fixed effects model and the random effects model. Therefore, A fixed effects model should be established and the panel model should be tested by F test and LR based on the fixed effects model, as shown in Table 6 below.

Table 6. F test and LR test results

Effects Test	Statistic	d.f.	Prob.
Cross-section F	1851.123	-295729	0.000
Cross-section Chi-square	13479.359	29	0.000

According to Table 6, the accompanying probabilities of the F statistic and the LR test are 0.000 and 0.000 respectively, both of which are less than 0.01, so the fixed effects model has a better fitting effect than the mixed section model, thereby performing fixed effects model estimation.

Table 7. Fixed effect model results

	stp	lqp	xjp	jlyxp	c
Coefficient	-0.020***	0.005***	-0.000***	-0.001***	19.627***
T-Statistic	-7.65	29.33	-4.34	-11.93	15.49
Std.Error	0.0026	0.0002	0.0004	0.0001	1.2667

*** means Prob. is less than 0.01
*** means Prob. is less than 0.05
*** means Prob. is less than 0.1

According to Table 7, the stock price of the energy-chemical industry has a small reverse impact on the carbon emission price of China's carbon trading market. Each unit of the stock price of the industry can change by 0.02 units, which is greater than the impact of other control variables on the carbon trading market. The coefficient values of the variables in the model results are small, indicating that the carbon trading market is not closely related to other financial markets. At present, the carbon trading market does not realize the original intention of resource integration. Therefore, the interaction between financial markets is weakened or even ignored, the external response mechanism is not perfect and there is no effective interaction between financial markets.

However, there is not only the relationship that one variable simply affects another variable in one direction between the carbon emission price of the carbon trading market and the stock price of the energy-chemical industry. The tripartite interaction relationship between the financial market, the carbon trading market and the energy-chemical industry may also exist. Although the panel analysis can obtain the change rule and characteristics of the two-dimensional space, if the var model can be deeply integrated, the deeper relationship between them can be obtained more thoroughly and the var model is established for testing.

4.2 Var model test

Since the relationship between the carbon emission price of China's carbon trading market and the stock price of the energy-chemical industry is more complicated, not the one-way relationship between one variable and another. All variables in the var model are treated as endogenous variables and each variable is affected by the hysteresis of other variables, which is suitable for exploring the dynamic correlation between different variables. Therefore, the var model for the carbon emission price of China's carbon trading market and the stock price of the energy-chemical industry is analyzed and the previous panel model is also tested. Due to the different performances in the seven pilot markets, we select four pilot markets with good market performance (the carbon trading pilot markets in Hubei, Shanghai, Guangdong and Shenzhen). And we select daily trading data of the four pilot markets from July 24, 2017 to July 24, 2018, for weighted averaged to form the daily carbon emission price of China's carbon trading market and the rate of change is expressed by rcarbon. For the energy-chemical industry, select the energy-chemical industry index that from Wind database in the same period and use rchemical to indicate the change rate of daily trading price of the energy-chemical industry.

In order to ensure that the regression results are not affected by the pseudo-regression, the ADF unit root test is first performed on rcarbon and rchemical to verify its stability, as shown in Table 8 below.

Table 8. Unit root test results

	rcarbon		rchemical	
	t-Statistic	Prob.	t-Statistic	Prob.
ADF test statistic	-24.056	0.000	-19.784	0.000
1% level	-3.448		-3.448	
5% level	-2.869		-2.869	
10% level	-2.570		-2.570	

According to Table 8, it can be seen that the absolute value of the t value of rcarbon and rchemical is larger than the absolute value of the t value at 1%, 5% and 10% level. And the accompanying probability of them is 0.000, indicating that the two sequences have no unit root and are stationary sequences and there is no pseudo-regression.

Through the ADF unit root test, there is a first-order single-integer relationship between the price of carbon emission rights and the stock price of energy-chemical industry. For further study, the Johansen cointegration test was used to conduct cointegration test.

Table 9. Johansen cointegration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
0*	0.3388	226.54	15.49	0.0001
1*	0.1911	76.78	3.84	0.0001

It can be seen from Table 9 that at a significant level of 5%, there are two cointegration relationships between the price of carbon emission rights and the stock price of the energy and chemical industry, which also means that the two have a long-term equilibrium trend. Therefore, the carbon price can affect the trend of stock prices for a long time.

After the endogenous variables in the var model are set, the lag period of the endogenous variables of the model must be further determined. The choice of the number of lag periods is particularly important for the estimation of the var model, since different lag periods will result in significant differences in the model estimation results, thereby the optimal lag period selection is performed, as shown in Table 10 below.

