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Has air pollution emission level in the Beijing–Tianjin–Hebei region peaked?
A panel data analysis

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ABSTRACT

The Beijing–Tianjin–Hebei (BTH) region is one of the important economic centers of China, but it suffers from severe air pollution. Based on the panel pollution-related data of 2013–2017, this research adopted a Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) equation to fit the relationship between pollution emission level and its related socio-economic indicators. The pollution emission level of the BTH region was fitted and projected by using the entropy evaluation method to measure the emission levels, the partial least squares algorithm to estimate the STIRPAT equation parameters, and the hybrid trend extrapolation model to forecast the future development of the above socioeconomic indicators. Empirical analysis showed that the fitting curve to air pollution emission level reached the peak in 2015 and then decreased with a fluctuating and slow process. The air pollution emissions in 2025 will decrease to the level of 2007. With regard to the impacts on the change of the air emission pollution level, industrial waste gas emissions play a decisive role. The influence of soot (dust) emissions is considerably smaller but still larger than that of SO\textsubscript{2} emissions. Besides, the slowing down of the economic development in the future will contribute to air quality improvement. However, the rapid growth of population in Hebei and Tianjin would hinder such improvement. Empirical analysis also implied that governments in this region should specially monitor the operation of building material industries to ensure the steady improvement of air quality.

1. Introduction

Currently, China is facing a serious air pollution issue. The air quality monitoring data show that the average concentration of inhalable particulate matter in China’s 338 largest cities is 3.3 times higher than the standard recommended by the World Health Organization (Greenpeace East Asia, 2019). As many diseases are highly related to the air conditions (Ghaffari et al., 2017; Nikoonahad et al., 2017; Miri et al., 2018a, 2018b), China’s public health is under serious threat.

Among the population and economic centers of China, the Beijing–Tianjin–Hebei (BTH) region ranks third in the size, only smaller than the “Yangtze River Delta” and “Pearl River Delta”. This region, which is located in northern China, has two megacities (Beijing and Tianjin) and 11 large and medium-sized cities belonging to the Hebei Province (State Council, 2014). At present, this region has a population percentage of 8.09% and contributes 9.77% of GDP in China (National Bureau of Statistics, 2018a). In contrast to the other major economic circles, because of the human activities (National Bureau of Statistics, 2018b), this region has more serious air pollution. In 2018, one half of China’s top 10 highly polluted cities are located in this region (Ministry of Ecology Environment, 2019). At one point, China has faced the risk of losing this important economic growth engine.

However, the air quality in the BTH region is improving or at least not further deteriorating in recent years. The concentrations of some types of pollution slowly decreased, and the number of days with good and excellent air conditions gradually increased in most cities (National Bureau of Statistics, 2018a; Ministry of Ecology Environment, 2019). This research aims to provide an in-depth discussion of the following issues: (1) whether this change is the inevitable result of social and economic development or the short-term effect of some environment-related policies and (2) the future developmental trend of the pollution level in this region.

This paper is structured as follows: After the introduction in Section 1, Section 2 reviews the studies related to this research. Section 3 introduces the methodology and data source. Section 4 presents the empirical results, which are then discussed in Section 5. Section 6 summarizes the key findings.

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2. Literature review

2.1. Air pollution in the BTH region

The air pollution issue in the BTH region has attracted the attention of many researchers. Most studies to date focus on three areas.

1) Cause of air pollution. The positive matrix factorization research conducted by Gao et al. (2018) found that PM2.5 pollution in the BTH region was dominated by vehicle and combustion emissions, including coal burning and biomass combustion, and soil and construction dust emissions. Wang et al. (2018a) evaluated the impacts of thermal power plants on air quality in the BTH region. The authors found that these thermal plants contributed 38%, 23%, 23%, 24%, and 24% of CO2, SO2, and NO2 emissions and PM2.5 and PM10 concentrations, respectively. Zhang et al. (2019a) analyzed the causes of haze and described the transport pathways of air pollutants. Yan et al. (2018), Wang et al. (2019a), and Xiao et al. (2020) also performed similar studies. These studies could explain the direct reasons of air pollution and offer technical measures to mitigate pollution emissions. However, the authors neglected the changes of the emission trend and could not present the time and scale of the pollution emission peak.

