What Drives the Carbon Price? - An Empirical Analysis of Chinese Emission Trading Scheme

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Abstract. In this paper, we focus on the major influential factors of the carbon price, by using both static panel model (FGLS) and dynamic panel model (PVAR) of each trading pilot in 2014-2018, totally six kinds of indicators were selected to establish the quantitative model to explain what drives the carbon price in China. We also employed the Bai-Perron test to identify the structural breakout points of carbon price fluctuation. This study finds that, in China, in terms of market fundamental influential factors, (1) the high-carbon energy price represented by coal has a negative impact on the carbon price, while the other energy indicators of oil and LNG are not statistically correlated; while (2) the cooling/heating days and temperature differences’ impacts are not statistically significant; (3) the relationship between industrial development, stock index and carbon price, is positively and negatively correlated, respectively, indicating that the Marco economy affects the carbon price at a high significance level. (4) However, in terms of non-market fundamental influential factors, the policy factors will not greatly affect the carbon price, indicating that the model we employed might not apply to the policy factor. (5) Besides, electricity production from wind power will lower the carbon price significantly due to it reduces the demand for carbon emission rights for the electricity sector in ETS. (6) Among all factors, coal price is the most significant influential factor. During the 1-10th period, the impact of coal price is small, and ranges 9.98-56.97%. As time passed by, the interpretation has gradually strengthened. After the 20th period, it stably explains about 70.37-73.87% on variance change of carbon price.

1. Introduction
As the biggest developing country and the top absolute CO₂ emitter (30.18% of the total human-induced GHG emissions, 2017) in the world, China actively promotes emission reduction and accelerates to construct an active carbon market [1]. From June 2013 to June 2014, the mandatory carbon trading market in all the pilot areas, including Beijing, Tianjin, Shanghai, Chongqing, Hubei Province, Guangdong Province, and Shenzhen opened in one year, and more than 2,000 enterprises included with coverage of emissions up to 1.2 billion tons. Based on the Interim Measures for the Administration of Voluntary Emission Reduction Trading of Greenhouse Gases issued by the NDRC (National Development and Reform Commission), the seven pilots have established unique trading systems based on regional characteristics. In this paper, we will use seven provincial ETS pilots as research samples to profoundly demonstrate the conceptual framework of carbon price drivers in China and provide support for the establishment of an active carbon market for the future (see Figure 1).
2. Literature review

2.1. Carbon price drivers

Carlo Carraro & Alice Favero (2009) analysed the main driving factors of the carbon price can be divided into two major categories: (i) market fundamentals directly related to CO₂ production and the demand and supply of CO₂ expenditures and (ii) policy issues, regulations and so on (see Table 1).

| Category                  | Definition                                                                 | Specific Drivers                                                                 |
|---------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Market Fundamentals       | Directly related to CO₂ production and the demand and supply of CO₂ expenditures | e.g., Energy Prices (including fuel price); Weather Condition (e.g., Temperatures and Extreme Weather Events); Industrial Production; Economic Activity |
| Non-Market Fundamentals   | Indirectly related to CO₂ production and the demand and supply of CO₂ expenditures | e.g., Policy and Institutional Decision (including data released, regulatory issues/Institutional decisions/announcement/the level of mitigation ambition); Renewable Energy Deployment (wind, solar ratio) |

2.2. Specific drivers

Energy Prices: Mansanet-Bataller et al. (2007) and Alberola et al. (2008) is the first analysis to reveal the relationship between energy markets and carbon dioxide prices. Based on the spot and futures data in the first phase EU-ETS, the previous group of authors determined that carbon prices in the EU-ETS are related to the use of fossil fuels (e.g., oil, natural gas, coal).

Weather Condition: In China, the overall air quality and climatic conditions such as extreme temperature, precipitation, and wind speed will also have a positive impact on the trading price of carbon emission rights. In terms of variables chosen, Zou (2013) used the monthly temperature difference as the climate index. In contrast, X. Chen et al. (2016) did not find that weather changes have a significant impact on carbon prices through their static and dynamic panel models.