Table 10. Optimal lag period selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1874.855	NA	1.01E-07	-10.433	-10.412	-10.425
1	1886.848	23.786	9.65e-08	-10.478	-10.413	-10.452
2	1889.199	4.636*	9.74E-08*	-10.469*	-10.360*	-10.426*
3	1893.889	9.197	9.70E-08	-10.472	-10.321	-10.412
4	1898.327	8.651	9.68E-08	-10.475	-10.280	-10.397
5	1901.534	6.217	9.72E-08	-10.470	-10.232	-10.376
6	1903.648	4.075	9.82E-08	-10.460	-10.179	-10.348

* indicates lag order selected by the certerion.
LR: sequential modified LR test statistic (each test at 5%)
FRE: Final prediction error.
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

As shown in Table 10, the optimal lag period is 2. Thus, the vector autoregressive model var(2) is established and the model formula is:

$$Y_t=\begin{bmatrix}-0.24 & -0.19\\ -0.03 & -0.02\end{bmatrix}Y_{t-1}=\begin{bmatrix}-0.05 & -0.17\\ -0.01 & -0.08\end{bmatrix}Y_{t-2}+\varepsilon_t;\quad Y_t=\begin{bmatrix}RCARBON\\ RCHEMICAL\end{bmatrix} \tag{1}$$

For var models with m lag periods and K endogenous variables, there are m*K eigenvalues. When the modulus of the inverse of all eigenvalues of the var model is less than 1, located within the unit circle, indicating that the var model is stable; if there is a modulus of the inverse of a eigenvalue equal to 1, located on the unit circle, then var model is unstable and needs to be reset. As shown in Figure 2, all the reciprocal modes of the var model are located in the unit circle and are concentrated on the origin, indicating that the established var model is relatively stable.

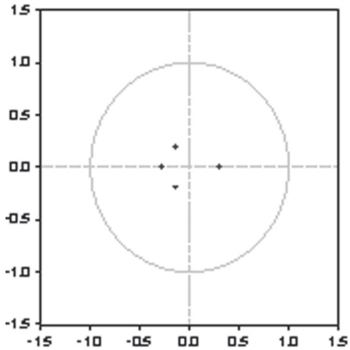

Figure 2. Modulus of the inverse of the eigenvalue

The Granger causality test is then performed on the variables in the var model. Granger causality test aims to find whether all the lags of a variable in the model have an effect on the current values of other variables. If there is an effect, it indicates that the variable has Granger causality for other variables; if the effect is not significant, it indicates that the variable does not have Granger causality for other variables. Thus, the Granger causality test is performed on rcarbon and rchemical, as shown in Table 11 below.

Table 11. Granger causality test results

Null hypothesis	Lag period	Observation value	F	P	Result
Rcarbon is not the Granger reason for rchemical	2	363	2.325	0.099	Rcarbon is the Granger reason for rchemical
Rchemical is not the Granger reason for rcarbon	2	363	1.025	0.359	Rchemical is not the Granger reason for rcarbon

According to Table 11, we can know: (1) rcarbon is the Granger reason for rchemical. (2) rchemical is not the Granger reason for rcarbon. It reflects that the effect between the two variables is one-way. Because Granger causality test only reflects the result of a local dynamic relationship change, it can not monitor the comprehensive and complex dynamic relationship between variables. In order to explore the full impact process of a variable change on another variable and get more comprehensive analysis of the conclusion, we draw the IRF impulse response function diagram to fully reflect the dynamic process between rchemical and rcarbon.

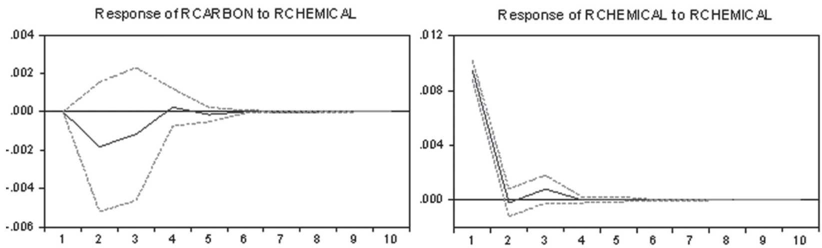

Figure 3. Impulse response diagram of rchemical fluctuation caused by variable shock

Cholesky orthogonal decomposition is performed on rcarbon-rchemical and rchemical-rchemical and each of them is given a standard deviation shock. After the adjustment of degree of freedom, Figure 3 is obtained. The solid line in Figure 3 indicates that the change of a variable after a certain shock and the dotted lines on both sides of the solid line indicate twice the standard deviation of the change. It can be seen from Figure 3 that the energy-chemical industry is greatly affected by its own shock and the influence is negative. The first two periods have the greatest impact. After the second and third periods, the impact becomes reversed and begins to decrease until it finally stabilizes. However, the energy-chemical industry has been affected greatly after the shock of the carbon trading market and the period of recovery is relatively long. After the fourth period, it becomes a negative influence and it is reduced and gradually stabilizes.

