The Carbon Emissions Calculation in Hubei China Via Using the LMDI and STIRPAT Models: A Comparative Study

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ABSTRACT

Global warming has become a widely recognized global environmental issue that poses significant threats to the ecological environment and human survival. This study applies the LMDI and STIRPAT models to decompose the factors affecting carbon emissions in Hubei province of central China, based on a comprehensive analysis of relevant domestic and international literature. Four main factors contributing to carbon emissions are identified: energy structure, energy intensity, economic development, and population size. Statistical yearbook data from 2010 to 2019 in Hubei province is collected through various methods such as querying and web crawling. The LMDI model is employed to calculate the contribution rates of each influencing factor, while the STIRPAT model is utilized to estimate the influence coefficients of these factors. Subsequently, a comparative analysis is conducted between the two models, and comprehensive recommendations for carbon reduction strategies in Hubei province are proposed.

KEYWORDS

Carbon emissions; LMDI model; STIRPAT model; Hubei province

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1 Introduction

(1) Background

Global greenhouse gas emissions are continuously increasing, leading to the crisis of global climate change. Carbon emissions are one of the primary driving forces behind this phenomenon. Since 2007, The carbon emissions of China have surpassed those of the United States, making it the highest emitter globally. To mitigate carbon emissions, China has formulated a series of action plans and reduction targets. These policies include encouraging the use of renewable energy, technological advancements, and low-carbon technologies to promote the economic greening and sustainable development. China recognizes that reducing carbon emissions is not only a requirement for sustainable development but is also in line with global environmental protection goals. China has expressed its commitment to implementing powerful policies, with the aim of achieving the peak of carbon emissions before 2030 and attaining carbon neutrality before 2060. Although carbon reduction poses significant pressure and challenges to the Chinese economy and environmental protection, it is deemed a necessary pathway to realize the goals of greening the economy and achieving sustainable development.

(2) Current domestic and international research

There is a substantial number of studies about carbon emissions and their influencing factors. As early as the 1970s, Ehrlich et al. (1971)[1] proposed the IPAT formula for assessing environmental impacts. The formula examines some important factors to analyze the impact on the environment. Building upon the research on the Kaya Identity, Dietz (1994)[2] developed the STIRPAT model as a stochastic form of the IPAT equation. He attempted to incorporate exponential factors into the model to analyze the disproportional effect of human factors on the natural environment. In the 1990s, scholars gradually conducted more precise research these issues and adopted the decomposition method as a key approach. Yoichi Kaya[3] proposed the Kaya Identity in 1989, which studies the primary factors influencing carbon emissions from four perspectives: national economy, population, energy intensity, and carbon intensity. Subsequently, researchers further expanded on the Kaya Identity to conduct additional research. From the 21st century onward, empirical analysis has gradually increased. The LMDI model (1998)[4], which is based on the Kaya Identity and its extensions, has become the most widely used and representative method. This model decomposes the change in a specific factor into the sum of changes in multiple dependent variables and analyzes the impact of each variable. Due to its complete decomposition of residual factors, strong operability, and reasonable results, the LMDI model has gained popularity among many researchers in the field of carbon emissions.

Bhattacharyya et al. (2004)[5] used the LMDI model to analyze Thailand's carbon emissions from 1981 to 2000. Ang et al. (2007)[6] addressed an unresolved issue in the decomposition method of the LMDI model, namely how to handle zero and negative values in the dataset. Their study provided a solution that enables the LMDI model to be applied to any decomposition scenario.

Sun et al. (2011)[7] utilized an extended version of the STIRPAT model to decompose the main factors affecting the development of a low-carbon economy in China. Results indicated that per capita GDP, energy-based carbon emissions, population size and energy consumption structure significantly and positively influenced carbon emissions. The influence on industrial structure, urbanization level, and international trade specialization was not evident.

Huang et al. (2016)[8] also employed the STIRPAT model to analyze the similar problems in Jiangsu Province. The results revealed that these four factors had an influence on carbon emissions, with each 1% change leading to varying proportions of carbon emission changes. Based on these findings, the authors proposed eight different development scenarios and predicted future energy consumption carbon emissions. In conclusion, effective reduction of carbon emissions can be achieved when population and economic growth remain at a low rate, accompanied by rapid technological advancements.

