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Research on the Influencing Factors of Carbon Emission Trading Prices

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Abstract: *China has actively developed a green economy and integrated the carbon emission trading market into its national strategic development. As a core part of the carbon trading market, the carbon trading price is crucial for improving the carbon emission rights market. Shanghai's carbon emission trading market is relatively mature, and studying the influencing factors of its carbon emission trading price is of great significance for the development of China's carbon market. This paper uses the VAR model to analyze the influencing factors of carbon emission trading prices in Shanghai. The results show that macroeconomic factors, energy price factors, and climate and environmental factors have significant impacts on the price. Macroeconomic and energy price factors have a negative impact on carbon prices, while the air quality index has a positive impact.*

Keywords: *Shanghai Carbon Emissions Trading, Price Influencing Factors, VAR Model*

1. Introduction

Since the first Industrial Revolution, global industry has developed rapidly, but this has been accompanied by severe environmental issues, particularly global warming caused by greenhouse gas emissions. To address climate change, the international community has successively adopted the United Nations Framework Convention on Climate Change and the Kyoto Protocol, proposing a mechanism for trading carbon emission rights. As a responsible major country, China actively promotes green development, proposes the "dual carbon" goal, and has established regional pilot carbon emission trading markets since 2013, ultimately launching a unified national carbon emission trading market in 2021. As the economic center of China, Shanghai's carbon emission trading market developed earlier and is relatively mature. Studying the influencing factors of Shanghai's carbon emission trading prices can not only provide a reference for pricing in the Shanghai carbon market but also offer theoretical support for the improvement of the national carbon market. This paper uses the VAR model to conduct an empirical analysis of Shanghai's carbon emission trading prices, aiming to reveal its impact mechanism and propose relevant policy recommendations. Enterprises incorporated into the trading system through market-based means buy and sell carbon emission quotas based on their own emission reduction costs, thereby promoting the upgrading of energy-saving, carbon reduction, and emission reduction technologies for enterprises, increasing the proportion of clean and renewable energy use, promoting green and clean production worldwide, and ultimately driving the achievement of "carbon peak" and "carbon neutrality," promoting green, healthy, and sustainable economic development.

2. Literature Review

The United Nations Framework Convention on Climate Change was adopted in 1992, and carbon emission trading gradually emerged. Kverndokk Snorre (1995) in the 1990s demonstrated the first principle of justice and political feasibility of tradable emission rights[1]. Xu et al. (1997) researched global carbon emissions from 1800 to 1900 and analyzed the five carbon-emitting regions with emissions and GDP data, and proposed a global carbon emission trading rights scheme based on population distribution, arguing that developing countries should receive more carbon emission rights, while developed countries should bear greater historical responsibility[2]. Since the 21st century, the study of carbon emissions trading has been refined to pricing, Christiansen et al. (2005) analyzed the EU carbon trading system, identifying key factors affecting prices[3]. Hao and Tian (2020) proposed a multi-objective chaotic sine cosine algorithm for improving prediction validity in carbon trading[4]. Zhang and

Xu (2020) used GARCH models to study carbon price fluctuations and risk mechanisms in China[5]. Lovcha et al. (2020) applied the SVAR model to distinguish economic factors and market microstructure impacts on carbon prices[6]. Le and Azhgaliyeva (2023) found that carbon pricing policies significantly reduced greenhouse gas emissions, particularly in heavy industry sectors[7].

In terms of energy factors, Yin et al. (2019) found that energy and industrial indices indirectly positively impact carbon trading prices in China using the SVAR model[8]. Rohan B and Qiu YZ (2020) noted that high coal storage per capita negatively affects carbon prices[9]. Li et al. (2021) analyzed driver characteristics of EU carbon futures prices, revealing short-term sensitivity to oil and gas prices, with oil having the most significant impact post-Paris Agreement[10]. Yu et al. (2021) found coal price to be the most influential on Beijing's carbon trading prices using the VAR model[11]. Ji et al. (2021) studied China's carbon trading pilot, identifying positive correlations between oil and carbon prices, negative for coal, and varied impacts of non-ferrous metal prices on Beijing and Shenzhen[12]. These findings aid policymakers in setting reasonable carbon prices and promoting market health.

