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Study on Price Fluctuation and Influencing Factors of Regional Carbon Emission Trading in China under the Background of High-quality Economic Development

Zeng Sheng*, +, Zhang Han+, 1, Qu Yuwei+, and Zeng Boya#

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ABSTRACT

The carbon emission trading market is an economic tool that reduces emissions and thus affects climate change and mitigates the greenhouse effect. In this study, the ARMA-GARCH model and Grey relational analysis are employed to explore the characteristics of carbon price fluctuations in seven regions of China and the possible impacts of six factors including energy prices, economic condition, policy, industrial structure, air quality, and foreign carbon trading price. It is concluded that the regional carbon emission trading prices in China have the characteristics of agglomeration, peak, heavy tail, memory and anti-leverage, which is largely influenced by energy prices, structural factors, policy and environmental factors. Moreover, there are great regional differences in the correlation between high-quality economic development and carbon prices.

1. INTRODUCTION

In recent years, the frequency and severity of extreme weather have risen year by year. According to the United Nations Office for Disaster Reduction, during the period from 1998 to 2017, the direct economic losses of disaster-stricken countries hit 2.91 trillion dollars, among which the loss of 2.25 trillion dollars come from climate-related disasters, accounting for 77% (such as in Figure 1). In other words, climate change has become one of the main obstacles to sustainable economic development. As a major emitter, China is significantly affected by climate change. At present, China's economic and social development has been shifting from high-speed growth to high-quality development. "Carbon peak and carbon neutrality" has been mentioned as the top national strategic goal, at this time, carbon emission trading is the most effective way to solve the climate change problem through economic means. In the process of carbon emission trading, carbon price is the core problem in the carbon market. Therefore, under the background of high-quality economic development, it is of great practical significance to study the characteristics of regional carbon price and related issues affecting factors.

* Research Center for Economy of Upper Reaches of the Yangtse River Chongqing Technology and Business University, Chongqing. 400067, China.

+ School of Finance and Fiscal Affairs, Chongqing Technology and Business University, Chongqing 400067, China.

School of Mechanical, Aerospace and Civil Engineering, University of Manchester, M13 9PL, United Kingdom.

1 Corresponding author:
Tel: + 86 188 7500 1725, Fax: + 86 023 627 693 77.
Email: cqzs2002@ctbu.edu.cn.

So how will the carbon price change in the context of high-quality economic development? The study found that the carbon quota price generally has fluctuation aggregation and regional differences [1], [2], and the existing literature mainly analyzes the heterogeneity fluctuations of carbon price time series using THECH model, lacking research on the process of carbon price time series self-regression (ARMA) [1]-[2]. In the study of the factors affecting carbon price, the existing literature is based on the Copula model, which compares the prices of carbon quotas in China and the United States and Central Europe [2]-[3], and China's carbon market starts late, with fewer data samples compared with the United States and Europe, which may lead to biased conclusions to some extent. Therefore, this paper selects the gray relational model suitable for the correlation of small sample analysis to analyze the factors affecting the carbon quota price of the seven pilot projects in China to obtain a more universal conclusion.

Fig. 1. Greenhouse gas emissions.

According to China's administrative divisions, the seven carbon emissions trading pilots are divided into five regions, namely, North China, Central China, East

China, South China and Southwest China. The daily data from January 1, 2017 to December 31, 2018 are selected as a sample to explore the fluctuations and factors of regional carbon prices and to further identify the reasons for the price differences and transaction activity in different carbon trading pilots in China to provide feasible suggestions for China to build a unified carbon trading market at different administrative levels in different regions. In addition, this paper creatively integrates high-quality economic development indicators [4] into the analysis of carbon price influence factors to further clear out regional differences in carbon price fluctuations and provide a reference for the unified carbon trading market in China [4].

This study also makes some contributions to the literature. First, regional carbon emissions prices in China are characterized by volatility, peak, thick tail, memory and certain anti-leverage, and previous studies have often ignored the carbon price anti-leverage. Second, among the six selected factors, it is found that energy price, industrial structure, policy, and environmental factors are the main factors affecting China's regional carbon price. Third, using the gray correlation model, we found that there are large regional differences between the high-quality development of China's economy and the carbon quota transaction price.

2. LITERATURE REVIEW

Over the past decade, a number of domestic and foreign scholars have placed an emphasis on diachronic change and revealed various features of carbon prices. In the field of probability distribution, many researchers have agreed on the doctrine that the EUA prices exhibit structural breaks, jumps, and heavy tails. Chevallier and Sévi in 2014 detail that, for the period from 2009 to 2010, carbon futures prices do not seem to contain a continuous (Brownian motion) component, and can be better characterized by a centered Lévy or Poisson process [5]. Balietti in 2016 pointed that most of financial markets' price volatility is persistent, clustered and seasonal, with high volatility in April under the EU ETS [1]. By analyzing two carbon markets in China and the EU with the help of DCC-MGARCH (1, 1) model, Chun in 2018 underlines that there are agglomeration effects in two markets, but the characteristics of market agglomeration and price volatility in the EU are more significant. When it comes to volatile memory [2], Feng *et al.* in 2011 used Random Surfer Model and R/S ratio analysis model to discover that carbon trading price has short-term memory [6], whereas Cong and Lo in 2017 believe that carbon price fluctuations in Beijing and Shenzhen have strong long-term memory [7].