2 Rated Knowledge

(1) LMDI model

The LMDI (Logarithmic Mean Divisia Index) model is developed based on the Kaya Identity. Building upon the Kaya Identity and incorporating the LMDI decomposition model, as well as referencing related research at home and abroad, the influencing factors in Hubei Province from 2010 to 2019 are decomposed into four factors: energy intensity, energy structure, economic development, and population size. The specific carbon emission decomposition model is as follows:

$$C = \Sigma_i C_i = \Sigma_i \frac{C_i}{E_i} \times \frac{E_i}{E} \times \frac{E}{G} \times \frac{G}{P} \times P \quad (1)$$

In the above equation, C represents the total carbon emissions, E denotes the total energy consumption, G denotes the regional Gross Domestic Product (GDP), and P represents the regional population. The index i denotes the energy consumption type. Ci is C from the i-th energy, while Ei represents the E of the i-th energy. By incorporating the specific meanings of the indicators in the LMDI model, the equation can be transformed as follows:

$$C = \Sigma_i F_i \times S_i \times I \times Y \times P \quad (2)$$

$$F_i = \frac{C_i}{E_i}\ ,\ S_i = \frac{E_i}{E}\ ,\ I = \frac{E}{G}\ ,\ Y = \frac{G}{P} \quad (3)$$

In the LMDI model, the decomposition of factors can be carried out using either an additive or multiplicative approach. This study utilizes the additive form of the LMDI model. In this formulation, Fi is the carbon emission coefficient, which shows the ratio of carbon emissions caused by unit consumption of the i-th energy source to its energy consumption. Si is the energy structure, which represents the ratio of energy consumption from the i-th energy source to the total energy consumption. I represents energy intensity, which shows the ratio of total energy consumption to regional GDP, reflecting the energy consumption per unit of economic output. Y is per capita GDP, representing economic development. P represents population size, representing the population scale.

According to the reference materials of IPCC, the coefficient Fi is assumed to remain unchanged over time. Therefore, this study ignored the influence of carbon emission coefficient. Under the additive decomposition mode, the following equation can be derived:

$$\Delta C = C_t - C_0 = \Delta S + \Delta I + \Delta Y + \Delta P \quad (4)$$

In the above equation, C_0 and C_t represent the initial and the final carbon emissions, respectively. In this study, the initial year is 2010, and the final year is 2019. ΔS, ΔI, ΔY, and ΔP represent the impact of changes in energy structure, energy intensity, economic development and population size, respectively. φS, φI, φY, and φP represent the contribution rates of the energy structure, energy intensity, economic development and population size, respectively. Therefore, the decomposition can be respectively showed as follows:

$$\Delta S = \Sigma_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{S_i^t}{S_i^0} \quad (5)$$

$$\Delta I = \Sigma_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{I^t}{I^0} \quad (6)$$

$$\Delta Y = \Sigma_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{Y^t}{Y^0} \quad (7)$$

$$\Delta P = \Sigma_i \frac{C_i^t - C_i^0}{\ln C_i^t - \ln C_i^0} \ln \frac{P^t}{P^0} \quad (8)$$

$$\varphi_s = \frac{\Delta S}{\Delta C}, \varphi_I = \frac{\Delta I}{\Delta C}, \varphi_Y = \frac{\Delta Y}{\Delta C}, \varphi_P = \frac{\Delta P}{\Delta C} \quad (9)$$

(2) STIRPAT model

The STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model originated from the IPAT equation can be expressed as follows:

$$I = P \times B \times T \quad (10)$$

In the formula, I is the environmental load; P represents the population size; B is the level of affluence; T represents the technical level. For overcoming the shortcomings of the IPAT equation, scholar Dietz (1994) introduced an index so that it can to be used to study the non-proportional effects. The expression is:

$$I = a \times P^b \times B^c \times T^d \times \mathrm{e} \quad (11)$$

In the formula, a is a constant term; b, c and d represent the index terms of P, B and T respectively; e represents the error term. According to the LMDI model, Si, I, Y and P are selected as independent variables to expand the STIRPAT model for comparative analysis. In order to eliminate the influence of heteroscedasticity, all variables are logarithmicized. The logarithmicized model is showed as follows:

$$\ln I = \ln a + \alpha \ln S_i + \beta \ln I + \gamma \ln Y + \delta \ln P \quad (12)$$

A multiple linear regression analysis is conducted on the STIRPAT model using the method of least squares.