In terms of climate factors, Roshan et al. (2019) studied the impact of climate environment on carbon emissions and their trading prices, and found that a warmer climate environment would cause a decline in greenhouse gas emissions, which had a significant impact on the trading price of carbon emission rights[13]. Ozturk et al. (2022) studies of the EU using new uncertainty indicators that capture transition and physical climate risks found that climate uncertainty is indeed an important driver of emission price fluctuations[14].

In terms of macroeconomic factors, John and Neda (2017) found positive correlations between industry and materials industry indices and carbon prices in Shenzhen and Guangdong[15]. Lin and Jia (2019) studied the impact of industry coverage, annual reduction factors, and free quota rates on China's carbon prices using a dynamic model[16]. Tan et al. (2020) analyzed the EU emissions trading system and found close connectivity between the carbon market and key financial markets, with weaker carbon-oil finance ties[17]. Li et al. (2022) used LASSO and MSVAR models to identify key carbon market determinants, revealing that during COVID-19, energy factors had a long-term impact, economic factors a short-term impact, economic recession caused market volatility, and the stock market positively influenced the carbon market[18].

To sum up, carbon emission trading, as a market-based carbon reduction tool, plays an important role in reducing greenhouse gas emissions. Past studies have deeply explored the influencing factors of carbon emission right trading price from different perspectives, including energy factors, climate factors and macroeconomic factors. From the literature, there are few references for the systematic research on the price factors of carbon emission trading in Shanghai. In addition, most of the research data on the factors affecting the pilot carbon price stay at the beginning of the pilot construction, and its timeliness remains to be discussed. Therefore, based on the above factors and the latest research results of domestic and foreign literature, this paper selects the trading day data of China's carbon emissions in the past three years to explore the influence of macroeconomic factors, energy factors and climate factors on the trading price of carbon emission rights in Shanghai.

3. Empirical Analysis

3.1. Model Selection and Data Source

In this paper, the VAR model is used to explore the relationship of Shanghai carbon emission trading price and its influencing factors. This paper selects four variables, namely Shanghai carbon emission right trading price SHEA (daily closing price), expressed by y, the source is Shanghai Environmental Energy Exchange; CSI 300 index CSI300, x1, data source is Shanghai Stock Exchange; power coal price CR, x2, data source is Wind database; Shanghai Air Quality Index AQI, x3, data source is Shanghai Environmental Testing Center. The data time span is selected from September 1,2022 to March 12,2024. Excluding the date without transactions, 381 trading days were collected. As the CSI 300 index, the macroeconomic index of the CSI 300 is used as the explanatory variable x1. Including the stock prices of all listed companies in Shanghai and Shenzhen, as a macroeconomic indicator can reflect the trend of the capital market and the money market, and can very well represent the macroeconomic development and prosperity of Shanghai. The energy price index selected in this paper is the power coal price in China, which is used as the explanatory variable x2. This mainly considers that domestic coal is still the main source of energy in Shanghai. The climate and environment index selected in this paper is the Shanghai Air Quality Index, which is used as the explanatory variable x3. Air quality index is considered to be the

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most important effective index for environmental evaluation, and is the quantitative expression of clean air quality and air pollution, mainly including the detection of CO_2, PM2.5, PM10, CO, O_3 and other pollutants..

3.2. Unit Root Staionarity Test

For VAR modeling, the original time series is first tested for stationarity. That is, according to compare the value of the t-statistic and the critical value, whether the original hypothesis of the unit root is rejected, that is, to judge whether the sequence is stable, the critical value at the 1% significance level is selected. If the t-statistic value is less than the percent threshold, the null hypothesis of unit root will be rejected, indicating that the sequence is stable, if not less than the white threshold, the unstable sequence. Or look at the p-value, if the p-value is lower than 0.05, if the result is below 0.05, the sequence can be stable, if the p-value is higher than 0.05, the sequence is not stable. Table 1 below shows the results of the ADF test. The first five lines in the table show the results of the stability test and the last five lines are the test after the first order difference. It can be seen that the t-statistic values of the variables x1 and x2 are greater than the 1% threshold and the p-values are greater than 0.05, therefore, they are all non-stationary sequences. Subsequently, the first order difference transformation of the raw data of y, x1, x2 and x3 sequences. It can be seen that the difference data reject the null hypothesis of unit root at the 1% significance level, and the p-value is less than 0.05, that is, these variables are stationary sequences after the first order difference, and the next analysis can be carried out.

