CHEMICAL ENGINEERING TRANSACTIONS

VOL. 66, 2018

A publication of AIDIC

The Italian Association
of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Songying Zhao, Yougang Sun, Ye Zhou

ISBN 978-88-95608-63-1; **ISSN** 2283-9216

DOI: 10.3303/CET1866088

Carbon Emission Performance in Chinese Extractive Industry Based on Stochastic Frontier Model and Stochastic Convergence Test

Fengtao Hua

School of Economics and Management, Anhui Normal University, Wuhu 241003, China
hittile@ahnu.edu.cn

The purpose of this study is to estimate the carbon emission performance and time trend of the extractive industry in China. In this paper, the stochastic frontier analysis was used to analyse the carbon emission intensity and estimate the potential of carbon emission reduction in this industry. Besides, the stochastic convergence model was applied to measure the difference of carbon emission intensity in this industry and test the time trend of carbon emission convergence. Finally, it’s concluded that at present, firstly, the carbon emission efficiency of the extractive industry takes a slowly rising trend, with greater potential for improvement; secondly, there exists the gap in carbon intensity between the sub-industries of the extractive industry, without any convergence trend. This reveals that the effective way to reduce carbon emissions of extractive industry is to narrow down the interindustry gap in carbon intensity.

1. Introduction

1.1 Research purposes

With the energy and environment pressure increasing, the low-carbon road is an inevitable choice for China’s economic development in the future. China clearly puts forward the goal of carbon emission reduction by 2020. By then, the unit GDP will drop by 40-50% compared with 2005. In the Thirteenth Five-Year Plan for National Economic and Social Development, it’s proposed that CO_2 emissions will reach its peak around 2030, and the carbon emissions per unit of GDP in 2030 will be 60%-65% lower than those in 2005. Non-petrochemical energy will account for about 20% of primary energy consumption (Lu et al., 2010). The extractive industry is a large carbon emitter in the energy consumption of all industries and is one of the traditional high-carbon industries. In order to fulfil the tasks of energy conservation and emission reduction and reduce the carbon emission intensity, it is necessary to effectively evaluate the carbon emission performance of the extractive industry.

1.2 An overview of carbon emission efficiency

Carbon emission efficiency refers to the economic benefits from the carbon emissions caused by the activities of social economy entities. There are two types of indicators about the carbon emission efficiency: single factor efficiency indicator and total factor efficiency indicator (Herrala and Goel, 2012; Bretschger et al., 2011). The former means the ratio of total carbon emissions to one certain factor, such as CO_2 emissions per unit of energy consumption or carbon emissions per unit of GDP (Hermeling et al., 2013; Fischer and Springborn, 2011). This indicator has a diversity of ratios, ignoring the relationship between other factors of economic activity and carbon emissions, with low precision. The latter refers to the economic effects based on the maximum expected output and minimum carbon emissions in the given conditions of input factors and technological endowments; actually, it means to calculate the technical efficiency of the decision unit under the constraints of carbon emissions.

Please cite this article as: Hua F., 2018, Carbon emission performance in chinese extractive industry based on stochastic frontier model and stochastic convergence test, Chemical Engineering Transactions, 66, 523-528 DOI:10.3303/CET1866088

2. Measurement method of carbon emission efficiency

Determining the production frontier boundary is the key to the measurement of technical efficiency. In this paper, the stochastic frontier analysis (SFA) was adopted, which is the production function of cross-sectional data independently proposed by Aigner et al. (1977) and Meeusen and Broeck (1977). Based on this function, Battese and Coelli (1995) made some improvements to process panel data and expand the application scope of model. Therefore, this paper selects this model to measure the carbon emission efficiency:

$$Y_{it} = f(x_{it};\beta)\cdot \exp(v_{it} - u_{it}) \tag{1}$$

Y is the output, *x* the input vector, and *β* the estimated parameter. The error term is the complex structure. Let v_i and u_i be the same as above, *z* is the variable that affects the technology inefficiency, and δ is the coefficient vector of the influencing factor. In order to reduce the risk of estimation bias by the production function error, the more flexible production function was selected in this paper. Taking the total industrial output (Y) as output and carbon dioxide (CO_2), labour (L) and capital (K) as input, formula (1) can be further expressed as