2) Impacts of air pollution. Chen et al. (2017) used BenMAP, a Windows-based computer program, to estimate the quantitative relationship between PM2.5 concentration and death toll. The authors found that the avoided death count would be in the range of 3,175 to 14,051 when the PM2.5 concentration decreases by 25% and reaches 60 μg/m3. Zhu et al. (2017) used spatial econometric methods to investigate the relationship between SO2 emissions and foreign direct investment. They confirmed the existence of the spatial effect of SO2 emissions. Zhang et al. (2018) used city-level panel data to explore the influence of urban pollution on labor supply. The estimation results indicated that the impact of pollution on labor supply is nonlinear, that is, labor supply first increases and then decreases after the peak is reached as environmental quality deteriorates. These studies evaluated the impacts of air pollution on social economy. However, similar to the above-mentioned studies on the causes of environment pollution, these works did not perform a forecast analysis of pollution emissions.

3) Adjustment directions for developmental policies to mitigate environmental pollution. Xing et al. (2017) used a module of least-cost control strategy optimization to seek the policy directions for attaining the air quality standards at a minimal cost. Li et al. (2019) used a computable general equilibrium model to calculate the cost of air pollution abatement policies. The authors found that the entire BTH region spent 1.4%-2.3% of GDP to support policy implementation and pointed out several directions to reduce the economic cost. Zhang et al. (2019b) developed a segmented equation model to investigate the health benefits of the residential “coal-to-electricity” policy. They found that Beijing obtained the most health benefits, and Hebei bore the highest cost. Similar to the above-mentioned studies, Zhang et al. (2016) and Wang et al. (2019b) also proposed key policy directions of pollution mitigation in the BTH region. The forecasting results in these studies are obtained through a scenario analysis. Specifically, the authors can identify the consequences of certain policies, not the long-term “natural” development result of pollution status.

2.2. Emission peak forecasting

A few studies have concentrated on the forecasting of the developmental trend of pollution emissions in the BTH region. Li et al. (2018) used a support vector machine–extreme learning machine model to forecast energy-related carbon emissions before 2030 in the BTH region. Ma et al. (2019) also performed a similar research. However, energy-related carbon emissions do not directly pollute the local air even though climate change is aggravating. The “near-zero emission” policy of power plants (Wang et al., 2018), clean residential heating (Zhang et al., 2019), and other similar policies have been implemented. Accordingly, carbon and pollutant (e.g., SO2, soot, and industrial waste gas) emissions do not synchronously change in this region. In this case, future pollution emissions cannot be speculated by using the carbon emission curve. Wu et al. (2018) used the improved grey model, a trend extrapolation method, to forecast the air quality before 2025 in the BTH region. The cure of the gray model always presents an increasing/decreasing trend (has no peak). This phenomenon makes this method suitable for short-term forecasting, and cannot predict the emission peak.

The environmental Kuznets curve (EKC) is a feasible idea to forecast pollution emissions. As early as the 1950s, Kuznets (1955) proposed a hypothesis that economic growth first increases and then decreases income inequality as an economy develops. Specifically, the relationship between the two indicators presents an inverted U-shape curve. In 1991, on the basis of the data analysis of many countries, Grossman and Krueger (1991) confirmed that the aforementioned curve also exists in the relationship between economic growth and environmental pollution. This inverted U-shape relationship was then named as EKC by Panayotou (1993) in 1993. EKC analysis has been successfully used in many regions in recent years to forecast pollution emissions (Sinha and Bhattacharya, 2017; Dong et al., 2018; Ding et al., 2019). A segmented quadratic equation is needed to fit the EKC for a precise forecasting of the pollution emission peak. The fitting and forecasting curve of this method is sensitive to the parameter of the quadratic term; thus, large samples belonging to the second stage of the segmented equation are required for parameter estimation (Gao et al., 2015). Collecting enough samples to meet this requirement is difficult in the BTH region, which has complex and changing social economic conditions. Besides, this method only considers the economic development level as the explanatory variable of pollution emissions. Consequently, the reliability of the forecasting results is questioned.