Table 1: ADF Unit Root Test Results

Variable	t-statistic	1% critical value	p	Stability
Y	-7.566	-3.982	0	Steady
X1	-0.638	-2.571	0.44	Unstable
X2	-0.863	-2571	0.34	Unstable
X3	-11.347	-3.982	0	Steady
First-order difference variable	t-statistic	1% critical value	p	Stability
dY	-11.812	-3.982	0	Steady
dX1	-18.945	-3.982	0	Steady
dX2	-11.265	-3.982	0	Steady
dX3	-15.211	-3.982	0	Steady

Data source: Eviews 10 experimental model

3.3. Optimal Lag Order

In this paper, we follow the principle that the p order of the AIC criterion is the same as the optimal lag order of the minimum lag order of the model. If the two principles are different, the optimal lag order under the multiple criterion in the operation result is taken as the optimal lag period of the model. From Table 2, we can find that the VAR model has different optimal lag order under the SIC criterion, so the lag 2 phase is chosen as the optimal lag order of the model in this paper.

Table 2: Optimal Lag Order Determination for the VAR Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1013.458	NA	2.50E-08	-5.355212	-5.313491	-5.338652
1	3035.532	3990.513	1.33E-12	-15.99752	-15.78891	-15.91472
2	3097.266	120.5212*	1.04E-12*	-16.24014*	-15.86465*	-16.09110*
3	3108.352	21.40634	1.07E-12	-16.21407	-15.67169	-15.99878
4	3121.055	24.2617	1.09E-12	-16.19658	-15.48732	-15.91506

Data source: Eviews 10 experimental model

3.4. Jonhanson Co-integration Test

To avoid the phenomenon of spurious regression caused by non-stationary time series, a co-integration test is conducted on the variables. The optimal lag order for the VAR model system is determined to be 2. In the co-integration test, the selected lag order is the lagged terms of the first difference. Therefore, the lag order for the co-integration test is one less than the optimal lag order of the VAR model, which is 1. Consequently, a VEC model with a lag order of 1 is constructed, and the results are shown in Table 3 and Table 4. If the p-value is set at 0.05, there are two co-integrating relationships;

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if the p-value is set at 0.1, all relationships are co-integrated. Thus, passing the co-integration test indicates that a VAR model can be established.

Table 3: Trace statistic test

Original assumption	Eigenvalues	Trace statistic	5% key value	p
0	0.236594	132.6274	47.85613	0.0000
1	0.06748	30.31058	21.131620	0.0436
2	0.006189	3.831933	14.264600	0.9166
3	0.003895	1.478974	3.841466	0.2239

Data source: Eviews 10 experimental model

Table 4: Maximum Eigenvalue Test

Original assumption	Eigenvalues	Maximum Eigenvalue Statistic	5% key value	p
0	0.236594	102.316800	27.584340	0.0000
1	0.06748	26.478650	21.131620	0.0080
2	0.006189	2.352959	14.264600	0.9802
3	0.003895	1.478974	3.841466	0.2239

Data source: Eviews 10 experimental model

3.5. Model Stability Testing

We employ the unit root test to examine the stability of the empirical model. If the reciprocal of the AR characteristic roots is less than 1 and falls within the unit circle, the model's stability is strong. If the reciprocal of the AR characteristic roots is greater than 1 and mostly lies outside the unit circle, the model's stability may be poor. The test results, as shown in Figure 1, indicate that apart from the unit roots assumed by the VAR model itself, all other characteristic roots are within the unit circle, and the majority of them are less than 0.5. Therefore, the VAR model constructed in this article is stable and has a certain degree of representativeness, allowing for further analysis of impulse response functions and variance decomposition.