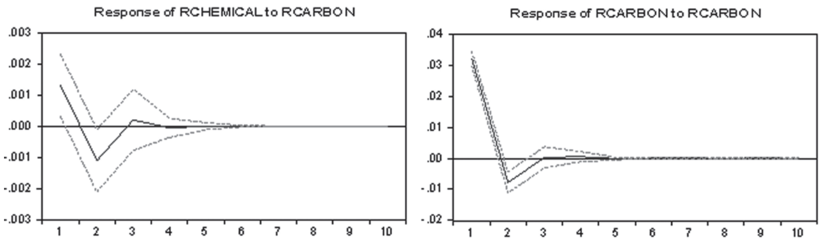

Figure 4. Impulse response diagram of rcarbon fluctuation caused by variable shock

Cholesky orthogonal decomposition is performed on rchemical-rcarbon and rcarbon-rcarbon and each of them is given a standard deviation shock. After the adjustment of degree of freedom, Figure 4 is obtained. It can be seen from Figure 4 that the carbon trading market is more affected by its own shock than the energy-chemical industry and after the second period, the impact is reduced and gradually stabilizes. However, the biggest effect of the carbon trading market after the shock of the energy-chemical industry is only about 0.001, reflecting that the fluctuations of carbon emission price are mainly affected by internal factors of itself. The main reason is that the market is in the primary construction stage, the endogenous mechanism is not perfect as well as the trading base and the regulatory mechanism are relatively weak.

Usually, the impulse response function can monitor the dynamic change of one variable after the shock of another variable and the variance decomposition can specify the influence of one variable on another variable to each disturbance item in the var model. Then the variance decomposition provides the relative impact degree of each disturbance factor of a variable on other variables in the var model and we can find the correlation between rchemical and rcarbon more intuitively and quantitatively. Then we use the var(2) model to analyze the contribution between variables.

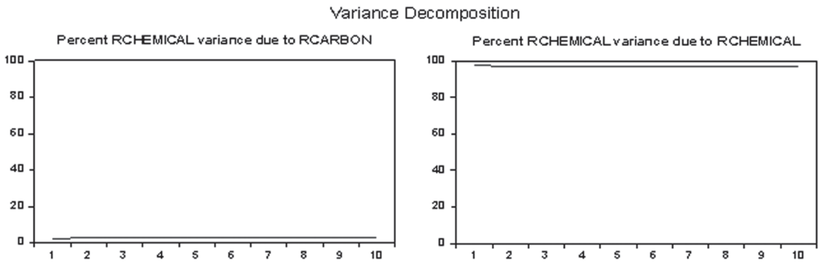

Figure 5. Results of chemical variance decomposition

As shown in Figure 5, the "Percent RCHEMICAL variance due to RCHEMICAL" indicates the contribution of rcarbon to the price change of rchemical and the "Percent RCHEMICAL variance due to RCARBON" indicates rchemical's own contribution to the price change of rchemical. As the number of periods increase, the contribution rate of each variable changes smoothly and there is no significant change. And rcarbon contributes a high rate to its own change, about 96%, but the contribution rate to the price change of rchemical is low, about 3%.

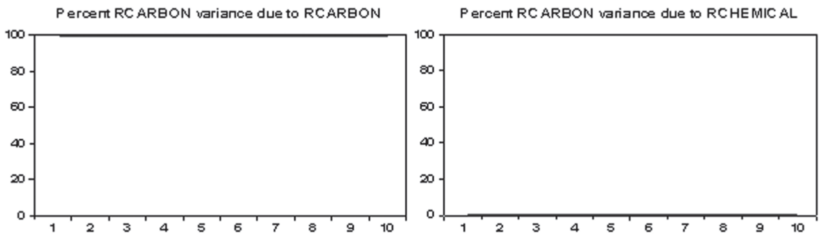

Figure 6. Results of rcarbon variance decomposition

As shown in Figure 6, the "Percent RCARBON variance due to RCARBON" indicates rcarbon's own contribution to the price change of rcarbon. The "Percent RCARBON variance due to RCHEMICAL" indicates the contribution of rchemical to the price change of rcarbon. As the number of periods increase, the contribution rate of each variable changes smoothly and there is no significant change. And rcarbon contributes a high rate to its own change, about 100%, but the contribution rate to the price change of rchemical is very low, almost 0, reflecting that the carbon trading market has little influence on the external financial market and has not formed a good internal and external interaction. The fundamental reason is that the external response mechanism is not perfect and the formation of market lacks power.