$$\begin{aligned} InY_{it} = {} & \beta_0 + \beta_1 \cdot InCO_{2it} + \beta_2 \cdot InK_{it} + \beta_3 \cdot InL_{it} \\ & + \beta_4 \cdot (InCO_{2it})^2 + \beta_5 \cdot (InK_{it})^2 + \beta_6 \cdot (InL_{it})^2 \\ & + \beta_7 \cdot (InCO_{2it}) \cdot (InK_{it}) + \beta_8 \cdot (InCO_{2it}) \cdot (InL_{it}) \\ & + \beta_9 \cdot (InK_{it}) \cdot (InL_{it}) + v_{it} - u_{it} \end{aligned} \tag{2}$$

Subtracting In CO_2 from both sides of formula (2), it's given as:

$$\begin{aligned} In\frac{Y_{it}}{CO_{2it}} = Iny_{it} = {} & \beta_0 + (\beta_1 - 1) \cdot InCO_{2it} + \beta_2 \cdot InK_{it} + \beta_3 \cdot InL_{it} \\ & + \beta_4 \cdot (InCO_{2it})^2 + \beta_5 \cdot (InK_{it})^2 + \beta_6 \cdot (InL_{it})^2 \\ & + \beta_7 \cdot (InCO_{2it}) \cdot (InK_{it}) + \beta_8 \cdot (InCO_{2it}) \cdot (InL_{it}) \\ & + \beta_9 \cdot (InK_{it}) \cdot (InL_{it}) + v_{it} - u_{it} \end{aligned} \tag{3}$$

Let $y_{it}=Y_{it}/CO_2$, the carbon emission efficiency is defined as the ratio of the expected output per unit of CO_2 output to the expected value of the production frontier boundary, i.e.:

$$TE_{it} = \frac{E(y_{it})}{E(y_{it} \mid u_{it} = 0)} = \exp(-u_{it}) \tag{4}$$

Formula (4) shows that the carbon emission efficiency value is between 0 and 1. The closer to 1, the higher the efficiency, and being equal to 1 means that it reaches the boundary of the production frontier and the existing technology is fully utilized (Ang, 2005; Ang et al., 1998). The parameters to be estimated in the formula were calculated using the simultaneous likelihood estimation method. The measurement software was Frontier4.1.

3. Data selection and empirical results

According to the methods in the *IPCC Guidelines for National Greenhouse Gas Inventories* (2006), the carbon emissions of various sub-industries in extractive industry is calculated by the product of various energy consumption and the corresponding CO_2 emission factor; the sample period is from 2007 to 2015; There are seven types of energy: coal, coke, gasoline, kerosene, diesel, fuel oil and natural gas. The CO_2 emissions is calculated as:

$$CO_{2it} = \sum (EC_{ijt} \times EF_j) \tag{5}$$

where, CO_{2it} is the total carbon emissions of i industry in t year; EC_{ijt} is the standard coal consumption of j industry in i year; EF_j is the carbon emission factor of energy j. Standard coal and CO_2 conversion standard coefficients for various energy sources are as follows Table 1.

In this paper, the input variables included CO_2 emissions, capital investment (net fixed assets), and labour input (average number of all employees) in the extractive industry; the output indicators were the main business incomes of various industrial sectors. According to the industry classification of *China Industrial Economic Statistics Yearbook* (2007-2015), the extractive industry is divided into seven sub-industries. A total of 410 observed values/sub-industries were collected.

Table 1: Standard Coal and CO_2 Conversion Coefficient for Various Energy Sources

Energy Types	Standard Coal Conversion Coefficient (kg Standard Coal/kg)	CO_2 Emission Factor (kg/Standard Coal)
Coal	0.714	2.791
Coke	0.974	3.134
Petrol	1.471	2.039
Kerosene	1.471	2.039
Diesel Oil	1.457	2.168
Fuel Oil	1.429	2.265
Gas	1.330 (kg/Standard)	1.624

Note: The converted standard coefficient of coal was derived from the *China Energy Statistical Yearbook 2014*, and the CO_2 emission factor was calculated by IPCC (2006).