Industrial Production: As is indicated by the literature, there is a specific connection between carbon price and industrial sector in China (Emilie Iberola 2008; Cold Snow, 2012). Similar to this study, Zou and Wei (2013) found that the industrial production index in macroeconomic indicators has a positive impact on carbon spot prices through long-term and short-term causality tests.
**Economic Activity:** In Chinese studies, Wei et al. (2018) used the theoretical modelling and experimental economics methods to compare the carbon market in the European Union, USA, and Chinese Guangdong Province as examples to analyse the three mechanisms of quantity stability, price stability, and price linkage stability, and tried to explore the Chinese carbon market. The study found that the macroeconomic cycle will have a significant impact on the price of carbon trading.

**Policy and Institutional Decision:** In China, Y. Zhang (2018) used the information published by the government and the exchanges at two different levels of government, and she found that exchange-level information on carbon credits significantly affects carbon prices; however, the impact of relevant government-level information is not significant.

**Renewable Energy Deployment:** Koch et al. (2014) studied the data from 2008–2013, they concluded that variations in the growth of wind and solar electricity production robustly affected the price of carbon.

3. Research methodology

3.1. Econometric model

In terms of determinants of carbon prices, we employ the static panel data models (FE, RE, and FGLS), dynamic panel data models (PVAR), and Bai-Perron breakpoints tests to reveal the influential factors and fluctuation of the Chinese carbon market.

**FGLS:** We will employ the FGLS method to perform as a robust regression on the model to avoid the problem of autocorrelation within panels and the heteroscedasticity across panels.

\[ y_{it} = \alpha_i + \beta_{ij}^* x_{ij} + \epsilon_{it} \quad i = (1,2,3) \quad j = (1,2,3,\ldots) \]

Among them, \( i = (1,2,3,4,5,6,7) \) represents seven different pilots, namely Beijing, Shanghai, Shenzhen, Guangdong Province, Hubei Province, Tianjin, Chongqing, \( j = (1,2,3,4,5,6,7,8,9,10) \) represents six different influential factors (See Table 2 below).

**PVAR:** We also employ the Panel Vector Autoregression Model (PVAR) for further analysis since OLS cannot describe the long-term dynamic effects under the influence of lag.

\[ y_{it} = \alpha_i + x_{it}^\beta + \gamma_t + \mu_{it} \]

Where \( P_{it} = (LnCoal_{it}, LnIndustry_{it}, LnStock_{it}, LnRE_{it}) \) is a variable vector of 4x1 based on panel data, \( i \) represents different pilots, and \( x_{it} = [P_{it-1}, P_{it-2} \ldots \ldots \ldots, P_{it-p}] \). Based on PVAR, this paper will further analyse the established model using Impulse-Responses and Analysis of Variance.

**Bai-Perron Breakpoint Test:** Besides, we will perform the Bai-Perron breakpoint tests to examine the structural mutations in the data generation process [2].

3.2. Variable selection

The carbon price appears as the explanatory variable of this study; that is, we aim to study the influence mechanism of the carbon price. In this paper, we focus on totally six kinds of indicators including energy price (coal, oil, and natural gas prices, switching price), weather condition (temperature difference/cooling days/heating days), industrial production, economic activity (GDP/stock index), policy factor and renewable energy deployment were selected to establish the quantitative model to explain what drives the carbon price in China.

| Table 2. Overview of relevant variables |
|---------------------------------------|
| **Variables** | **Variables** | **Unit** | **Frequency** | **Source** | **Expected** |
| Dependent Variable: | Carbon price | Carbon | CHY/t | Monthly | Tanpaifang.com | / |
| Independent Variables: | | | | |
| 1. Energy Prices: | Electrical Coal Index | Coal | CHY/t | Monthly | imceed.cn | - |
| | Natural Gas price | LNG | CHY/t | Monthly | cngold.org | + |
| | Oil Price | Oil | CHY/L | Monthly | cngold.org | - |
| | Switching price | Switching | CHY/MWh | Monthly | Own calculation | + |
| 2. Weather Condition: | | | | | | |
4. Empirical result and discussion

4.1. Descriptive statistics

The overall sample consists of 360 available monthly average carbon trading prices spanning from 2014-2018 in the seven trading emission pilots (see Table 3).