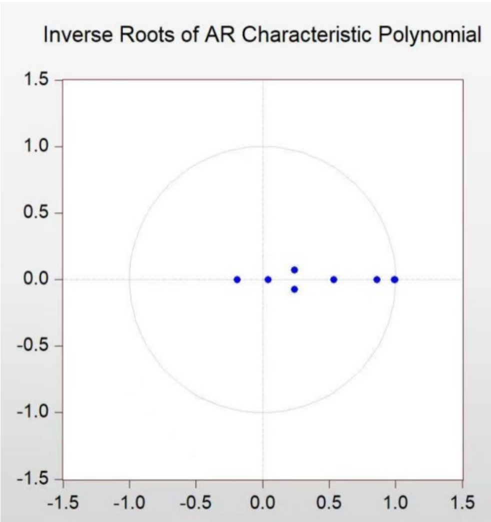

Figure 1: AR Eigenvalue test

3.6. Pulse Response Analysis

We use the impulse response function to analyze the response of the Y variable after applying a shock of one standard deviation to each of X1, X2, and X3, with the lag periods (in this article, one lag period equals one day). Figure 2 shows the paths of the impulse response values for the Shanghai carbon emissions trading price fluctuations caused by an external shock to the system, where the horizontal axis represents the number of observation periods and the vertical axis represents the impulse response values of the Beijing carbon emissions trading market price. This article selects a response observation period of 381, so after 381 periods, the impact of shocks on the carbon prices in all carbon markets for all explanatory variables tends to stabilize or continue to decline to zero.

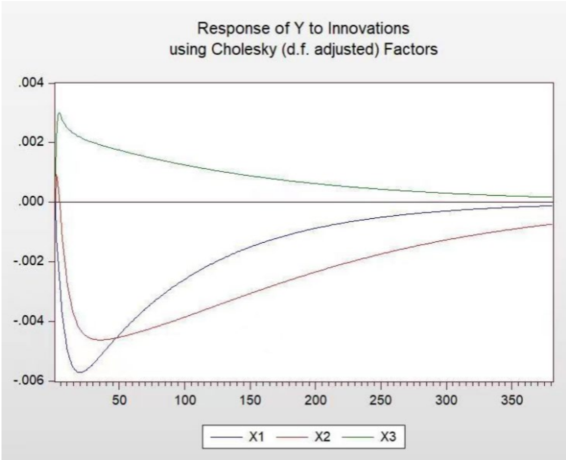

Figure 2: Pulse response graph of Y to Innovations

The following Figure 3 explains the impulse response of the Shanghai carbon emission trading price fluctuations caused by shocks to X1, X2, and X3, respectively. From the perspective of macroeconomic factors, the CSI 300 Index shows a negative impact, which first increases and then decreases from period 1 to period 150, and finally stabilizes around period 381.

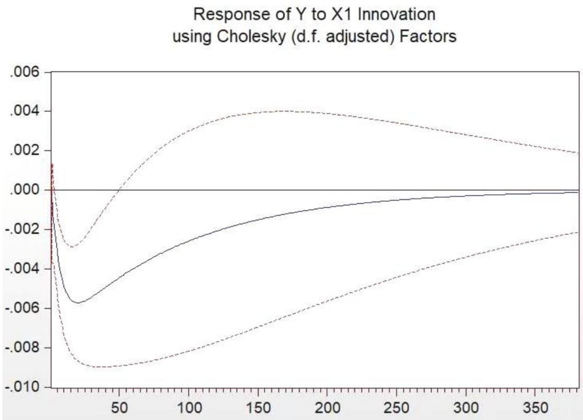

Figure 3: Pulse response graph of Y to X1 Innovation

Figure 4 shows that, in terms of energy price factors, the price of coal in China is similar to the CSI 300 Index, having a negative impact, with the greatest influence around period 25, and eventually tending to zero by period 381.

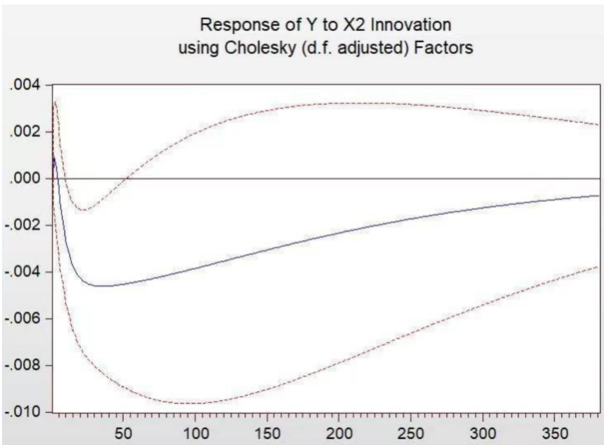

Figure 4: Pulse response graph Y to X2 Innovation

Figure 5 shows that, in terms of climate and environmental factors, the air quality index has a positive impact, reaching the maximum around the 10 period, and also tending to 0 after the 381 period.

