Drivers of energy-related CO₂ emissions under structural adjustment in China

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Abstract. Taking the indicators related to structural adjustment from 1996 to 2015 as the factors, the influencing factors of national energy-related CO₂ emissions was simulated based on the improved STIRPAT model. The findings include: (1) the five major industries, coal, steel, building materials, petrochemicals and non-ferrous metals, had the most significant positive driving effect on China's energy-related CO₂ emissions; (2) the real estate inventory indicators basically conformed to the Kuznets N-shaped curve, and indirectly drove energy-related CO₂ emissions through the impact on the urbanization process or related industries; (3) the driving characteristics of carbon dioxide emissions from energy consumption were mainly determined by the features of socio-economic development, urbanization and industrialization in different stages. Thus, the key to ensure green coordinated development is to correctly handle the relationship between economic growth, urbanization, industrialization and carbon dioxide emission control of energy consumption in different stages of economic and social development.

1. Introduction
China has been one of the world’s major emitter of carbon dioxide[1-2]. In 2015, in the Paris Climate Change Agreement, China has set the medium-term and long-term target: to peak CO₂ emissions around 2030; to cut CO₂ emissions per unit of GDP by 60-65% from 2005 levels, and put forward specific measures in terms of industrial and energy transformation. The release of noxious or toxic substances into the air from industries are an important source of urban air pollution. To regulate these substances, industries have been required to meet strict emissions standards for CO₂ over the last several decades[3]. The analysis of the driving mechanism of structural adjustment and other factors on carbon emissions and the effect of relevant policy implementation have becoming the theoretical research hotspot.

At present, existing studies explore the effects and the driving force of economic, social, industrial, energy and other related factors on carbon emissions. At the national level, Deng et al. [4] and Rong et al. [5] used Logarithmic Mean Divisia Index (LMDI), Pressure-State-Response model and other methods to study the driving effects of population size, economic development, energy intensity and energy structure factors on carbon emissions, and explored the causes and regularities of regional
differentiation of carbon emissions. At the provincial level, Tong et al. [6] and Chen et al. [7] used STIRPAT model to evaluate the driving effects of total import and export volume, total social fixed asset investment, secondary industry output value, GDP, per capita GDP, and proportion of secondary industry on carbon emissions. At the industry level, LMDI and other approaches were applied to study the driving factors of carbon emissions from the perspectives of industrial structure and energy intensity[8-9]. Although some domestic and foreign studies were carried out on the possible environmental impact of supply-side structural reform, they still remained in the stage of theoretical deduction, mechanism analysis and suggestions[10-22]. Furthermore, due to the limitations of methods, models and data integrity, more macro indicators such as GDP, population, the proportion of three industries and energy structure were selected in current studies, with weak pertinence. For instance, under the framework of STIRPAT model, the driving factor is generally set as the proportion of the secondary and the tertiary sector in the national economy, but cannot be refined to specific industries and cannot be deep analyzed according to the impact of different industries on different regional environmental conditions. Shao et al.[23-24] and Guan et al. [25] supplemented and expanded the STIRPAT model, which further enhanced the pertinence of driving factors. Therefore, the improved STIRPAT model was adopted in this study to evaluate the transmission effect of industrial capacity, real estate inventory and other major indicators of structural adjustment and operation on carbon dioxide emissions.

2. Model construction

2.1. Model and methods
On the basis of the existing methods, this study expands the original STIRPAT model using the principles of intra-system autocorrelation and spatial autocorrelation, with several new independent variables. The extended version of the model is expressed in Eq. (1):

\[
\ln I_j = a + \sum_{m=1}^n v_m V_{mj} + \varepsilon_j
\]  

(1)

Where I represents environmental influence, that is, the carbon dioxide emissions; a is a numeric constant; V denotes each supply-side variable that may have a driving effect on carbon dioxide emissions; \( v \) is the correction factor corresponding to each variable; \( \varepsilon \) represents random error vector; the subscript i denotes the year, j is each basic evaluation unit, m represents independent variable, and n is the total number of independent variables.