In addition to the characteristics of regional carbon price, domestic and foreign scholars have conducted much research on its influencing factors. There is no doubt that economic growth, energy prices and weather conditions are identified as key drivers of EUA prices [8]-[12].

In recent years, more and more investigations expand horizons to macroeconomic activity, indicating carbon prices have been demonstrated to be closely associated with energy prices and macroeconomic activity at the theoretical and empirical level [13]-[14]. For instance, Alberola *et al.* in 2008 explore the positive effect of industrial production during periods of economic expansion, confirming the relationship between macroeconomics and the price of carbon. With regard to the impacts of policies and mechanism [15], Lin and Jia in 2019 argue that carbon price is sensitive to the mechanism of Emission Trading Scheme, which means more stringent carbon reduction targets will raise carbon prices, when fewer industries and higher free allowance rate will push prices up significantly [16]. Wen *et al.* in 2020 investigate the asymmetric relationship between the CET markets in China using the NARDL model. They find there are significantly negative long-run and short-run asymmetric relationships between the CET market and the overall stock market [17].

Based on the above literature review, we found that in the study of carbon price fluctuations, the existing literature mostly focuses on foreign carbon prices and some pilots' prices in China, revealing that rate of return has the characteristics of volatility, peak, thick tail, memory, which is consistent with the result of this study. On the contrary, the study finds it has a certain anti-leverage in Chongqing and Shanghai, which means good news brings more volatility than bad one. Anti-leverage indicates a relatively mature regional carbon market, but it is not consistent with current situation in Chongqing for a strong correlation with policy dividend support, which is elaborated by follow-up analysis.

In terms of the influencing factors of carbon price, the available literature has studied the single carbon trading market in the US, the EU and China through the Copula cluster model, with fewer studies on the seven pilots, and our research has helped to bridge this gap. At the same time, this paper introduces the high-quality economic development index and analyzes the driving factors of China's carbon quota price, which is of great practical significance in the process of China's economy moving from high-speed growth to high-quality development.

3. METHODOLOGY AND EMPIRICAL RESULTS

3.1 Analysis of Price Fluctuation of Regional Carbon Emission Trading in China

ARMA-GARCH model is used in this paper to analyze the characteristics of carbon price fluctuation in seven regions including Beijing (BEA), Fujian (FJEA), Guangdong (GDEA), Hubei (HBEA), Shanghai (SHEA), Shenzhen (SZA) and Chongqing (CQEA).

3.1.1 ARMA model

Autoregressive Moving Average Model (ARMA), created by Box and Jenkins, is composed of an autoregressive model AR (p) and a moving average model MA (q). The general expression of ARMA (p, q) is:

$$u_t = c + \phi_1 u_{t-p} + \cdots + \phi_p u_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} (t = 1, 2, \cdots, T) \quad (1)$$

Where ε_t is a white noise sequence with a mean of 0 and a variance of σ^2. p and q are the lag orders of AR and MA, respectively. Since the p and q orders are unknown, p and q should be determined before the parameter estimation. This study attempts to assign values to p and q from 1 to 4. According to the AIC criterion, the optimal order of carbon trading in each region is determined.

3.1.2 GARCH model

Autoregressive Conditional Heteroscedasticity Model (ARCH), proposed by Engle in 1982, is mainly used to explain the conditional heteroscedasticity of price fluctuations in financial markets, that is, the dependence of error term's conditional variance on its previous value. The general expression is shown in Equation 2:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_p u_{t-p}^2 \quad (2)$$

Since the variance of the disturbance term u_t often depends on the previous change, many parameters need to be estimated, which significantly affects the accuracy of result. Therefore, Bollerslev proposed a generalized ARCH model, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model in 1986, which pointed out that the conditional variance of the random error term, depends on both the previous value of the conditional variance and the square of the previous value of the error term. The general expression GARCH (p, q) is shown in Equation 3:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (3)$$

In Equation 3, p is the order of ARCH term and q that of GARCH term. In the process of empirical research on carbon prices, it is generally believed that the first-order GARCH model can characterize the time series of carbon prices, that is, GARCH (1, 1) model:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (4)$$

In Equation 4, ω is a constant term, αu_{t-1}^2 is the ARCH term representing the amount of change at the previous moment, and $\beta \sigma_{t-1}^2$ is the GARCH term representing the variance at the previous moment. Because the impact of financial markets often is manifested as an asymmetric effect, Zakoian introduced the TGARCH model in 1990, in order to describe the asymmetric effect of different information on the rate of return. The general expression is shown in Equation 5:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \gamma u_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \quad (5)$$

In formula (5), d_{t-1} is a virtual variable, which is assigned 1 when $u_{t-1} < 0$ and 0 when $u_{t-1} > 0$. In this model, the good news $(u_t > 0)$ and the bad news $(u_t < 0)$ have different effects on the conditional variance: when the good news produces a shock of α, the negative news has an impact on $\alpha+\gamma$. If $\gamma \neq 0$, which is asymmetric. Specifically, if $\gamma > 0$, there is a leverage effect with enhancing information shock and increasing volatility in price; if $\gamma < 0$, the volatility is reduced.

