CO$_2$ emissions and economic development: China’s 12th five-year plan

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1. Introduction

In the past two decades (1989–2008), the average annual growth rate of China’s real GDP has been nearly 10.91%. At the same time, total energy consumption has also increased from 969.34 to 2850 million tons of Standard Coal Equivalent (SCE). The major portion of the China’s energy consumption is in non-renewable resources. In 2008, fossil energies accounted for over 91% of the total energy consumption, of which over 68% came from coal (NBSC, 2009). The combustion of fossil fuels has emitted large amounts of CO$_2$. Since 2007, China has become the largest CO$_2$ emitter in the world, accounting for over 25% of the world’s total emissions in 2009 (EIA, 2011). According to trend analysis, China’s CO$_2$ emissions will further increase rapidly in the next several years (Meng and Niu, 2011a). The consumption of fossil energy has affected China’s living environment (Wang, 2010). More importantly, CO$_2$ emitted from the combustion of fossil fuels is mainly responsible for the greenhouse effect, which has far-reaching effects on our lives (Liu, 2007). China’s sustainability will become increasingly difficult if it maintains the development mode it has employed in the past. Many researchers have studied China’s energy consumption and CO$_2$ emissions to search for possible measures to improve its emission intensity (He et al., 2010; Donglan et al., 2010; Duan, 2010; Tan et al., 2011; Feng et al., 2011; Zhou et al., 2011; Yi et al., 2011). They have advanced many valuable measures but have not considered the periodical characteristics of China’s macro-policy.

China has reconsidered and adjusted its development policies in every fifth year since 1953, except for the years 1963–1965. This management system is called the Five-Year Plan. As a socialist country, the Chinese government has the powerful capability to control its socio-economic development. The Five-Year Plans have greatly affected China’s economic growth rate, energy consumption structure, investment orientation, and so on. Since the 11th Five-Year Plan, China has paid close attention to its energy intensity, energy saving targets, and use of renewable energy (Lin et al., 2008; Wang and Chen, 2010), but the effects of CO$_2$ emissions control have not been satisfactory. 2011 is the first year of the 12th Five-Year Plan. With the increasing number of environmental disasters as well as the emission pressures both at home and abroad, the Central Committee of the Chinese Communist Party has decided to implement more effective measures to control China’s CO$_2$ emissions. Energy policy, especially how to adjust the relationship between economic growth and CO$_2$ emissions, is one of the most important parts of the plan.

At present, three main models can be used to decompose CO$_2$ emissions. First is the Divisia decomposition approach, which decomposes the variation of CO$_2$ emissions into the influences of industrial structure adjustment and technological innovation. Second is the DEA and Malmquist productivity index model, which decomposes the variation of CO$_2$ emissions into the non-renewable energy consumption. Third is the Partial-Least Square (PLS) regularity test method, which decomposes the variation of CO$_2$ emissions into the economic development factors. Outlier analysis reveals three important areas for CO$_2$ reduction: (a) decreasing the share of coal to the total energy consumption and replacing it with non-fossil energies; (b) controlling vehicles used in the cities as well as (c) adjusting industrial structure. Furthermore, based on the social and economic realities of China, the current paper designs six feasible development scenarios for the period covered by the 12th Five-Year Plan and predicts the values of each factor in each scenario. The values can test the implementation of China’s CO$_2$ control development concept. The experiences obtained by outlier analysis can be of significant reference value for realizing the predicted scenarios.

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influence of efficiency change, pure technical efficiency change, and scale efficiency change. Third are the environmental impact, Population, Affluence, and Technology (IPAT) and Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) models, which decompose the variation of CO2 emissions into the influences of population, affluence, and technology. Compared with the former two models, the decomposition results of IPAT and STIRPAT are more easily measured by statistical data and are more convenient for use in policy adjustment. Therefore, we selected the IPAT and STIRPAT models to find the quantitative relationship between CO2 emissions and their influencing factors.