After the basic model is constructed, a linear regression model is applied to analyze the relationship between different supply-side independent variables and carbon dioxide emissions. In the model, carbon dioxide emissions \( I_{ij} \) after logarithmic transformation is used as the dependent variable, while the independent variable \( V_{mij} \) is also logarithmically transformed. Assume that the error terms in the regression model obey normal distribution and are independently and identically distributed:

\[
y_{ij} = \beta^T X_{ij} + \varepsilon_{ij}
\]  

(2)

In this case, y represents the dependent variable, X denotes the annual characteristic vector of each evaluation unit (province, autonomous region, and municipality directly under the Central Government), \( \beta \) corresponds to the coefficient \( v_m \) in Eq. (1), representing the parameter that needs to be estimated, and \( \varepsilon \) represents the random error term. In the specific model analysis, there is certain correlation between the data of the same province in different years, and between the data of different provinces in the same year, while the serial correlation will make the data unable to meet the assumption of independent error term. If the serial correlation in the data is not corrected, the parameters cannot be estimated accurately. Therefore, a two-factor error model is used to solve this problem, that is, a random factor term \( \varphi_{ij} \) of specific province (assume it is normally distributed with
a mean of 0 and a variance of $\sigma^2$) and a fixed factor term $\mu_c$ of city (subscript $c$ is the code of the evaluation unit) are added to the model. Finally, Eq. (2) is rewritten as:

$$y_{ij} = \beta^T x_{ij} + \epsilon_{ij} + \varphi_j + \mu_c$$  \hspace{1cm} (3)

Besides, considering that each province, municipality directly under the Central Government and autonomous region has its own unique social and economic characteristics, and industrial structure, a generalized random parameter model is used to solve spatial heterogeneity. Compared with the traditional regression model, in the generalized random parameter model, each region has its own parameter estimate instead of a fixed overall parameter estimate. The likelihood function of each district and county can be written as follows:

$$L_j = P(y_{1j},...,y_{21j} \mid x_{1j},...,x_{21j}, \beta_j) = \prod_{i=1}^{21} P(y_{ij}, \beta_j x_{ij}) = \int g(\beta \mid \theta) \prod_{i=1}^{21} P(y_{ij}, \beta^T x_{ij}) \, d\beta.$$  \hspace{1cm} (4)

In Eq. (4), $\theta$ is the parameter of the distribution $g$ (such as the mean and variance), while $g(\beta \mid \theta)$ is the overall parameter distribution. Assume that $\beta$ obeys multivariate normal distribution, $\theta$ can be expressed as $\mathbf{(b, \Omega)}$, where $b$ denotes the estimate of the mean of $\beta$, then $\Omega$ represents the estimate of the covariance matrix of $\beta$, which can be expressed as Eq.(5):

$$\beta \sim \text{MVN}(b, \Omega)$$  \hspace{1cm} (5)

Since the integral term in Eq. (4) will make calculation difficult in parameter estimation, a simulation-based method is used to approximate the likelihood equation in Eq. (4). In each simulation, a $\beta$ value will be randomly generated from the multivariate normal distribution $\text{MVN}(b, \Omega)$, and $R$ simulations will produce $R$ $\beta$ values, so that we can calculate the integration of $\beta$ by averaging. According to the above method, the simulation-based likelihood function can be expressed as Eq. (6):

$$SLL = \sum_{j=1}^{18} \log(\prod_{i=1}^{21} f(y_{ij}, \beta_j x_{ij})) = \sum_{j=1}^{18} \log\left(\frac{1}{R} \sum_{r=1}^{R} \prod_{i=1}^{21} P'(y_{ij}, \beta_j^r x_{ij})\right)$$  \hspace{1cm} (6)

Where $r$ represents the $r$-th simulation. Such method of estimating the random parameter model is called simulation-based maximum likelihood estimation. Specifically, by using Cholesky decomposition, the covariance matrix can be expressed as $\Omega = \Gamma \Gamma'$, which also ensures that the covariance matrix is positive definite matrix. In each simulation, the obtained parameter $\beta_j$ can be considered as adding the overall mean term and the standard normal distribution (w) multiplying the matrix obtained by Cholesky decomposition:

$$\beta_j = b + \Gamma w$$  \hspace{1cm} (7)