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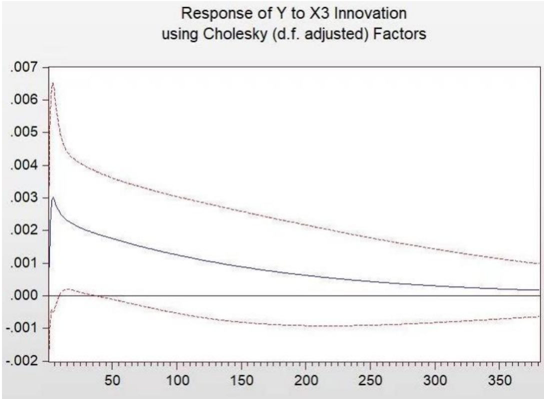

Figure 5: Pulse response graph Y to X3 Innovation

3.7. Variance Decomposition

According to the analysis results shown in Figure 6, the fluctuation of carbon emission right trading price is mainly driven by its own factors, and is significantly influenced by historical data. However, with the increase of the number of periods, the influence of historical factors on the price fluctuations gradually weakened, and reached a relatively stable state after 300 periods. Nevertheless, historical factors are still the main influencing factors. On the other hand, the impact of the CSI 300 index, power coal prices and the Shanghai air quality index on carbon emission trading prices has all increased from scratch and gradually increased. Specifically, the impact of power coal price on the carbon price increased the most rapidly after 50 periods, and tended to stabilize after 300 periods, and its impact on the carbon price almost matched the fluctuation of the carbon price itself. This was followed by the impact of the CSI 300 index, while the impact of the Shanghai air quality index was relatively small. Eventually, all factors tend to have an equilibrium.

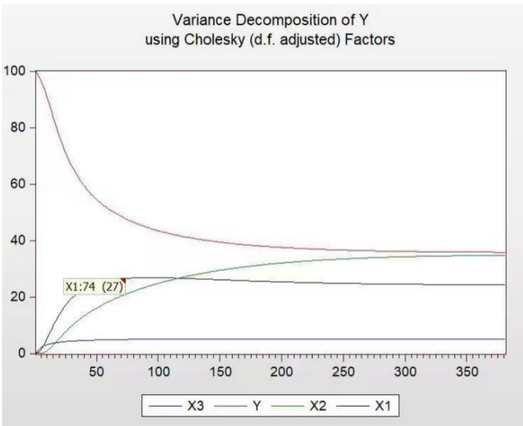

Figure 6: Variance Decomposition

4. Conclusions

Through analysis using the VAR model, the study reveals the impact of macroeconomic factors, energy price factors, and climatic environmental factors on the price of Shanghai carbon emission rights. By conducting impulse response analysis and variance decomposition, it was found that the Shanghai and Shenzhen 300 Index and the price of thermal coal have a negative effect on the trading price of Shanghai carbon emission rights, while the Shanghai Air Quality Index has a positive effect on the trading price. Firstly, macroeconomic factors have a negative impact on the trading price of Shanghai carbon emission rights. In the impulse response analysis, the impact of the Shanghai and Shenzhen 300 Index shows a trend of first strengthening and then weakening from period 1 to period 150, reaching a stable state by period 381. Variance decomposition indicates that the impact of the Shanghai and Shenzhen 300 Index on the changes in the trading price of Shanghai carbon emission rights is relatively small. Secondly, energy price factors also have a negative impact on the trading price of Shanghai carbon emission rights. In the impulse response analysis, the impact of the price of thermal coal reaches a peak around period

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25, then gradually weakens, and approaches zero by period 381. Variance decomposition shows that the impact of the price of thermal coal on the changes in the trading price of Shanghai carbon emission rights is significant, comparable to the impact of its own shock. Lastly, the Shanghai Air Quality Index has a positive impact on the trading price of Shanghai carbon emission rights. In the impulse response analysis, the impact of the Shanghai Air Quality Index reaches its maximum around period 10, and then gradually weakens to zero after period 381. The results of variance decomposition indicate that the impact of the Shanghai Air Quality Index on the changes in the trading price of Shanghai carbon emission rights is the smallest.

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