Ehrlich and Holdren (1971, 1972) were the first to advance the IPAT model, known as I=IPAT, to decompose quantitatively human impact on the environment into the factors of population, affluence, and technology. As a follow-up study, Waggoner and Ausubel (2002) further decomposed the T in IPAT into consumption per unit of GDP (C) and impact per unit of consumption (T). Hence, their model was written as I=IPACT and called ImPACT. IPAT, ImPACT, and other similar models have no essential difference; they have been widely used in analyzing energy consumption and economy development (Geoffrey and Hammond, 2004; Ma and Stern, 2008; Saikkku et al., 2008; Feng et al., 2009; Gao et al., 2010; Di et al., 2011). However, as a common premise, the aforementioned models assume that each variable in each scenario. Section 4 provides the summary and conclusions based on the results of the previous sections.

2. Methodologies

2.1. STIRPAT model

In the present study, the STIRPAT equation (Dietz and Rosa, 1994) is written as

\[ I_t = a P_t^b A_t^c T_t^d e_t \]  \hspace{1cm} (1)

where \( I_t \) is the value of CO2 emissions; \( P \) is the population; \( A \) is the annual disposable income per capita; \( T \) is the CO2 emissions per unit of GDP; \( a, b, c, \) and \( d \) are the parameters; \( e \) is the error term; and \( i \) is the \( i \)th sample.

Eq. (1) keeps the multiplicative logic of the IPAT model. By computing the logarithm, it becomes the following form:

\[ \ln I_t = \ln(a) + b \ln P_t + c \ln A_t + d \ln T_t + \ln(e_t) \]  \hspace{1cm} (2)

Compared with Eq. (1), Eq. (2) obtains the parameters more easily; therefore, it is used in the present paper to simulate the relationship between CO2 emissions and economic development factors.

2.2. PLS and outlier test method

The PLS algorithm is selected to obtain the parameters of Eq. (2) to diminish the influence of multicollinearity. Furthermore, the following outlier test method offers many useful experiences of China’s CO2 emission control.

Define the contribution rate of the \( i \)th sample to all components as

\[ T^2_i = \frac{1}{n-1} \sum_{h=1}^{m} \frac{t^2_{ih}}{\text{var}(t_{ih})} \]  \hspace{1cm} (3)

where \( t_{ih} \) is the \( i \)th value in the \( h \)th extracted component (vector) in PLS modeling; \( m \) is the number of extracted components; and \( n \) is the number of samples.

The value \( T^2_i \) reflects the influence of the \( i \)th sample. If it is too large, then the impact of the \( i \)th sample to the regression curve is considerable; the \( i \)th sample is then called an outlier.

To test the outliers, Tracy et al. (1992) constructed an \( F \) test statistic:

\[ \frac{n^2(n-m)}{m(n^2-1)} T^2_i \sim F(m,n-m) \]  \hspace{1cm} (4)

If

\[ T^2_i \geq \frac{m(n^2-1)}{n^2(n-m)} F_{d}(m,n-m) \]  \hspace{1cm} (5)

the \( i \)th sample is considered an outlier at a confidence level of \( 1-\alpha \).

If there are two components (\( m=2 \)), Eq. (3) is written further as follows:

\[ T^2_i = \frac{1}{n-1} \left( \frac{t^2_{1i}}{\text{var}(t_{1i})} + \frac{t^2_{2i}}{\text{var}(t_{2i})} \right) \]  \hspace{1cm} (6)

and Eq. (5) is written as

\[ \frac{t^2_{1i}}{\text{var}(t_{1i})} + \frac{t^2_{2i}}{\text{var}(t_{2i})} \geq \frac{2(n-1)(n^2-1)}{n^2(n-2)} F_{d}(2,n-2) \]  \hspace{1cm} (7)

If the equal sign in Eq. (7) holds true, the boundary line of the outliers is an ellipse. Using \( t_{1i} \) and \( t_{2i} \) as axes, we draw the ellipse and points for each sample on a two-dimensional surface. According to Eq. (7), samples outside the ellipse are considered outliers.

The PLS can obtain the most stable parameters of Eq. (2). As a further development of PLS, the outlier test algorithm can tell us which samples are different from others. Further analyses of these outliers will obtain many effective experiences.

2.3. Grey model

China has maintained a stable population policy since the 1980s. The annual rate of population increase has fallen smoothly in the past few years. The figure of the change rate of population is an exponential decrease curve. There has been no sign that China will significantly change its population policy in the next
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