4.3 Comparison with developed countries

In order to compare the development of the carbon trading market in developing countries with developed countries, the world's largest carbon trading market EU-ETS is now added and models are built for comparison. We select the same period as the previous model (July 24, 2017 to July 24, 2018) EU-ETS daily trading data (represented as eucarbon) and European Energy Industry Index (represented as euchemical), then calculate the rate of change of both, represented as reucarbon and reuchemical.

In order to ensure that the regression results are not affected by the spurious regression, the ADF unit root test is first performed on reucarbon and reuchemical to verify its stability, as shown in Table 12 (in appendix).

According to Table 12, it can be seen that the absolute value of t value of reucarbon and reuchemical are larger than the absolute value of t value at 1%, 5% and 10% level, and the accompanying probability is 0.000, indicating that the two sequences have no unit root and are stationary sequences, so there is no pseudo-regression. Therefore, we continue with the optimal lag period selection, as shown in Table 11 (in appendix).

According to Table 13, the optimal lag period is 0, indicating that there is no dynamic feature between reucarbon and reuchemical. And the optimal lag period for China's carbon trading market is 2, which also reflects that after several years of development, the internal endogenous mechanism of EU-ETS has developed fast and reached a relatively mature and stable state. Thus, the Granger causality test is performed on reucarbon and reuchemical, as shown in Table 14 (in appendix).

From Table 14, we can get: (1) reucarbon is not the Granger reason for reuchemical (2) reuchemical is the Granger reason for reucarbon. It reflects that the impact between EU-ETS and the European energy-chemical industry is one-way. We continue to draw the two-variable IRF impulse response function diagram, as shown in Figure 7 (in appendix).

It can be seen from Figure 7 that after the carbon emission price of EU-ETS and the index of European energy-chemical industry are affected by each other, the fluctuation is small. And compared with the stationary of China's carbon trading market after four periods, it takes shorter time. Also it reflects that the external response mechanism of EU-ETS is mature and its ability to cope with external changes is stronger than China.

In summary, the carbon emission price of EU-ETS can not effectively affect the stock price of the energy-chemical industry and the stock price of the industry can have an effective impact on the carbon emission price of EU-ETS. The two are one-way effects. And when this effect is generated, it can be adjusted quickly and returned to the normal fluctuation range.

5. Conclusion and Discussion

The Granger causality tests in the panel model and the var model, the results of variance decomposition and the impulse response analysis all indicate that there is an asymmetric correlation between the carbon emission price of in the carbon trading market and the stock price of the energy-chemical industry in China, in which the effect of the carbon emission price on the stock price changes in the energy-chemical industry is more significant than the effect of stock price changes on the carbon emission price. The effect of the energy-chemical industry’s stock price on the carbon emission price of the carbon trading market is almost negligible, suggesting that the carbon emission price may be a determinant of the stock price. The fluctuation of the carbon emission price may affect the fluctuation of the energy-chemical industry’s stock price, but impact of the share price of the energy industry on the market price of carbon emission rights is very small. Therefore, this one-way relationship affects the regulation effect of the carbon trading market and the emission reduction efficiency of the energy-chemical industry.

By comparing the trading price of EU-ETS with the European energy industry index, although both EU-ETS and China's carbon trading market have asymmetric one-way influences, there are still big differences in the market performance, internal foundation and external mechanism construction of the carbon trading markets in developed countries and developing countries.

Learning from EU-ETS can help developing countries like China achieve their emission reduction targets in a cost-effective manner and encourage high-energy and high-emission companies to contribute to their emission reduction actions and promote their sustainable development. The carbon trading markets are increasing, the daily trading volume of these markets is gradually increasing and the market scale is expanding in China. However, the carbon emission price of the carbon trading market and the stock price of energy-chemical company have not formed a transmission and the fluctuations of carbon emission price are more likely to be affected by their own prices. Therefore it will not encourage enterprises to voluntarily reduce their willingness and it is not conducive for the carbon trading market to get the attention of enterprises.