Provided by the Wind database and China Carbon Emissions Trading Network, the daily prices of the seven trading pilots from January 1, 2017 to December 31, 2018 are selected as a sample for analysis. The number of actual data is 2554, excluding holidays and the closing period of each pilot. In addition, it's worth noting that the data of Tianjin pilot is not modeled and analyzed, because it is too little to reflect its market information accurately. Due to the volatility of regional price and the requirement of stable data in ARMA model, the logarithmic difference is taken in this paper to make it smooth. The time series chart and descriptive statistics of logarithmic return on regional carbon prices are shown in Figure 2 and Table 1, respectively.

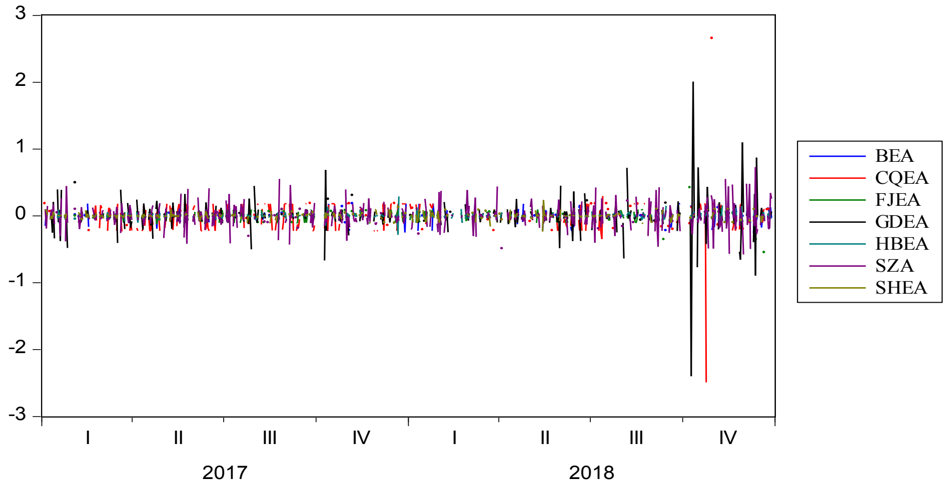

Fig. 2. Time series chart of the number of yields in China's regional carbon trading market.

Table 1. Descriptive statistical values of carbon price rates of return for each pilot.

Variety	BEA	FJEA	GDEA	HBEA	SHEA	SZA	CQEA
Observations	268	339	440	479	308	441	272
Mean	0.000391	-0.003382	0.000481	0.000867	0.000059	-0.001261	-0.002458
Median	0.003477	-0.000257	0	0	0	-0.003481	0.006086
Maximum	0.183751	0.420833	2.007539	0.29004	0.237704	0.728318	2.654429
Minimum	-0.254991	-0.550046	-2.397179	-0.282303	-0.236389	-0.578147	-2.488915
Std. Dev.	0.081787	0.074337	0.227784	0.04094	0.050773	0.175187	0.269896
Skewness	-0.579485	-1.309123	-0.903281	0.251064	-0.146641	0.251206	0.602055
Kurtosis	4.752841	15.69801	46.20367	13.94582	5.879561	4.894753	61.62895
Jarque-Bera	49.30823	2374.337	34280.06	2409.384	107.5162	70.60607	38973.11
Probability	0	0	0	0	0	0	0

Table 2. ADF test.

Variety	BEA	FJEA	GDEA	HBEA	SHEA	SZA	CQEA
t-Statistic	-16.09413	-16.02896	-11.94789	-23.07608	-20.52327	-15.71611	-20.7606
1% level	-3.454719	-3.449504	-3.445302	-3.443834	-3.451491	-3.445093	-3.454353
prob.*	0	0	0	0	0	0	0

Through Figure 2, we can see that the currency yield of the average transaction price of the seven regional carbon trading days fluctuates around the value of 0, and the effect of volatility agglomeration is obvious.

The means of the seven regions all fluctuate around 0. The gap between the maximum and minimum value is relatively large and the figures of all pilots' kurtosis are greater than 3. From the perspective of skewness, the figures of Hubei, Shenzhen and Chongqing are right-skewed distribution, while those of Beijing, Fujian, Guangdong and Shanghai are left-skewed distribution. According to the J-B test, their concomitant probabilities are 0. To sum up, the carbon prices of seven pilots have the features of fluctuation and agglomeration, peak and heavy tail, and they do not follow the normal distribution.

3.1.3 Empirical analysis

Firstly, the data should be processed by the ADF test (see Table 2). The test results indicate that the statistics of the seven pilots are less than the critical value at the test level of 1% and the concomitant probability is 0, so that the original hypothesis is strictly rejected and the sequence is stable.