Table 2: Variable-definition

Variable	Symbol	Definition
Industry Output	Y	Main Business Income ($100 million), 2007 as The Base Year
Labour Input	L	Employees at the end of the year (tens of thousands of people)
Capital Input	K	Net Annual Fixed Assets ($100 million), 2007 as The Base Year
Carbon Dioxide	CO_2	Carbon Dioxide Emissions (Million Tons)

Based on the stochastic frontier model, the simultaneous maximum likelihood estimation was made for the 7 sub-industries in the extractive industry from 2007 to 2015 to obtain the calculated results of the parameters to be estimated as shown in Table 3 (calculation results are retained as 3 decimal places).

Table 3: Regression result of carbon emission result in China's industrial sector

variable	Coefficient (T value)	variable	Coefficient (T value)
β_0	3.058^{***}(9.004)	β_5	-0.302^{***}(5.401)
$\beta_{1\text{-}1}$	-1.947^{***}(11.497)	β_6	-0.094^{**}(2.074)
β_2	0.558^{***}(5.221)	β_7	-0.127^{***}(3.911)
β_3	0.771^{***}(3.246)	β_8	-0.233^{***}(4.990)
β_4	0.574^{***}(12.875)	β_9	0.179^{***}(2.215)
σ^2	0.703^{***}(12.817)		
γ	0.842^{***}(5.004)		
Log function value	998.024		

Note: The t-statistics are indicated in parentheses, and ***, **, and * indicate rejection of the null hypothesis at the significant levels of 1%, 5%, and 10% respectively.

According to Table 3, the coefficient (β_1-1) is -1.947, indicating that as the carbon emission scale increases, the carbon emission efficiency gradually decreases. The ranges of the values (β_1~β_6) and the coefficient symbol are in accordance with the economic implication and statistical significance. In addition, the γ value was 0.842, which was significant at the 1% level, with the satisfactory fitting degree, indicating that the inefficiency of carbon emissions is the main reason that the extractive industry deviates from its production frontier.

Table 4 shows that in the extractive industry of China, the carbon emissions from mining and washing, oil and gas extraction, and other mining industries are highly efficient, with carbon emission efficiency above 0.8; in the non-ferrous mining and non-metallic mining and dressing, the carbon emission efficiency is the lowest, which does not exceed 0.5, with the difference of about 0.3 from the highest three industries. This indicates that there are great differences in the carbon emission efficiency of various sub-industries in the Chinese extractive industry. Also, the overall carbon emission efficiency of the industry in Chinese extractive industry is approximately 0.61 to 0.74 every year, that is, the annual carbon emission reduction potential is approximately 24% to 39%. From Fig.1 (carbon emission efficiency of various sub-industries in the extractive industry), it can be seen that, in addition to the auxiliary industries for extraction, the carbon emission efficiency of other industries shows a gradual upward trend from 2007 to 2015. The entire extractive industry rose from 0.617 in 2007 to 0.737 in 2015, a slight decrease from 2011 to 2013. According to the above data analysis, the overall efficiency of the industry is not high and the increase is small and unstable(Springmann et al., 2015). There is a huge space for carbon emission reduction. Therefore, the carbon emission efficiency of the extractive industry, especially non-ferrous mining and non-metallic mining and dressing should be improved. It is of great significance for the extractive industry to take the “green” sustainable path of energy conservation and emission reduction.