Assumed $\Gamma$ is a diagonal matrix, then $\Gamma \Gamma'$ is the variance matrix of the mean values of random parameters, and the corresponding distribution value of each parameter can be estimated. In addition, in the specific analysis, this study also used the Bayesian method to estimate the parameters of each province, municipality directly under the Central Government and autonomous region. Specifically, the distribution equation of the parameter $\beta$ based on the region $j$ is expressed by $h(\beta \mid Y_j, X_j, \theta)$ which can be written as follows based on the Bayesian formula:

$$h(\beta \mid Y_j, X_j, \theta) = \frac{P(Y_j \mid X_j, \beta) g(\beta \mid \theta)}{P(Y_j \mid X_j, \theta)}$$  \hspace{1cm} (8)
The parameter estimate unique to each region is the mean of the conditional distribution h:

$$
\hat{\beta}_j = \frac{\int \beta P(Y_j | X_j, \beta) g(\beta | \theta) d\beta}{P(Y_j | X_j, \theta)} = \frac{\int \beta P(Y_j | X_j, \beta) g(\beta | \theta) d\beta}{\int P(Y_j | X_j, \beta) g(\beta | \theta) d\beta}
$$

(9)

Similarly, since there is an integral term in Eq. (9), similar simulation estimation principle can be used to estimate $\hat{\beta}_j$.

2.2. Samples and data

In 2015, the Central Economic Working Conference put forward five major tasks of supply-side structural reform, namely, cutting overcapacity, destocking, deleveraging, reducing corporate costs and shoring up weak spots, which directly or indirectly involve the production of CO$_2$ from energy consumption. For example, in the case of excess capacity, it will lead to more industrial production, plant construction, facility operation, etc., burning more energy and thus emitting more CO$_2$[26-29]. Accordingly, taking the national data from 1996 to 2015 as the study sample, the independent variables are obtained from the five major tasks indicators.

2.2.1. Indicators of cutting overcapacity. Capacity utilization and output of major industrial products are key indicators to measure the situation of overcapacity. In terms of capacity utilization, on the basis of considering the availability of data and the comparability between different regions, the industrial output assets ratio (the ratio of industrial sales value to the industry fixed assets) is selected as the measurement standard. Meanwhile, the production of a number of industries with serious overcapacity, including steel, coal, petrochemical, building materials, papermaking and nonferrous metals, is selected as the independent variable, as shown in Table 1.

Profitability is an important indicator to identify zombie enterprises. According to the energy consumption structure of various industries in China in 2015, the proportion of industrial energy consumption in the total energy is 69.44%, indicating that the energy consumption of various enterprises is mainly concentrated in industries. Therefore, the industrial profits to cost ratio is selected as the main driving factor for the impact of zombie enterprises disposal on regional energy-related CO$_2$ emissions.

2.2.2. Indicators of destocking. From the perspective of supply-side, the floor space of completed buildings is selected to measure the surplus of real estate inventory in Chinese provinces (districts, cities). From the perspective of market side, the destocking potential is still mainly concentrated in cities [30-33]; urban consumers and urban financing population enjoy greater purchasing power in real estate market. Therefore, the urbanization rate and the proportion of urban financing population are selected to evaluate the scale of regional real estate market and the potential for steady development, as the main factors for the impact of destocking on regional energy-related CO$_2$ emissions.

2.2.3. Indicators of deleveraging, reducing corporate costs and shoring up weak spots. The core of deleveraging and cost reduction is to decrease the leverage ratio and operating costs of enterprises. The asset liability ratio of industrial enterprises (industrial enterprises total debt to total assets) and the cost ratio of industrial enterprises (principal business cost to sales revenue ratio) are selected as the main driving factors. The key to shoring up weak spots is to enhance the independent innovation capability to achieve leapfrog growth. Accordingly, we select the ratio of R&D expenditures to GDP as the influencing factor.