Table 3. Descriptive statistics

| Variable                  | Observation | Mean     | Std. Dev | Minimum  | Maximum  |
|---------------------------|-------------|----------|----------|----------|----------|
| Carbon                    | 360         | 29.5005  | 16.40536 | 1.624375 | 84.1181  |
| Coal                      | 360         | 502.7961 | 105.5143 | 302.5325 | 755.9392 |
| LNG                       | 360         | 6.513576 | 0.715377 | 5.35007  | 8.3779   |
| Oil                       | 360         | 3941     | 873.7589 | 2880.95  | 7267.58  |
| Switching                 | 360         | 12824.52 | 3460.616 | 8074.886 | 25866.29 |
| TEMDIF                    | 360         | -0.6007  | 8.172335 | -15.7682 | 17.91    |
| Cooling                   | 360         | 22.90139 | 37.31483 | -9       | 169      |
| Heating                   | 360         | 49.2     | 84.78455 | -5       | 408      |
| Industry                  | 360         | 6.263268 | 3.943888 | -6.26364 | 15.38636 |
| GDP                       | 360         | 9.97063  | 2.289043 | 1.378738 | 17.67768 |
| Stock                     | 360         | 3380.856 | 628.1361 | 2145.23  | 4934.501 |
| RE                        | 360         | 1.944298 | 1.905825 | 0.1      | 10.1     |

4.2. Unit root test

We conclude that statistics of these variables except for coal price, oil price and GDP strongly reject the null hypothesis (H0: unit-roots exist on all panels), however, after converting the oil price series into coal price and oil price growth rate series, there is no unit root was found in the transformed series. Therefore, we drop GDP, and transform the coal price and oil price into its growth rate.

4.3. Correlation test

In order to avoid multicollinearity, this article will test the correlation between variables. We notice that the VIF values of each variable except LNG price and switching price are far less than 10. Therefore, there is multicollinearity among the eleven explanatory variables chosen in the model. Thus, we drop switching price. Also, we test whether there is a correlation between variables. As can be seen from the correlation coefficients in Table 4 below, only variables of weather condition in the model is weakly correlated (correlated coefficient is greater than 0.3 but less than 0.7).
Table 4. Pearson correlation matrix

|       | rCoal | rOil | LNG  | TEMDIF | Cooling | Heating | Industry | Stock | Policy | RE  |
|-------|-------|------|------|--------|---------|---------|----------|-------|--------|-----|
| rCoal | 1.00  |      |      |        |         |         |          |       |        |     |
| rOil  | 0.06  | 1.00 |      |        |         |         |          |       |        |     |
| LNG   | -0.14 | -0.07| 1.00 |        |         |         |          |       |        |     |
| TEMDIF| -0.03 | -0.06| 0.33 | 1.00   |         |         |          |       |        |     |
| Cooling| 0.06  | 0.03 | -0.24| -0.56  | 1.00    |         |          |       |        |     |
| Heating| -0.09 | -0.22| 0.30 | 0.53   | -0.36   | 1.00    |          |       |        |     |
| Industry| 0.03  | 0.04 | -0.13| -0.07  | 0.11    | 0.02    | 1.00     |       |        |     |
| Stock  | 0.02  | 0.06 | -0.06| 0.02   | 0.00    | -0.02   | -0.18    | 1.00  |        |     |
| Policy | -0.08 | 0.03 | 0.00 | -0.01  | 0.16    | 0.00    | 0.08     | -0.04| 1.00   |     |
| RE    | -0.05 | 0.01 | 0.04 | 0.04   | 0.20    | -0.19   | 0.17     | 0.10  | 0.21   | 1.00|

4.4. Estimation results

4.4.1. Static panel model regression

For final selection, three models of the fixed-effect model, the random effect, and the mixed-effect model are still used to estimate and compare the differences.