Secondly, in the light of AIC information criteria, authors assign p and q (i.e. p (q) = 1, 2, 3, 4), and then determine the optimal order of carbon transactions in each region (see Table 3). The results are as follows: Beijing ARMA (1, 4), Fujian ARMA (1, 3), Guangdong ARMA (3, 4), Hubei ARMA (2, 4), Shanghai ARMA (2, 4), Shenzhen ARMA (3, 4), Chongqing ARMA (1, 1).

Thirdly, after the ARCH test of the residual sequence of the model, the results are shown in Table 4. It is demonstrated that when the lag length takes 1, the P values corresponding to F and T statistics (Obs*R-square) in five pilots other than Shenzhen reject the original hypothesis at a significant level of 5%. Moreover, when the lag length takes 7, the P value of Shenzhen is less than 5%, accordingly rejecting the original hypothesis, which indicates that there is conditional heteroscedasticity in the residual sequence of ARMA (p, q) models in each region.

Finally, the GARCH model is introduced and the GARCH (1, 1) model is established to estimate the ARMA (p, q) of each pilot. The pilot parameters are estimated as those shown in Table 5. To be specific, the coefficients of carbon trading pilot in Chongqing and Shanghai are greater than 1, which may have a leverage effect. The TGARCH model is used to modify the coefficient, as shown in Table 6.

Table 3. AIC values for each pilot.

ARMA(*p*, *q*)	Variety						
	BEA	FJEA	GDEA	HBEA	SHEA	SZA	CQEA
ARMA(1,1)	-2.162670	-2.344565	-0.439679	-3.722884	-3.191152	-0.975420	0.182444
ARMA(1,2)	-2.166096	-2.339868	-0.450718	-3.732827	-3.185805	-0.980354	0.184981
ARMA(1,3)	-2.178916	-2.382410	-0.453712	-3.724968	-3.180256	-0.981853	0.187613
ARMA(1,4)	-2.261820	-2.381363	-0.450245	-3.729691	-3.174019	-0.977774	0.194800
ARMA(2,1)	-2.163901	-2.336027	-0.443625	-3.728794	-3.185526	-0.972626	0.189494
ARMA(2,2)	-2.211014	-2.353194	-0.444577	-3.727837	-3.188429	-0.981588	0.184656
ARMA(2,3)	-2.203517	-2.381122	-0.446865	-3.728753	-3.193557	-0.986425	0.189786
ARMA(2,4)	-2.253758	-2.373444	-0.449250	-3.737047	-3.224047	-0.983948	0.194176
ARMA(3,1)	-2.177752	-2.378986	-0.448621	-3.725533	-3.181825	-0.975156	0.192962
ARMA(3,2)	-2.198812	-2.378099	-0.441654	-3.723072	-3.189242	-0.977517	0.191555
ARMA(3,3)	-2.192467	-2.339229	-0.441589	-3.732589	-3.192707	-0.982503	0.198928
ARMA(3,4)	-2.245327	-2.367612	-0.455810	-3.725294	-3.218317	-1.000408	0.203680
ARMA(4,1)	-2.243405	-2.372192	-0.444620	-3.720286	-3.180485	-0.961298	0.200829
ARMA(4,2)	-2.244923	-2.366297	-0.448520	-3.725658	-3.187638	-0.975176	0.202662
ARMA(4,3)	-2.252784	-2.339240	-0.444899	-3.731377	-3.184371	-0.988422	0.208334
ARMA(4,4)	-2.249752	-2.336292	-0.441184	-3.735498	-3.181334	-0.995788	0.214925

Table 4. Conditional heteroscedasticity test values for different lag number.

Variety	Number of lag is 1				Number of lag is 7			
	Variety	Statistic	Variety	Prob.	Variety	Statistic	Variety	Prob.
BEA	F	29.75301	Prob. F(1,264)	0.0000	F	5.07003	Prob. F(7,252)	0.0000
ARMA(1,4)	T	26.94203	Prob. Chi-Square(1)	0.0000	T	32.09659	Prob. Chi-Square(7)	0.0000
FJEA	F	129.6144	Prob. F(1,335)	0.0000	F	22.75849	Prob. F(7,323)	0.0000
ARMA(1,3)	T	94.01356	Prob. Chi-Square(1)	0.0000	T	109.3311	Prob. Chi-Square(7)	0.0000
GDEA	F	6.835294	Prob. F(1,434)	0.0092	F	1.341035	Prob. F(7,422)	0.2292
ARMA(3,4)	T	6.760322	Prob. Chi-Square(1)	0.0093	T	9.357059	Prob. Chi-Square(7)	0.2280
HBEA	F	33.11108	Prob. F(1,474)	0.0000	F	4.679419	Prob. F(7,462)	0.0000
ARMA(2,4)	T	31.07972	Prob. Chi-Square(1)	0.0000	T	31.11694	Prob. Chi-Square(7)	0.0001
SHEA	F	29.83052	Prob. F(1,303)	0.0000	F	4.644057	Prob. F(7,291)	0.0001
ARMA(2,4)	T	27.33616	Prob. Chi-Square(1)	0.0000	T	30.04562	Prob. Chi-Square(7)	0.0001
SZA	F	3.235251	Prob. F(1,435)	0.0728	F	2.673499	Prob. F(7,423)	0.0102
ARMA(3,4)	T	3.226132	Prob. Chi-Square(1)	0.0725	T	18.26054	Prob. Chi-Square(7)	0.0108
CQEA	F	94.33607	Prob. F(1,268)	0.0000	F	18.90771	Prob. F(7,256)	0.0000
ARMA(1,1)	T	70.2959	Prob. Chi-Square(1)	0.0000	T	89.9732	Prob. Chi-Square(7)	0.0000

Table 5. Parameter values of ARMA-GARCH model.