In summary, we find that as financial markets, China's carbon trading market and the energy-chemical industry have not showed effective interactions and linkages between them. This situation is caused by both internal and external factors:

(1) The internal endogenous mechanism is less than perfect and the trading base and regulatory mechanism are weak.

As an emerging product of the national energy conservation and emission reduction strategic plan, China's carbon trading market is still in the primary construction stage and its influence is limited to a few regions and enterprises which have participated in the pilot market as well as it has not been fully implemented across the country. However, the development of various carbon trading pilot markets in China is also uneven. The internal financial derivatives in the market are relatively simple and diversified development has not been achieved as well as the construction of relevant accounting systems and regulatory systems is less than perfect. Due to lack of an authoritative emission reduction certification institution in the market, no accounting standard system has been established yet. The problems also include that the information quality of the trading market is bad, the transaction costs are increased, the market operation efficiency is low and it is difficult for enterprises to obtain reasonable income. Furthermore, there is a lack of talented people and advanced technology to enhance the international competitiveness of China's carbon trading market.

(2) The external response mechanism of carbon trading market in China is not perfect and the market formation is insufficient.

Information asymmetry is a serious challenge for the carbon trading market. Because of this problem, buyers and sellers need to pay higher information costs. On the one hand, information authenticity cannot be guaranteed due to different statistical calibers. On the other hand, the lack of timely release of key information exists. If these problems cannot be solved well, the problem of one-way impact obtained from empirical analysis will always exist. The initial quota is the first and most important part of the transaction, but it is easy to be manipulated by human factors, causing the lack of trading power of the company. Although there are seven carbon trading pilot markets in China, all markets still have low liquidity and the market effectiveness level is low. Therefore, it is increasingly important to establish a standardized and efficient information platform and response mechanism, which is of great significance for improving the internal influence of the carbon trading market and the effective linkage with financial markets.

References

Aguiar-Conraria, L., Soares, MJ, & Sousa, R. (2018). California's carbon market and energy prices: a wavelet analysis. Philosophical Transactions of the Royal Society a-Mathematical Physical and Engineering Sciences, 376(2126)

Andersen, J. J., & Greaker, M. (2018). Emission Trading with Fiscal Externalities: The Case for a Common Carbon Tax for the Non-ETS Emissions in the EU. Environmental & Resource Economics, 71(3), 803-823.

Balachandran, B., & Nguyen, J. H. (2018). Does carbon risk matter in firm dividend policy? Evidence from a quasi-natural experiment in an imputation environment. Journal of Banking & Finance, 96, 249-267.

Borghesi, S. and A. Flori (2019). "With or without U(K): A pre-Brexit network analysis of the EU ETS." Plos One 14(9).

Brennan, L., & Owende, P. (2010). Biofuels from microalgae-A review of technologies for production, processing, and extractions of biofuels and co-products. Renewable & Sustainable Energy Reviews, 14(2), 557-577.

Brouwers, R., Schoubben, F., Van Hulle, C., & Van Uytbergen, S. (2016). The initial impact of EU ETS verification events on stock prices. Energy Policy, 94, 138-149.

Bunn, D. W., Redondo-Martin, J., Munoz-Hernandez, J. I., & Diaz-Cachinero, P. (2019). Analysis of coal conversion to biomass as a transitional technology. Renewable Energy, 132, 752-760.

Calel, R., & Dechezlepretre, A. (2016). Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. Review of Economics and Statistics, 98(1), 173-191.

Callan T, Lyons S, Scott S, Tol RSJ, Verde S. (2009). The distributional implications of a carbon tax in Ireland. Energy Policy, 37, 407-12.

Chang, C. L., et al. (2019). "Establishing national carbon emission prices for China." Renewable & Sustainable Energy Reviews 106: 1-16.

Chen, J. K., & Xiang, D. (2019). Carbon efficiency and carbon abatement costs of coal-fired power enterprises: A case of Shanghai, China. Journal of Cleaner Production, 206, 452-459.

Chen, W. Y., Wu, Z. X., He, J. K., Gao, P. F., & Xu, S. F. (2007). Carbon emission control strategies for China: A comparative study with partial and general equilibrium versions of the China MARKAL model. Energy, 32(1), 59-72.

Chen, Z. M., & Chen, G. Q. (2011). Embodied carbon dioxide emission at supra-national scale: A coalition analysis for G7, BRIC, and the rest of the world. Energy Policy, 39(5), 2899-2909.