Table 4: Carbon Emission Efficiency in Various Industries

	2006	2008	2009	2010	2011	2012	2013	2014	2015
Mining and Washing of Coal	0.801	0.827	0.892	0.801	0.881	0.877	0.865	0.880	0.887
Petroleum and Natural Gas	0.809	0.804	0.811	0.869	0.842	0.884	0.854	0.865	0.870
Ferrous Metal Ores	0.414	0.447	0.481	0.524	0.568	0.506	0.533	0.593	0.590
Non-Ferrous Metal Ores	0.515	0.491	0.528	0.516	0.581	0.549	0.552	0.564	0.591
Nonmetal Ores	0.817	0.804	0.821	0.807	0.857	0.864	0.860	0.871	0.902
Support Activities Mining	0.413	0.424	0.416	0.485	0.491	0.410	0.496	0.451	0.424
Mining of Other Ores	0.801	0.817	0.827	0.834	0.858	0.905	0.911	0.922	0.928
All Industry	0.617	0.621	0.610	0.635	0.665	0.670	0.658	0.710	0.737

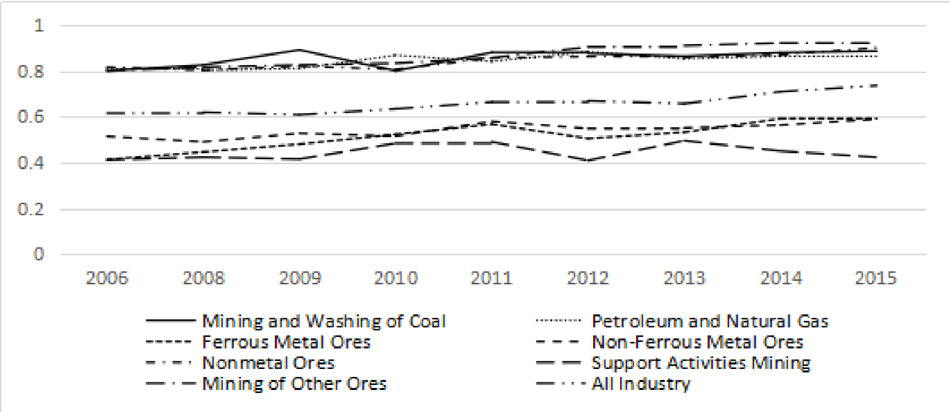

Figure 1: Carbon emission efficiency of various sub-industries in the extractive industry

4. Analysis for stochastic convergence of carbon emission efficiency in various sub-industries of extractive industry

Stochastic convergence is to test whether one variable has a persistent impact on another variable. It effectively solves the problem whether there exists the convergence in the short term (Shrestha & Timilsina, 1996; Torvanger, 1990). Assuming that the relative carbon intensity of each industry tends to its respective compensating-differentials-equilibrium level over the long term, and it does not change over time, then, the relative carbon intensity RCI (relative carbon intensity) of each industry at time t can be written as the sum of RCI^e and u_t:

$$RCI_t = RCI^e + u_t \tag{6}$$

$$u_t = v_0 + \beta \cdot t + v_t \tag{7}$$

where, RCI^e is the equilibrium level that does not change with time; u_t is the deviation degree of the relative carbon emission from the equilibrium level, which is decomposed into a definite linear trend and stochastic process; v_0 is the initial deviation of the carbon emission intensity from the equilibrium level, and β is the deterministic convergence rate. Then, the formula (6) is re-written as:

$$RCI_t = \alpha + \beta \cdot t + v_t \tag{8}$$

where, $\alpha=RCI^e+v_0$. If RCI_t doesn't have a unit root, then the impact on RCI_t is only temporary, and will still return to its compensating-differentials-equilibrium level in the long term, indicating that the carbon emission intensity of the industry is randomly converged. In this paper, based on the method of Evans & Krass (1996) and Carlino & Mills (1996), it's assumed that for each industry, at n=1, 2, ……; if and only if the difference between the carbon emissions degree y_{nt} of n industry in year t and the average y^*_t of the carbon emissions of all industries during the year t is the stable series, the carbon emission intensity of these n industries shows the convergence trend.

$$\Delta(y_{n,t}-y_t^*)=\delta_n+\rho_n(y_{n,t-1}-y_{t-1}^*)+\sum_{i=1}^{\rho}\Delta(y_{n,t-1}-y_{t-i}^*)+u_{n,t} \tag{9}$$