Variety		BEA	FJEA	GDEA	HBEA	SHEA	SZA	CQEA
Mean Equation	C	0.000409	-0.005478	-7.32E-05	-0.000215	-0.000264	-0.001122	-0.053328
	AR(1)	0.443105	-0.486349	-0.991426	0.932378	1.3016	-0.961877	0.185975
	AR(2)	-	-	0.56197	-0.588942	-0.789757	0.642719	-
	AR(3)	-	-	0.692042	-	-	0.789723	-
	AR(4)	-	-	-	-	-	-	-
	MA(1)	-0.481776	0.499211	0.384258	-1.308223	-1.603584	0.361846	-0.227715
	MA(2)	0.00946	-0.016426	-1.312615	0.882274	1.030199	-1.320825	-
	MA(3)	-0.090453	-0.092513	-0.479133	-0.056404	-0.062906	-0.456647	-
	MA(4)	-0.243813		0.422123	-0.139134	-0.031652	0.49025	-
Variance Equation	C	0.00203***	0.000489***	0.024026	0.000569***	8.17E-05***	0.000148	0.008611**
		(0.0004)	(0.0002)	(0.0157)	(0.0001)	(0.0000)	(0.0002)	(0.5731)
	RESID (-1)^2	0.552758***	0.453536***	0.146978**	0.285415**	0.348376***	0.034351***	0.979931***
		(0.1382)	(0.1006)	(0.0634)	(0.1178)	(0.0634)	(0.0117)	(0.2970)
	GARCH (-1)	0.177134	0.49732***	0.342574	0.331177**	0.689875***	0.962877***	0.193854
		(0.1157)	(0.0997)	(0.4183)	(0.1608)	(0.0396)	(0.0153)	(0.1485)
AIC		-2.469013	-2.802438	-0.546289	-3.820461	-3.438577	-1.058466	-0.33199

Table 6. Revised parameter estimates for Chongqing and Shanghai pilots.

Variable		CQEA	SHEA
Mean Equation	C	-0.03177***	-0.000111
	AR(1)	0.075428	1.30338***
	AR(2)	-	-0.791672***
	MA(1)	-0.087126	-1.607974***
	MA(2)	-	1.039563***
	MA(3)	-	-0.068031
	MA(4)	-	-0.031615
Variance Equation	C	0.011982***	8.24E-05***
		(0.0044)	(0.0000)
	RESID(-1)^2	1.537655***	0.37762***
		(0.4718)	(0.1097)
	RESID(-1)^2*(RESID(-1)<0)	-1.207547***	-0.046821
		(0.4720)	(0.1361)
	GARCH(-1)	0.121941	0.686533***
		(0.1186)	(0.0417)
AIC		-0.380206	-3.432405

Judging from the parameter estimation of mean equation, the return (C) on carbon emissions in Beijing is positive, which indicates that the carbon price of Beijing Carbon Exchange is relatively stable during the sample period; but its value is small, which implies low activity and shallow liquidity in the carbon trading market in Beijing. On the contrary, the return on carbon emissions (C) in the remaining six pilots, such as Fujian and Guangdong, are negative, revealing that it is hard for the six pilots to attract external investment during this period of development.

Considering the parameter estimation of variance equation, the estimates of ARCH and GARCH coefficients of the remaining five pilots, except Chongqing and Shanghai, are between 0 and 1 under certain constraints. To be specific, the sums of two estimates in Fujian and Shenzhen are 0.950856 and 0.997228 respectively, very close to 1. This demonstrates that subjected to long-term external shocks, carbon prices in Fujian and Shenzhen have declined at a slower rate and eventually stabilized. In contrast, the sums of two estimates in Beijing, Guangdong and Hubei are far less than 1, revealing that the duration of external shocks in the three pilots is less than that of Fujian and Shenzhen, especially the carbon market in Guangdong with the shortest duration which is related to its trading methods such as listed bidding, listing point selection and agreement transfer.

Shenzhen, the first carbon trading pilot in China, has a good market mechanism and high activity. Meanwhile, its GARCH coefficient is 0.962877. It indicates that after external shocks, the conditional variance of its carbon price return with a strong memory of volatility is greatly affected by the early carbon price, which is relevant to multiple trading varieties (such as SZA2013, SZA2014, etc.) in Shenzhen carbon trading market. On the contrary, the ARCH coefficient in Beijing is larger than the GARCH one, which illustrates that the carbon price return rate of Beijing pilot is more susceptible to external environmental changes.