Cong, R. G., & Wei, Y. M. (2010). Potential impact of (CET) carbon emissions trading on China's power sector: A perspective from different allowance allocation options. Energy, 35(9), 3921-3931.

Davis, S. J., & Caldeira, K. (2010). Consumption-based accounting of CO_2 emissions. Proceedings of the National Academy of Sciences of the United States of America, 107(12), 5687-5692.

Deng, M. Z. and W. X. Zhang (2019). "Recognition and analysis of potential risks in China's carbon emission trading markets." Advances in Climate Change Research 10(1): 30-46.

Diaz-Rainey, I., & Tulloch, D. J. (2018). Carbon pricing and system linking: Lessons from the New Zealand Emissions Trading Scheme. Energy Economics, 73, 66-79.

Dissanayake, S., Mahadevan, R., & Asafu-Adjaye, J. (2018). How efficient are market-based instruments in mitigating climate change in small emitter South Asian economies? Economic Modelling, 75, 169-180.

Dissou Y, Siddiqui MS. (2014). Can carbon taxes be progressive? Energy Econ, 42, 88-100.

Fang, G. C., et al. (2018). "How to optimize the development of carbon trading in China-Enlightenment from evolution rules of the EU carbon price." Applied Energy 211: 1039-1049.

Fang, G. C., et al. (2020). "Research on the influence mechanism of carbon trading on new energy-A case study of ESER system for China." Physica a-Statistical Mechanics and Its Applications 545.

Gunel, G. (2016). What Is Carbon Dioxide? When Is Carbon Dioxide? Polar-Political and Legal Anthropology Review, 39(1), 33-45.

Jalil, A., & Feridun, M. (2011). The impact of growth, energy and financial development on the environment in China: A cointegration analysis. Energy Economics, 33(2), 284-291.

Jiang, J. J., Ye, B., & Ma, X. M. (2014). The construction of Shenzhen's carbon emission trading scheme. Energy Policy, 75, 17-21.

Jiang, M. X., Zhu, B. Z., Wei, Y. M., Chevallier, J., & He, K. J. (2018). An intertemporal carbon emissions trading system with cap adjustment and path control. Energy Policy, 122, 152-161.

Jiang, Y., et al. (2018). "Factors affecting the pilot trading market of carbon emissions in China." Petroleum Science 15(2): 412-420.

Koch, N., Fuss, S., Grosjean, G., & Edenhofer, O. (2014). Causes of the EU ETS price drop: Recession, CDM, renewable policies or a bit of everything?-New evidence Energy Policy, 73, 676-685.

Lee, Y. J., et al. (2020). "Analysis of the Informational Efficiency of the EU Carbon Emission Trading Market: Asymmetric MF-DFA Approach." Energies 13(9).

Leslie, G. (2018). Tax induced emissions? Estimating short-run emission impacts from carbon taxation under different market structures. Journal of Public Economics, 167, 220-239.

Li, J., Tharakan, P., Macdonald, D., &Liang, X. (2013). Technological, economic and financial prospects of carbon dioxide capture in the cement industry. Energy Policy, 61, 1377-1387.

Li, W., Lu, C., Ding, Y., & Zhang, Y.-W. (2017). The impacts of policy mix for resolving overcapacity in heavy chemical industry and operating national carbon emission trading market in China. Applied Energy, 204, 509-524.

Liu, J. P., et al. (2018). "Regional carbon emission evolution mechanism and its prediction approach driven by carbon trading - A case study of Beijing." Journal of Cleaner Production 172: 2793-2810.

Liu, Z. Q., Geng, Y., Dai, H. C., Wilson, J., Xie, Y., Wu, R., . . . Yu, Z. J. (2018). Regional impacts of launching national carbon emissions trading market: A case study of Shanghai. Applied Energy, 230, 232-240.

Mohanty, A. K., Misra, M., & Hinrichsen, G. (2000). Biofibres, biodegradable polymers and biocomposites: An overview. Macromolecular Materials and Engineering, 276(3-4), 1-24.

Monasterolo, I., Zheng, J. I., & Battiston, S. (2018). Climate Transition Risk and Development Finance: A Carbon Risk Assessment of China's Overseas Energy Portfolios. China & World Economy, 26(6), 116-142.

Moreno, B., & da Silva, P. P. (2016). How do Spanish polluting sectors' stock market returns react to European Union allowances prices? A panel data approach. Energy, 103, 240-250.

Oberndorfer, U. (2009). EU Emission Allowances and the stock market: Evidence from the electricity industry. Ecological Economics, 68(4), 1116-1126.