3 Experimental Process

(1) Data collection

The study relies on five primary sources of data, namely carbon emission data, GDP data, population data, total primary energy consumption, and the consumption data for three main primary energy sources: coal, oil and natural gas. Given that publicly available carbon emissions data is only accessible up until 2019, a time span of ten years from 2010 to 2019 was selected for data collection and analysis. The main sources of data include the annual "Hubei Statistical Yearbook," "China Energy Statistical Yearbook," and the China Emissions Accounts and Datasets (CEADs). Various methods were employed to gather the required data, including Python web scraping techniques and manual data collection procedures.

(2) LMDI model analysis

The contribution rates of the four factors decomposed by the LMDI model are shown in Figure 1.

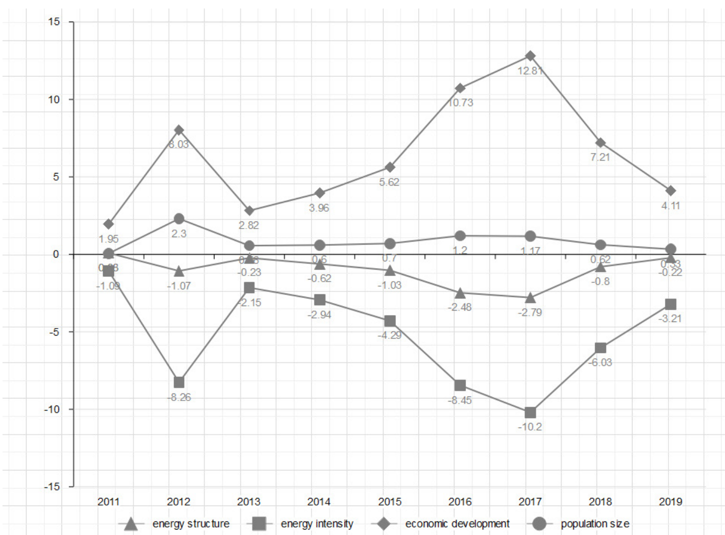

Figure 1. Contribution rates of the four influencing factors

From Figure 1, economic development in Hubei Province during the period of 2010-2019 had a significantly larger positive impact on carbon emissions, whereas energy intensity had a notably larger negative effect on carbon emissions. The negative impact of energy intensity on carbon emissions effectively offset the increase in carbon emissions attributable to economic development. Moreover, the mitigating impact of energy intensity on the carbon emissions resulting from economic development progressively amplified after 2015 but began to decline after 2017. In 2019, the total effect increased compared to previous years; however, the contributions of energy intensity and economic development decreased. This indicates a slowdown in the growth rate of energy intensity and economic development. Notably, energy intensity steadily counteracted the positive impact of economic development. The population size and changes in energy structure remained relatively stable during the analyzed period, with the contribution rate of population size consistently positive and the effect of energy structure consistently negative.

(3) STIRPAT model analysis

The regression equation based on the least square method is:

$$\ln I = 0.35 \ln S_1 - 0.796 \ln S_2 - 0.428 \ln S_3 - 1.261 \ln I + 1.061 \ln Y - 3.542 \ln P + 32.83 \quad (13)$$

The comparison of actual and predicted carbon emissions is shown in Figure 2.