In the light of the revised ARMA (2, 4) - TARCH (1, 1) coefficients, the asymmetric coefficient in Shanghai is -0.046821, and the lever effect coefficient of ARMA (1, 1) - TGARCH (1, 1) in Chongqing is -1.207547, both of which are negative. It shows that the fluctuation of carbon trading prices in Shanghai and Chongqing has a "counter-leverage" effect during this period. That is to say, positive news brings a more violent fluctuation than negative one, which indicates that complete market mechanism makes investors a more optimistic interest expectation for carbon market.

In summary, China's regional carbon prices are characterized by volatility, peak, heavy tail, memory and anti-leverage. Meanwhile, their early fluctuation and external shocks have a certain impact on the variation of regional carbon price. On the one hand, the early fluctuation of carbon price is manifested as the endogenous market mechanism that influences price fluctuation and the price feedback mechanism that causes the continuous fluctuation of carbon prices. On the other hand, external shocks are usually noted as persistent fluctuation of carbon prices resulting from policies and special events on carbon prices, such as energy price changes, climate deterioration and so on. Based on available data, this paper will analyze the impact of external shocks on regional carbon price fluctuation.

3.2 Analysis of Factors Influencing the Price of Regional Carbon Trading

3.2.1 Model selection, variables and data description

Due to late establishment and small sample size, Grey relational analysis is employed, which is suitable for small sample analysis of relationships. Grey relational analysis is a method of quantitative description and comparison for the development of a system. It is mainly used to identify main and secondary factors when the development of systems (such as social system, economic system, agricultural system, etc.) is determined by multiple factors. The basic idea is to obtain the correlation between the reference sequence and the comparison sequence based on the similarity of their curves: the closer the curves are, the stronger the correlation is. The sequence of system data is assumed as in Equation 6:

$$\begin{cases} X_0 = (x_0(1), x_0(2), \cdots, x_0(n)) \\ X_1 = (x_1(1), x_1(2), \cdots, x_1(n)) \\ \qquad \cdots\cdots \\ X_i = (x_i(1), x_i(2), \cdots, x_i(n)) \\ \qquad \cdots\cdots \\ X_m = (x_m(1), x_m(2), \cdots, x_m(n)) \end{cases} \tag{6}$$

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \xi \max_i \max_k |x_0(k) - x_i(k)|}$$
$$\xi \in (0,1), k = 1, 2, \cdots, n; i = 1, 2, \cdots, m \tag{7}$$

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)), i = 1, 2, \cdots, m \tag{8}$$

where X_0, $X_1, \ldots X_m$ are related factor sequences, ξ is the resolution coefficient usually assigned 0.5, and $\gamma(X_0, X_i)$ is grey correlation between X_0 and X_i with the range from 0 to 1.

The main calculation is as follows: the first step is to find the initial value of each sequence by $X_i' = X_i / x_i'(1) = (x_i'(1), x_i'(2), \cdots, x_i'(n); i = 0, 1, 2, \cdots, m$; the second step is to find the difference sequence by $\Delta_i(k) = |x_0'(k) - x_i'(k)|$, $\Delta_i = (\Delta_i(1), \Delta_i(2), \cdots, \Delta_i(n)), i = 1, 2, \cdots, m$; the third step is to find local maximum M and local minimum m: $M = \max_i \max_k \Delta_i(k)$, $m = \min_i \min_k \Delta_i(k)$; the fourth step is to calculate the correlation coefficient by Equations 7 and 8.

Due to data availability and impact significance, this paper explores the possible impacts of six factors including energy prices, economic condition, policy, industrial structure, air quality and foreign carbon trading price. Among them, the per capita GDP in economic factors, the proportion of tertiary industries in structural factors and the AQI index in environmental factors are all indicators of high-quality economic development [4].

(1) Energy prices. Foreign and domestic scholars tend to select coal and oil prices to represent energy prices [18], No. 92 gasoline price(X_3) is chosen for wide usage and slight regional difference. Besides, in that China's coal consumption accounts for about 60% of total energy consumption and the construction of carbon market is based on electronic

power industry, electricity and coal prices(X_1) in every pilot are included. In addition, China is vigorously advancing natural gas reforms to improve the utilization of low-end natural gas, so the market price of industrial pipeline gas(X_2) is chosen as the energy price factor.

(2) Economic development. At present, China's economy still relies on heavy industries with high energy consumption and high emissions. In the process of rapid economic growth, there is a two-way relationship between carbon emissions and economic prosperity. Meanwhile, foreign direct investment and stock market also affect carbon price [19]. Therefore, this study chooses the pilots' GDP per capita(X_5) and the CSI 300 Index(X_4) to represent economic development and the degree of market prosperity.

(3) Policy factors. In recent years, there have been constant disputes between economic development and environmental protection, and policy support has played an important role in balancing their relationship between the two [20]. This study selects the policy system issued by the pilots' development and reform commission as virtual variable, whose value is 1 if there is at least one policy issued during the month, otherwise it is 0. The number of policies(X_6) issued is determined by searching for policy information that contains the words "carbon emissions" or "carbon trading" in the title on the website of pilots' development and reform commission.