Oestreich, A. M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the

EU Emissions Trading Scheme. Journal of Banking & Finance, 58, 294-308.

Oladi, R., Caplan, A. J., & Gilbert, J. (2018). Sequestration and the engagement of developing economies in a global carbon market. Resource and Energy Economics, 52, 50-63.

Orlov, A., & Grethe, H. (2012). Carbon taxation and market structure: A CGE analysis for Russia. Energy Policy, 51, 696-707.

Pao, H. T., Fu, H. C., & Tseng, C. L. (2012). Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model. Energy, 40(1), 400-409.

Poland, C. A., Duffin, R., Kinloch, I., Maynard, A., Wallace, W. A. H., Seaton, A., . . . Donaldson, K. (2008). Carbon nanotubes introduced into the abdominal cavity of mice show asbestos-like pathogenicity in a pilot study. Nature Nanotechnology, 3(7), 423-428.

Rafiee, A., Khalilpour, K. R., Milani, D., & Panahi, M. (2018). Trends in CO_2 conversion and utilization: A review from process systems perspective. Journal of Environmental Chemical Engineering, 6(5), 5771-5794.

Schreifels, J. J., Fu, Y. L., & Wilson, E. J. (2012). Sulfur dioxide control in China: policy evolution during the 10th and 11th Five-year Plans and lessons for the future. Energy Policy, 48, 779-789.

Smale, R., Hartley, M., Hepburn, C., Ward, J., & Grubb, M. (2006). The impact of CO_2 emissions trading on firm profits and market prices. Climate Policy, 6(1), 31-48.

Song, X., Lu, Y., Shen, L., & Shi, X. (2018). Will China's building sector participate in emission trading system? Insights from modelling an owner's optimal carbon reduction strategies. Energy Policy, 118, 232-244.

Sousa, R., & Aguiar-Conraria, L. (2015). Energy and carbon prices: a comparison of interactions in the European Union Emissions Trading Scheme and the Western Climate Initiative market. Carbon Management, 6(3-4), 129–140.

Stuart, D., Gunderson, R., & Petersen, B. (2019). Climate Change and the Polanyian Countermovement: Carbon Markets or Degrowth? New Political Economy, 24(1), 89-102.

Supekar, S. D., & Skerlos, S. J. (2014). Market-Driven Emissions from Recovery of Carbon Dioxide Gas. Environmental Science & Technology, 48(24), 14615-14623.

Tang, L., Wu, J., Yu, L., & Bao, Q. (2015). Carbon emissions trading scheme exploration in China: A multi-agent-based model. Energy Policy, 81, 152- 169.

Tessonnier, J.-P., Rosenthal, D., Hansen, T. W., Hess, C., Schuster, M. E., Blume, R., Schloegl, R. (2009). Analysis of the structure and chemical properties of some commercial carbon nanostructures. Carbon, 47(7), 1779-1798.

Tian, Y., Akimov, A., Roca, E., & Wong, V. (2016). Does the carbon market help or hurt the stock price of electricity companies? Further evidence from the European context. Journal of Cleaner Production, 112, 1619-1626.

Wang, B., Sun, Y. F., & Wang, Z. H. (2018). Agglomeration effect of CO_2 emissions and emissions reduction effect of technology: A spatial econometric perspective based on China's province-level data. Journal of Cleaner Production, 204, 96-106.

Wang, L. H., et al. (2019). "A New Grey Relational Analysis Model Based on the Characteristic of Inscribed Core (IC-GRA) and Its Application on Seven-Pilot Carbon Trading Markets of China." International Journal of Environmental Research and Public Health 16(1).

Wang, Q. (2010). Effective policies for renewable energy-the example of China's wind power-lessons for China's photovoltaic power. Renewable & Sustainable Energy Reviews, 14(2), 702-712.

Wu, X. F., Xu, Y. C., Lou, Y. T., & Chen, Y. (2018). Low carbon transition in a distributed energy system regulated by localized energy markets. Energy Policy, 122, 474-485.

Xie, J. Y., Dai, H. C., Xie, Y., & Hong, L. X. (2018). Effect of carbon tax on the industrial competitiveness of Chongqing, China. Energy for Sustainable Development, 47, 114-123.

Ye, D., Liu, S., & Kong, D. (2013). Do efforts on energy saving enhance firm values? Evidence from China's stock market. Energy Economics, 40, 360-369.

Yeh, S. (2007). An empirical analysis on the adoption of alternative fuel vehicles: The case of natural gas. Energy Policy, 35(11), 5865-5875.