2.3. Collinearity test

Because there are a large number of independent variables selected, some of which are derived from a unified industrial system or statistical system, such as the production of pig iron, crude steel and steel, the asset liability ratio and cost ratio of industrial enterprises and etc., there may be certain correlation
and collinearity in the actual simulation of the model, which would affect the simulation calculation results of the model. Thus, the multivariate collinearity diagnosis is conducted on each selected independent variable in the Logistic regression model to eliminate the influence of index collinearity on the fitting results of the STIRPAT model.

In the linear regression model, the cross products matrix $X'X$ has at least one characteristic root that is very small and close to 0, which means that there is a collinear relationship between the column vectors of $X$, and the Logistic regression parameters estimates are solved by the Newton-Raphson iteration method. The basic equation is shown in Eq. (10) [34-36]:

$$
\hat{\beta}_n = (X'WX)^{-1}X'WZ
$$

(10)

$$
Z = X\hat{\beta}_{n-1} + W^{-1}(y - \hat{y})
$$

(11)

Where $W$ is a diagonal matrix, its diagonal element is $w_{ii} = \hat{p}(1 - \hat{p})$, the variance of $\hat{\beta}_n$ is $\text{var}(\hat{\beta}) = \left[i(\hat{\beta})\right]^{-1}, i(\hat{\beta}) = -\partial^2 \log L / \partial \beta \partial \beta \big|_{\beta = \hat{\beta}} = X'WX$, and $L$ is the corresponding likelihood function.

Based on the results of the collinearity test, 10 independent variables like crude steel output were eliminated from the original 22 independent variables, and the remaining 12 independent variables are shown in Table 1.

### 3. Simulation results

Taking 30 provinces (autonomous regions and municipalities) of China as a whole, the improved STIRPAT model is applied to establish regression equations for the 12 independent and dependent variables that have passed the collinearity test (as show in Table 1) ; and the contribution degree and driving mechanism are analyzed. The contribution of China's supply-side operations on CO$_2$ emissions can be obtained in Table 2.

Capacity utilization is the strongest driving factor. All indicators related to capacity are significant, and the coke production, cement production, plastics in primary forms production, ten kinds of nonferrous metal production and pig iron production are all reach the highly significance level of 1%. The industrial output assets ratio is significant at the significance level of 5%, and the industrial profits to cost ratio is significant at 10%. Both of these two indicators have negative impact on regional energy-related CO$_2$ emissions. It is foreseeable that the cutting overcapacity action will play a noteworthy role in reducing carbon dioxide emissions from energy consumption in China.

Destocking has a positive driving effect to a certain extent. The floor space of completed buildings indicator is not significant, and the urban financing population proportion indicator is generally significant. Considering the high collinearity relationship between the urbanization rate of permanent residents and the proportion of urban financing population, it can be seen that urbanization development has a generally significant driving force. The increase of urbanization level and the proportion of financing population indirectly reflects the growth of real estate destocking capacity, which leads to a certain degree of growth of energy-related CO$_2$ emissions.

Industrial deleveraging and corporate cost reduction are greater driving forces, however, the effect of action to shoring up weak spots is not obvious. The R&D expenditure that represents the action of shoring up weak spots is not significant. The asset liability ratio of industrial enterprises, which represents the leverage level of industrial enterprises, is a generally significant indicator with positive impact. Combined with the collinearity analysis of the cost ratio of industrial enterprises, it can be seen that industrial deleveraging and corporate cost reduction will decrease the leverage level and operating costs of industrial enterprises, and play a positive role in China's energy-related CO$_2$ emissions.
Table 1. Selection of the collinearity test indicators.