(4) Structural factors. China's rapid economic development mainly depends on the industrial structure of high investment, high consumption and high pollution. The industrial structure determines the distribution of production resources like labor, capital, technology, and energy among different industries, and has a crucial impact on resource consumption and carbon emissions [21]. Therefore, the proportion of tertiary industry(X_7) is selected as a variable to analyze carbon trading prices.

(5) Environmental factors. As a product of climate change, the carbon market is vulnerable to weather [22]. For example, during the cold wave, the consumption of fossil energy and electricity power soar with the rising demand for heating, and thereby carbon prices increase accordingly. The monthly air quality index (AQI, X_8) is selected as an environmental indicator. The larger the AQI value is, the worse the air quality is, and the larger the carbon emissions are.

(6) Foreign market factors. European Union Carbon Emissions Trading System (EU-ETS) has been the most active and important carbon emissions trading system in the world since 2005, occupying more than 85% of global market. Based on this, the EU's carbon allowance (EUA, X_9) price becomes an important reference for global carbon trading market [1-2]. Therefore, the EUA price is selected as the foreign impact indicator for analysis.

Based on data availability and error minimization in high and low frequency conversions, monthly data were selected to analyze the influencing factors of carbon price. The monthly data of each factor from January 1, 2017 to December 31, 2018 are extracted from the Wind database, China Carbon Emissions Trading Network and China air quality online monitoring and analyzing platform. The prices represent the monthly average of daily transaction prices in each pilot market, and the Real GDP per capita is the monthly value of the pilot GDP divided by its population and the number of policies monthly issued by the pilot's development and reform commission is regarded as policy factors.

3.2.2 Grey relational analysis

The price of carbon trading market is taken as a characteristic sequence, and the remaining 9 influencing factors are the sequence of comparative factors. To begin with, each sequence is made to be dimensionless, and then the difference of sequences and their maximum and minimum are calculated, and finally, the grey correlation is calculated to measure the impact of each factor on the carbon price of the pilot. Furthermore, the results of grey relational analysis are shown in Figure 3.

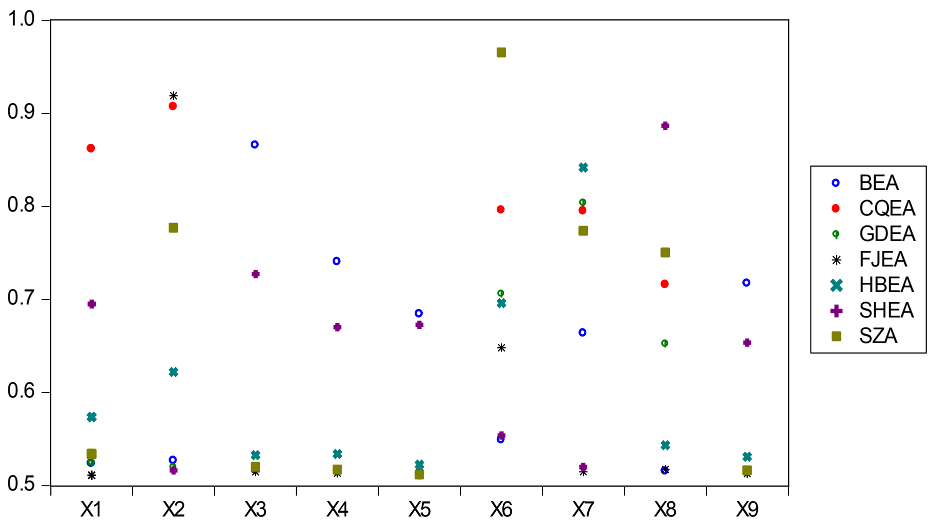

Fig. 3. The results of Grey relational analysis.

According to Figure 3, nine (9) factors have different impacts on carbon prices of different pilots, main reasons are as follows: first, there are some regional differences in the level of economic development and energy consuming preferences; second, low market liberalization leads to the fragmentation of regional carbon prices; third, without uniform standards for trading rules and pricing mechanism, China's carbon market is still in the primary stage.

This paper regards the development of some carbon trading pilot as the development of the overall carbon trading market in its region, because the pilot is a miniature of the carbon trading market in its region. To be specific, this paper analyzes carbon emissions trading from five major regions, including North China, Central China, East China, South China and Southwest, which are represented by Beijing, Hubei, Shanghai and Fujian, Guangdong and Shenzhen, as well as Chongqing respectively.

East China is mainly affected by the air quality index (X_8). Apart from air quality, Shanghai's carbon price is also susceptible to energy prices. In July 2018, the release of *"Thirteen-Five" comprehensive work plan of energy saving and emission reduction and control of greenhouse gas emissions in Shanghai* improves air quality and then impacts carbon price. In addition, both air quality and policy play an important role in Fujian's carbon price.