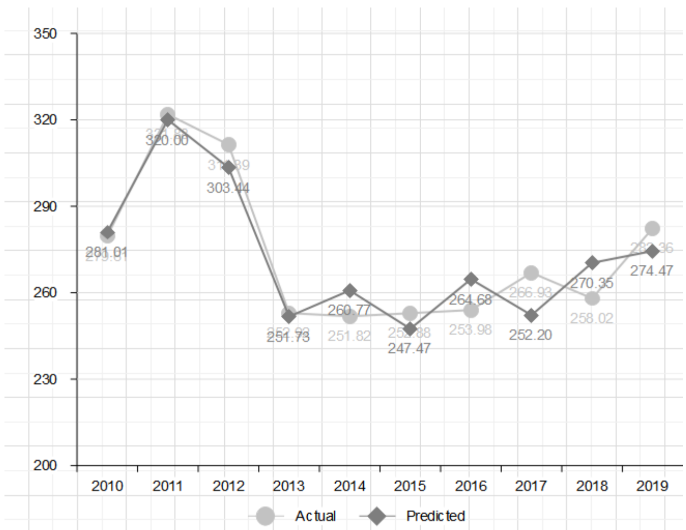

Figure 2. The comparison of actual and predicted carbon emissions

According to the regression equations, in the context of Hubei Province, when other variables are held constant, a 1% growth in the proportion of raw coal in the energy structure is associated with an average increase of 0.35% in carbon emissions. Conversely, a 1% rise in the proportion of crude oil in the energy structure leads to an average decrease of 0.796% in carbon emissions. Similarly, a 1% increase in the proportion of natural gas in the energy structure results in an average decrease of 0.428% in carbon emissions. Furthermore, a 1% growth in energy intensity is associated with an average decrease of 1.261% in carbon emissions. Additionally, a 1% rise in per capita GDP leads to an average increase of 1.061% in carbon emissions, while a 1% increase in population size is related with an average decrease of 3.542% in carbon emissions.

These findings indicate a negative correlation between energy structure, energy intensity, population size and carbon emissions. Notably, population size exhibits the highest influence, followed by energy intensity. Economic development demonstrates a positive correlation with carbon emissions.

(4) Comparative analysis of the two models

Comparing the LMDI model with STIRPAT model, it can be found that the LMDI model mainly emphasizes the contribution rate. However, it fails to quantitatively describe the long-term effects, making it more suitable for quantitative analysis of influencing factors during a specific time period. Conversely, the STIRPAT model can uncover the trend effects but does not provide a description of the contribution rates of individual factors within a specific time frame. Hence, although both methods consider the same influencing factors, the influences of these factors on carbon emissions are somewhat inconsistent.

A comprehensive analysis of the results from both methods suggests that energy intensity and energy structure are the primary factors contributing to the reduction of carbon emissions in Hubei Province. Decreasing them, and increasing the proportion of natural gas positively impact the decrease of carbon emissions. Additionally, proper control of population also works in Hubei Province, while economic development stimulates an increase in carbon emissions.

4 Conclusions and Suggestions

For Hubei Province, recommendations and strategies for carbon emissions reduction can be formulated based on four influencing factors.

In terms of economic development, it is important to accelerate the growth of low-carbon industries. The rise of low-carbon industries has posed challenges to traditional industries while creating market opportunities for new industries such as renewable energy, ecological agriculture, and environmental protection. Regional governments can provide macro planning and encourage and support companies to expedite the establishment and development of low-carbon industries. It is also essential to develop reasonable tax policies for the low-carbon industry. This can be achieved by adjusting the tax burden for low-carbon industries and enterprises and reducing the damage to natural resources and pollution, thereby incentivizing business transformation, upgrading, and fostering a green economic transition.

In addition to improving the level of low-carbon technology, efforts should also be made to promote innovation capacity within companies to drive the development of low-carbon technologies. For instance, Hubei Province's automotive industry is one of the key industries, and emphasis should be placed on enhancing the industry's level of low-carbon technology, encouraging research in low-carbon technologies, and thereby reducing the carbon emissions of the automotive sector.

In terms of energy structure, attention should be given to the issues of greening, clean energy, and energy conservation. From the perspective of improving energy utilization efficiency, it is crucial to focus on developing new clean energy sources and maximizing the use of diverse resources to ensure higher quality energy supply. This includes renewable energies such as solar power, tidal energy, wind energy, among others. Additionally, increasing the proportion of natural gas consumption is also of great importance, as the utilization rate of natural gas in Hubei Province remains relatively low. It is necessary to enhance the use of natural gas among enterprises and individuals while reducing the reliance on coal and crude oil.

Regarding population size, effectively controlling population growth is becoming increasingly vital for carbon emissions mitigation. Enhancing environmental awareness among residents plays a crucial role. Strengthening environmental education, raising public awareness of environmental protection, promoting low-carbon lifestyles, and encouraging residents to choose more environmentally friendly transportation modes such as public transport or cycling, as well as reducing the use of single-use items, are measures that can help residents better understand the importance of environmental protection.

In conclusion, this paper employs LMDI and STIRPAT models to analyze the carbon emissions in Hubei Province over a decade spanning from 2010 to 2019. The study identifies four major influencing factors, including energy structure, energy intensity, economic development and population size, and assesses their respective degrees of impact and contribution rates on carbon emissions. Ultimately, on the basis of the analysis findings, this research presents tailored policy suggestions for carbon emission reduction in Hubei Province.

About the Author

Chen Zhou undergraduate of School of Business and Management of Jilin University, and his research field is Big Data.

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