| Supply-side | Preliminary screening | Test result |
|-------------|-----------------------|-------------|
| **Capacity** | Coke production (coal industry) | Keep |
| | Machine-made paper and paperboard production (paper industry) | |
| | Pig iron production (steel industry) | Keep |
| | Crude steel production (steel industry) | |
| | Steel production (steel industry) | |
| | Cement production (building materials industry) | Keep |
| | Flat glass output (building materials industry) | |
| | Plastics in primary forms production (petrochemical industry) | Keep |
| | Sulfuric acid production (petrochemical industry) | Keep |
| | Caustic soda production (petrochemical industry) | |
| | Chemical pesticides production (petrochemical industry) | |
| | Agricultural nitrogen, phosphorus and potash fertilizers production (petrochemical industry) | |
| | Ten kinds of non-ferrous metals production (non-ferrous metals industry) | Keep |
| | Aluminum production (non-ferrous metals industry) | |
| | Industrial output assets ratio | Keep |
| | Industrial profits to cost ratio | Keep |
| **Inventory** | Floor space of completed buildings | Keep |
| | Urbanization rate | |
| | Urban financing population proportion | |
| **Other indicators** | Asset liability ratio of industrial enterprises | Keep |
| | Cost ratio of industrial enterprises | |
| | Research and development expenditure (% of GDP) | Keep |
Table 2. Simulation results of the impact of China's supply-side operations on CO\textsubscript{2} emissions.

| Variables                                | Parameter estimates | Standard deviation | pr (>|t|)   |
|------------------------------------------|---------------------|--------------------|----------|
| Constant                                 | 7.545               | 0.497              | 0.137252 |
| Capacity                                 |                     |                    |          |
| Coke production ***                      | 0.4668              | 0.0541             | <2e-16   |
| Pig iron production ***                  | 0.3354              | 0.0242             | 0.000852 |
| Cement production ***                    | 0.3732              | 0.0164             | <2e-16   |
| Plastics in primary forms production *** | 0.3294              | 0.0295             | <2e-16   |
| Sulfuric acid production **              | 0.0967              | 0.0659             | 0.01563  |
| Ten kinds of non-ferrous metals production *** | 0.3861         | 0.0317             | <2e-16   |
| Industrial output assets ratio **        | -0.0564             | 0.0434             | 0.023625 |
| Industrial profits to cost ratio *       | -0.0262             | 0.0509             | 0.079373 |
| Inventory                                |                     |                    |          |
| Floor space of completed buildings       | 0.0029              | 0.0102             | 0.770399 |
| Urban financing population proportion *  | 0.032               | 0.0284             | 0.067981 |
| Others                                   |                     |                    |          |
| R&D expenditure (% of GDP)               | 0.0039              | 0.0751             | 0.641994 |
| Asset liability ratio of industrial enterprises* | 0.0217         | 0.0718             | 0.050393 |

Note: 1. Based on the improved STIRPAT model, log transformation is performed for all continuous independent variables. 2. In terms of parameter estimates, the positive values denote positive effects, while the negative values denote negative effects; the greater the absolute value, the stronger the effects. 3. No* means not significant (pr>0.1); * indicates significant at the 10% level (0.05<pr<0.1); ** indicates significant at the 5% level (0.01<pr<0.05); *** indicates significant at the 1% level (pr<0.01).

4. Conclusion

Against the overall background of the comprehensive implementation of the supply-side structural reforms, this study takes the energy-related CO\textsubscript{2} emissions, which account for the vast majority of greenhouse gas emissions in China as the main research object. Then, through the improved STIRPAT model, the driving influence of industrial capacity, real estate inventory and other independent variables on energy-related CO\textsubscript{2} emissions under structural adjustment are analyzed. The main conclusions are as follows:

(1) Coal, steel, building materials, petrochemical, non-ferrous metal, the five major industries, have relatively concentrated overcapacity. The production scale and capacity scale are the most significant independent variables with positive impacts on China’s regional energy-related CO\textsubscript{2} emissions, whose significance level are generally above 5%.

(2) The simulation results of the urban financing population proportion indicator, which denotes the real estate demand, in each group basically conform to the Kuznets N-shaped curve. Whereas, the driving effect of the floor space of completed buildings, representing the real estate supply, is based on the urbanization level, and indirectly realized through the urbanization process or the impact of building materials and steel industry.

(3) The driving influence of China's supply-side operation on regional energy-related CO\textsubscript{2} emissions are mainly determined by the comprehensive economic and social development and the
phased characteristics of urbanization and industrialization. As China's economic growth has entered a new normal— it is the key to correctly handle the relationship between economic growth, urbanization, industrialization and energy consumption and carbon dioxide emission control, to achieve green coordinated development.

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