Yin, J., Su, C., Zhang, Y., & Fan, X. (2018). Complexity Analysis of Carbon Market Using the Modified Multi-Scale Entropy. Entropy, 20(6).

Yin, Y. K., et al. (2019). "Factors Affecting Carbon Emission Trading Price: Evidence from

China." Emerging Markets Finance and Trade 55(15): 3433-3451.

Yu, Z., Geng, Y., Dai, H., Wu, R., Liu, Z., Tian, X., & Bleischwitz, R. (2018). A general equilibrium analysis on the impacts of Regional and sectoral emission allowance allocation at carbon trading market. Journal of Cleaner Production, 192, 421-432.

Zeng, J.M., 2016. A Summary of the Operation of China's Carbon Trading Pilot Areas.

Zhang, S. F. and P. Andrews-Speed (2020). "State versus market in China's low-carbon energy transition: An institutional perspective." Energy Research & Social Science 66.

Zhang, Y. J. (2011). The impact of financial development on carbon emissions: An empirical analysis in China. Energy Policy, 39(4), 2197-2203.

Zhang, Y.-J., Wang, A.-D., & Da, Y.-B. (2014). Regional allocation of carbon emission quotas in China: Evidence from the Shapley value method. Energy Policy, 74, 454-464.

Zhang, Z. H., Dong, M. F., Hao, X. H., Han, L. J., Song, S. Y., & Yao, W. (2019). Evaluation of cleanup procedures in pesticide multi-residue analysis with QuEChERS in cinnamon bark. Food Chemistry, 276, 140-146.

Zhao, Y., Wang, C., Sun, Y., & Liu, X. (2018). Factors influencing companies' willingness to pay for carbon emissions: Emission trading schemes in China. Energy Economics, 75, 357-367.

Zhu, H., et al. (2018). "The heterogeneous response of the stock market to emission allowance price: evidence from quantile regression." Carbon Management 9(3): 277-289.

Appendix

Table 12. Unit root test results

	reucarbon		reuchemical	
	t-Statistic	Prob.	t-Statistic	Prob.
ADF test statistic	-15.825	0.000	-15.737	0.000
1% level	-3.455		-3.456	
5% level	-2.872		-2.873	
10% level	-2.572		-2.573	

Table 13. Optimal lag period selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1234.208	NA*	6.00e-08*	-10.952*	-10.922*	-10.940*
1	1237.405	6.308	6.04E-08	-10.945	-10.854	-10.909
2	1240.350	5.759	6.10E-08	-10.936	-10.784	-10.875
3	1241.693	2.603	6.25E-08	-10.912	-10.700	-10.827
4	1242.870	2.258	6.41E-08	-10.887	-10.614	-10.777
5	1247.342	8.507	6.38E-08	-10.891	-10.557	-10.757
6	1247.679	0.636	6.59E-08	-10.859	-10.464	-10.700

Table 14. Granger causality test results

Null hypothesis	Lag period	F	P	Result
reucarbon is not the Granger reason for reuchemical	363	1.200	0.310	reucarbon is not the Granger reason for reuchemical
reuchemical is not the Granger reason for reucarbon	363	2.043	0.045	reuchemical is the Granger reason for reucarbon

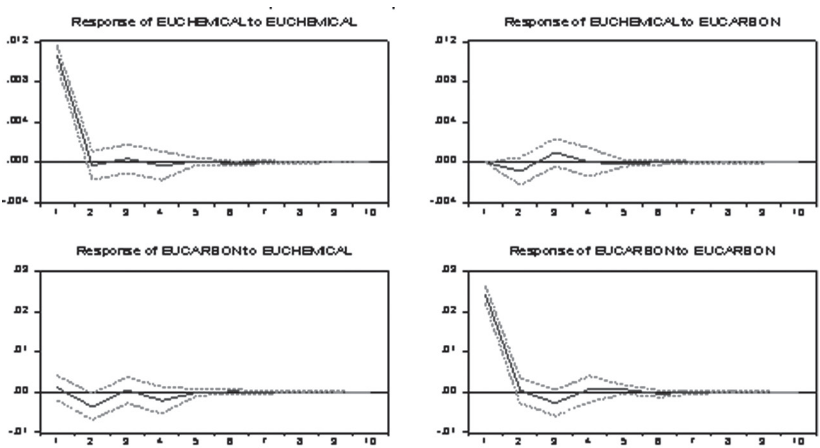

Figure 7. IRF impulse response function diagram