Table 5. Panel model estimation results (FE, RE)

| Variable | Random effects model | Fixed effect model |
|----------|----------------------|--------------------|
|          | Coef.    | P-value | Coef.    | P-value |
| rCoal    | -23.1761 | 0.059   | -21.5611 | 0.005   |
| rOil     | 32.54448 | 0.113   | 30.93419 | 0.017   |
| LNG      | 0.003423 | 0       | 0.003503 | 0       |
| TEMDIF   | -0.00478 | 0.972   | -0.0891  | 0.311   |
| Cooling  | -0.00444 | 0.867   | 0.000208 | 0.99    |
| Heating  | -0.0019  | 0.873   | -0.00116 | 0.886   |
| Industry | 0.201799 | 0.337   | 0.380789 | 0.007   |
| Stock    | -0.00693 | 0       | -0.00617 | 0       |
| Policy   | 8.535254 | 0       | 0.364467 | 0.745   |
| RE       | -1.51282 | 0.001   | -1.67407 | 0.003   |
| cons     | 36.71944 | 0       | 37.26535 | 0       |
|          | 1.00     |

Wald chi²(10) = 98.61  F(10,342) = 15.23

Observations | 359 | 359

R² | 0.2208 | 0.1544

p-Value | 0.0000 | 0.0000

The results in table 5, indicating that R² of the random-effect model is 22.08%, which is equal to the mixed-effect model and higher than the fixed-effect model. However, the R² value is quite low. Furthermore, in this paper, we will use a Wooldridge test for the 1st order autocorrelation test and perform an LR test for heteroscedasticity test in the model. In our test, in terms of Wooldridge test, we can obtain F (1,6)=6.965(Prob>F=0.0386), thus we conclude that there exists 1st-order Autocorrelation within panels; and in terms of LR test, we obtain the Wald chi²(11) = 89.61 (Prob>chi²=0.0000), thus we conclude that there exists heteroscedasticity across the panels. Therefore, in this paper, we will employ the FGLS method to perform as a robust regression to avoid the problems of 1st order autocorrelation within panels and heteroscedasticity across panels [3].
Table 6. FGLS estimation results

| Variables | Regression 1 | Regression 2 | Regression 3 |
|-----------|--------------|--------------|--------------|
| rCoal     | -12.01* (7.409) | -15.57* (9.206) |              |
| Industry  | 0.412*** (0.133) | 0.380** (0.152) |              |
| Stock     | -0.00311*** (0.00104) | -0.00377*** (0.00108) |              |
| RE        | 0.412*** (0.133) | -1.408*** (0.488) |              |
| rOil      | 28.26*** (9.352) | 15.06 (10.97) |              |
| LNG       | 0.000595 (0.000541) | 0.000848 (0.000658) |              |
| TEMDIF    | 0.0256 (0.0649) | 0.0345 (0.0741) |              |
| Cooling   | 0.00684 (0.0111) | 0.00969 (0.0131) |              |
| Heating   | 0.00538 (0.00438) | 0.00342 (0.00515) |              |
| Policy    | -0.646 (0.492) | -0.730 (0.594) |              |
| Constant  | -0.00311*** (0.00104) | 23.76*** (2.556) | 36.20*** (5.027) |

Observations: 335, 330, 316

Wald chi²: Wald chi²(4) = 36.07, Wald chi²(6) = 14.98, Wald chi²(10) = 45.78

Prob > chi²: 0.0000, 0.0204, 0.0000

Number of id: 7, 7, 7

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Findings of our econometric analysis suggest that the carbon price reacts to market fundamentals, indicating that the carbon market can effectively reflect relevant information of energy markets, industrial production and economic activity for the scarcity of carbon allowance.