In formula (9), the convergence should be determined by whether the autoregressive parameter ρ_n is zero: if the carbon emission intensity between industries is convergent, then ρ_n is negative; if it's divergent, then ρ_n is zero. The calculation formula for the relative carbon intensity RCI of various industries is:

$$RCI_{n,t}=In(y_{n,t})-In(y_t^*)=In(\frac{y_{n,t}}{y_t^*}) \tag{10}$$

According to the meaning of the above model, the test was made for the stochastic convergence of relative carbon emissions, i.e., whether there exists the unit root in formula (11). The unit root test is divided into two types: variable unit root test and panel data unit root test. The former includes IPS, ADF-Fisher, and PP-Fisher method; the latter includes ADF, PP, KPSS, DF-GLS, and MZ test method. Considering the short span of the sample periods in this paper, three test methods of IPS, ADF-Fisher and PP-Fisher, as well as the three lag-periods were selected. The test results are as follows:

Table 5: The Effect of Random Convergence Test

	test tatistic	ADF-Fisher			PP-Fisher			IPS
	lag phase	1	2	3	1	2	3	
Mining and Washing of Coal	statistics (p value)	0.370 (0.814)	0.119 (1.104)	-1.372 (0.955)	0.694 (0.776)	-1.112 (0.557)	0.924 (0.411)	0.275
Petroleum and Natural Gas		0.472 (0.377)	0.527*** (0.078)	0.825 (0.772)	0.831 (0.901)	0.533 (0.718)	-1.608 (1.399)	0.927
Ferrous Metal Ores		0.583 (0.411)	0.213 (0.381)	0.517 (0.472)	0.383*** (0.085)	0.661 (0.418)	0.211 (0.191)	1.247
Non-Ferrous Metal Ores		0.745 (0.660)	-1.005 (0.972)	2.040 (1.954)	-1.044 (0.992)	1.005 (0.976)	1.124 (1.104)	-0.559
Nonmetal Ores		0.910 (0.739)	0.601 (1.087)	-1.546 (1.322)	0.492 (0.329)	0.339 (0.514)	-1.025 (1.271)	0.887
Support Activities Mining		1.244 (1.071)	0.183 (0.204)	-0.677 (0.572)	0.956 (1.584)	-0.947 (1.224)	0.223 (0.190)	0.351
Mining of Other Ores		1.314 (1.124)	1.280 (1.214)	-0.557 (0.417)	0.670 (0.721)	1.447 (1.270)	-0.417 (0.625)	-1.263
All Industry		0.743 (0.698)	-1.290 (0.884)	0.883 (0.625)	0.334 (0.419)	0.497 (0.372)	1.247 (0.899)	0.674

Note: The lag order of the IPS indicator is determined by the AIC criterion.

From the test results in Table 5, it can be seen that, except for the two-order lagging ADF-Fisher test in coal mining and washing industry and the 1-order lag PP-Fisher test in the non-ferrous mining industry, all test estimates at the significant level of 10% are consistent with the original assumption that there exists the unit root. Therefore, basically it can be judged that the seven sub-industries of the extractive industry in China do not have the time trend of stochastic convergence. This means that the carbon emission efficiency gaps in the sub-industries of the extractive industries will not be automatically eliminated in terms of overall or internal relations (Leontief & Ford, 1971).

5. Conclusions

In this paper, the stochastic frontier analysis and stochastic convergence analysis were conducted to empirically test the carbon emission efficiency of the extractive industry in China and the differences between sub-industries. The following conclusions are made:

Firstly, as a whole, the carbon emission efficiency of extractive industry is slowly rising, and there is room for further improvement. This means that in the Thirteenth Five-Year Plan in China, the extractive industry can achieve emission reduction targets under the condition that the industry output is further increased. The conclusion is in accordance with the view of Zhang et al. (2013). Second, within the extractive industry, there is a huge interindustry gap in carbon emission efficiency, and this gap has continued to widen. This indicates that in the process of carbon emission reduction, the costs paid by various industries are not the same, and then reducing the carbon intensity gap between industries is an effective measure to achieve the overall emission reduction target of the extractive industry.

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