South China is critically influenced by policy factors (X_6). Shenzhen, the first pilot in China, belongs to Guangdong Province, so its policy dividend has a large effect on carbon prices in Guangdong Province. The major difference between the two is that with the growing contribution of the tertiary industry to economic growth, the impact of the proportion of tertiary industries (X_7) on Guangdong's carbon price is quite significant, while Shenzhen is more susceptible to the impact of industrial gas prices (X_2), because pipeline natural gas becomes more and more popular with the rising phenomenon of urban villages in Shenzhen.

Central China is mainly affected by the proportion of tertiary industries (X_7). In recent years, the investments in electricity, gas and other livelihood projects, as well as the proportion of tertiary industries in Hubei Province has increased year by year, which reduces its cost of carbon transaction to some extent. Additionally, Hubei Province has passed carbon trading legislation, which makes its carbon trading procedures more systematic and comprehensive. Therefore, its impact on policy (X_6) is also relatively large.

North China is mainly affected by domestic economy (X_4) and foreign carbon prices (X_9). On the one hand, due to its unique political and economic status, many financial institutions and carbon asset management companies gathered here. On the other hand, the EU carbon market stabilization mechanism has effectively reduced the supply of carbon quotas in the market and thus push up carbon price, while Beijing's carbon trading market strengthen foreign cooperation.

Southwest China is mainly affected by energy prices (X_1, X_2). Supply-side structural reform leads to industrial concentration that rises the efficiency of fossil energy and decreases carbon price. Meanwhile, because of its strategic position in the "Belt and Road", Chongqing experiences the influence of policy on carbon price.

In conclusion, the carbon price in the east region is strongly affected by air quality, central region by the proportion of tertiary industries, south region by the policy, north region by domestic economy and foreign carbon price, and southwest region by energy prices. At the same time, the high-quality economic development index has different influences upon the carbon prices of different regions. Strong correlation implies that the region should pay attention to both high-quality economic development and carbon emissions. To be specific, the proportion of tertiary industries(X_7) has a strong correlation with the carbon prices of Central and South China, and the AQI Index (X_8) has a great influence on that of East China, but the correlation between the Real GDP per capita (X_5) and carbon prices is relatively weak in each pilot.

4. CONCLUSION AND RECOMMENDATION

In conclusion, this study explores the characteristics of carbon price fluctuations in seven regions of Chin by the ARMA-GARCH model and the data extracted from the Wind database and China Carbon Emissions Trading Network, and analyzes the possible impacts of six factors including energy prices, economic condition, policy, industrial structure, air quality and foreign carbon trading price in the terms of the Grey relational analysis. The findings are as follows:

Firstly, China's regional carbon prices are characterized by volatility, peak, thick tail, memory and certain anti-leverage. On the one hand, the carbon price of each region has the characteristics of volatility, peak and thick tail. On the other hand, the carbon prices of Shenzhen and Shanghai have a certain memory, especially in Shenzhen, while the carbon prices in Chongqing and Shanghai have a certain characteristic of anti-leverage, especially in Chongqing.

Secondly, in different regions, the influencing factors have different effects on carbon prices. To be specific, the carbon price in the East is greatly affected by air quality, Central region by the proportion of tertiary industries, South region by the policy, North region by domestic economy and foreign carbon price, and Southwest region by the energy price.

Thirdly, the correlation degree between high-quality economic development and carbon price shows great regional differences. Specifically, the proportion of tertiary industries (X_7) has a great influence on the carbon prices of central China and Southern China, and the AQI Index (X_8) has a greater impact on the carbon prices of the eastern region, while the Real GDP per capita (X_5) of the pilot has a relatively small impact on carbon prices in each region.

Based on the results of this study, the authors provide several suggestions on ways in which China may reduce its CO_2 emissions so as to promote high-quality economic development.

Firstly, the government needs to curb arbitrage in different regional carbon trading markets, promote the orderly development of carbon trading markets, actively promote the construction of a unified carbon trading market in China, unify the trading rules of carbon trading markets in different regions, continuously strengthen the "market signal" function of carbon quota prices, and realize the unhindered flow of carbon quotas across regions; Strengthen regional cooperation, open up technical barriers, gradually reduce the differences in the cost of reducing emissions of enterprises in different regions, further block market speculation, create a more level playing field for enterprises, and make every effort to promote China's low-carbon economic development.

Secondly, the government should strengthen the integration and innovation of traditional financial markets and carbon markets in order to improve the liquidity of regional carbon markets. On the one hand, to increase product innovation in the carbon trading market, actively learn from foreign advanced experience, through "introduction" and "going out", break China's existing quota trading and certification of emission reduction trading model, vigorously innovate and develop carbon trading products to meet the new needs emerging in the context of high-quality development; Think of new talents to promote the long-term development of the carbon trading market.

Thirdly, the government should maintain the coherence of carbon market policies and achieve a smooth transition from regional markets to single markets. On the one hand, China is in the key stage of simulation and perfection of the construction of the national carbon trading market, and the regional carbon trading price is generally influenced by policy factors. Therefore, in the process of carbon trading market policy adjustment, we should improve the transparency of carbon market policy, strengthen interregional information transmission and sharing, reduce the uncertainty of carbon emission trading price, and maintain investors' enthusiasm to participate in carbon market trading

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