Firstly, in terms of energy prices, 1% of the growth rate of coal price will reduce 15.57% carbon price at a significance level of 10%. However, in some specifications, the impacts of oil price and LNG price are not significant, which are out of our expectations. The reason might be that, during 2014-2018, in China’s primary energy consumption structure, oil and natural gas consumption accounted for a relatively small amount are also not significant as the coal as a dominant energy account for 60-70% in China, while oil and natural gas both account for less than 10% [4],[5],[6].

Secondly, it can be seen from Table 6 that the coefficient of the influential factors of the cooling/heating days and temperature difference are not significant. These results indicate that cooling/heating days and temperature difference do not have an impact on CO₂ price changes, these findings of weather variables are in line with previous studies, e.g. Rickels et al. (2010) who also find a positive effect of the coal price but insignificant results for their weather variables, regarding European case [7].

Thirdly, we analyse the industrial production factors. From the estimation results, it can be seen that the growth rate of industrial add and the carbon price are positively correlated with a coefficient of 0.380. This finding is also consistent with the traditional theories, according to Li (2015), Chinese environmental Kuznets curve does not match the traditional inverted "U" environmental Kuznets curve, that is, in China; the level of economic development is still in the stage where economic development and environmental pollution are not decoupled. The growth of industrial production will continue to increase environmental pollution, carbon emissions will further increase, and the demand for carbon emission rights will also increase. Ultimately, the carbon price has increased [8].

Fourthly, traditional theory believes that a mature stock market can reflect the operating conditions of the economy. A prosperous stock market means that the economy is operating well, leading to increased carbon emissions in economic activities, which in turn increases the demand for carbon emission rights, and thus carbon prices rise. from the impact of the economic activity on the carbon price, the results of financial markets that are also related to the carbon price are consistent with traditional theories, but in a relatively small coefficient -0.004, and the negative impact is out of our expectation, may due to Chinese stock market are still not mature at a primary status. Furthermore, in terms of non-fundamental factors, such as availability of reliable information, expectations or speculation on policies or policy implementation, on activities of other market players,
on the future development of overall economic markets and prices, may also affect the carbon price, at least in the short term. However, based on our model, the policy variable is not significant; the result indicates that the policy factor will not affect the carbon price, due to this model might not apply to the policy factor.

Finally, we found that the electricity production of wind power will lower carbon price statistically significant, which complies with Kenneth’s (2012) studies on EU-ETS, renewable energy deployment does not cause a reduction in CO\(_2\) emissions but it displaces CO\(_2\) emissions within the ETS sectors - both within the electricity sectors itself and between the electricity sector and other ETS sectors. The reduction in demand for emission rights due to generation from renewable energy translates into a lower carbon price.

4.4.2. Dynamic panel vector autoregressive Model (PVAR)

**Impulse Response Functions (IRF):** Since the panel VAR model requires many coefficients to estimate so that it is difficult to interpret the economic meaning, however, it mainly analyses the results of the impulse and variance response test.

Firstly, we use three indicators of AIC, BIC, HQIC to select the lag order of the VAR, the results show that it is reasonable to establish a 4-order VAR model at a significant level of 5% (see Table 7).

**Table 7.** Selection the order criteria for panel VAR

| Lag | AIC   | BIC     | HQIC    | Lag | AIC   | BIC     | HQIC    |
|-----|-------|---------|---------|-----|-------|---------|---------|
| 1   | -12.75| -11.9671| -12.4359| 6   | -15.5508| -12.2566| -14.215 |
| 2   | -13.6002| -12.4165| -13.124  | 7   | 39.6593 | 43.6452 | 41.2775 |
| 3   | -14.8169| -13.1877| -14.1599| 8   | 34.2005 | 38.9383 | 36.1254 |
| 4   | -15.8363*| -13.7129*| -14.9782*| 9   | 54.4958 | 60.0911 | 56.7696 |
| 5   | -15.7793| -13.1033| -14.696  | 10  | 47.3425 | 53.8586 | 49.9893 |

Secondly, we furtherly perform an AR Root test on the VAR (4) model. There does not exist a unit root that falls outside the unit circle. Therefore, the construction of the VAR model satisfies stationary requirements. Finally, in order to analyse the relationship between carbon prices and coal prices, industry, stock, and renewable energy, we perform an impulse response analysis and variance decomposition based on the panel VAR model (see Figure 2).

![Figure 2: AR Root test for PVAR](image-url)
Figure 3: IRF Graph

From the graph of impulse response function above (see Figure 3), the positive impact of coal price on carbon price is significant. If coal price gives a positive shock to the carbon price in the 32-60th period, it will have a continuous impact on the carbon price.

Industrial production will have a negative impact on the carbon price in the long term, if industrial production continues to rise; the companies will seek clean technology to produce.

Also, fluctuations in the stock market have a big impact on carbon trading prices in the 32-60th period, which is also related to the fact that local governments try to employ more financial instruments in the carbon market and introduce more participants and investors into the carbon market for liquidity.

Besides, if a negative shock is applied to the renewable energy in the 32-60th period, it will also have a significant impact on the carbon price, but the impact will not stabilize. This indicated that the company would like to look for more alternative energy, such as renewable energy, to replace coal.

Variance Decomposition: The variance decomposition results indicate that the variance of the carbon price is mainly explained by itself, but its interpretation has declined over time. Among other factors, coal price has the most significant impact on carbon price. During the 1-10th period, the impact of coal price is small, and ranges 9.98-56.97%. As time passed by, the interpretation has gradually strengthened. After the 20th period, it has entered a steady status, which can stably explain about 70.37-73.87% on carbon price variance change. The results also show that the stable impact of the coal price has a long lag period (1.66 years).

4.4.3. Bai Perron structural break-point test

According to the data overall information criterion, under the condition that the maximum structural change point is 5, the number of structural mutation points determined by the modified LWZ (Schwarz Criterion) standard method. By observing the dates in the structure breakout, we can find that: firstly, the carbon price of each pilot has undergone multiple structural mutations; secondly, the occurrence date of the structural mutation coincides with the planned compliance date, and there is always a sudden change in April-July for the carbon price of each pilot except Shanghai, Guangdong and Chongqing, and the manifestation was a significant fluctuation of the carbon price(see Table 8).

Table 8. Bai Perron Structural Break-point Test

| Pilot     | Breaks | 1st time       | 2nd time       | 3rd time       | 4th time       | Compliance Date |
|-----------|--------|----------------|----------------|----------------|----------------|-----------------|
| Beijing   | 3      | 21/08/2014     | 14/05/2015     | 25/04/2016     |                | 15/06           |
| Shanghai  | 3      | 17/12/2014     | 10/06/2015     | 22/12/2016     |                | 27/06-30/06     |
| Shenzhen  | 3      | 16/07/2014     | 04/05/2015     | 13/07/2016     |                | 30/06-01/07     |
5. Conclusions

In this paper, we innovatively selected the data from 2014-2018 for seven ETS pilots and employed both the static and dynamic panel model to identify the carbon price drivers. Specific to Chinese case, energy prices, extreme weather, industrial production and economic activity that represents market fundamental influential factors, among them, coal price has a significant negative impact on carbon prices, and the growth of industrial add and stock index have significant positive/negative impact on carbon prices, while oil and natural gas, cooling/heating days, temperature difference have no significant impact on carbon prices. In terms of policy and renewable energy deployment representing non-market fundamental influential factors, the policy factor is not significant, while electricity production from wind power will lower carbon price significantly. Among all factors, coal price is the most significant influential factor. During the 1-10th period, the impact of coal price is small ranges 9.98-56.97%. As time passed by, the interpretation has gradually strengthened. After the 20th period, it stably explains about 70.37-73.87% on carbon price variance change. The results also show that the stable impact of the coal price has a long lag period (1.66 years).

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