In the early 1970s, Ehrlich and Holdren (1971, 1972) were the first to propose the IPAT model (known as I = PAT) to decompose quantitatively human impact on the environment (I) into various factors, such as population (P), affluence (A), and technology (T). The limitation of IPAT and other similar models is that they assume each factor has the same influence on the decomposed impact. Dietz and Rosa (1994) advanced the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to overcome this limitation. The aforementioned technique has been successfully used to model the nonproportionate impacts of variables on the environment statistically (Rafiq et al., 2017; Liu and Xiao, 2018; Yu and Du, 2019). The present study adopted this idea for the pollution analysis in the BTH region.

Three basic data processing techniques are needed when using the STIRPAT model to forecast the pollution emission level of the BTH region. The first one is the comprehensive evaluation method. STIRPAT analysis needs a variable to reflect the pollution emission level, which is codetermined by several emission indicators. The comprehensive evaluation method measures the pollution emission level by using these indicators. In this research, the entropy evaluation algorithm (Tang et al., 2019) was selected as the comprehensive evaluation method. Compared with the other well-used methods, such as analytic hierarchy process (Ramya and Devadas, 2019) and Likert scale (Kam, 2020), this algorithm emphasizes the impacts of indicators with big changes and needs no human intervention. The other technique is parameter estimation. The logarithmic form of the STIRPAT model is a linear equation. Considering the limited sample used in this research and the existence of multicollinearity, the parameters estimated by ordinary least squares (OLS) algorithm lack stability. This research adopted the partial least squares algorithm (PLS) (Wang, et al., 2005) to estimate the parameters of the above-mentioned equation. A trend extrapolation method for independent variables is needed when using the STIRPAT
model for pollution-level forecasting. The trends of these variables are often obscured in the case of small samples. Hence, this research used a hybrid trend extrapolation model (Meng et al., 2014) for the trend extrapolation of the above-mentioned variables. The advantage of this model is its ability to fit many common (e.g., linear and exponential) trends automatically.

3. Materials and methods

The present study focused on the “natural” development trend of pollution emissions and then revealed the reasons of the current relatively good air conditions. The future pollution status was also forecasted. To carry out this research, the following methods and data were used.

3.1. STIRPAT model

The relationship equation of STIRPAT (Dietz and Rosa, 1994) is written as follows:

\[ I = a \times P^b \times A^c \times T^d + \varepsilon \]  

(1)

where \( I \) represents the emission level of pollutants; \( P \) represents the population size; \( A \) represents the wealth of a country or region; \( T \) represents technological level; \( a, b, c, \) and \( d \) are equation parameters; and \( \varepsilon \) is the fitting error.

Eq. (1) is often written in logarithmic form to facilitate parameter estimation. Specifically,

\[ \ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln \varepsilon \]  

(2)

where \( b, c, \) and \( d \) reflect the elastic relationship between the independent and the dependent variables. Given the linear structure, the OLS and PLS algorithms can directly estimate the model parameters.

3.2. PLS and outlier test method

The PLS algorithm is a feasible method to estimate the parameters of Eq. (2) by using small and multicollinear samples. Let

\[
X = [x_{ij}]_{n \times 3} = \begin{bmatrix} \ln P_1 & \ln A_1 & \ln T_1 \\ \ln P_2 & \ln A_2 & \ln T_2 \\ \vdots & \vdots & \vdots \\ \ln P_n & \ln A_n & \ln T_n \end{bmatrix} 
\]

and

\[
Y = [y_i]_{n \times 1} = [\ln I_1, \ln I_2, \ldots, \ln I_n]^T
\]

(3)

where \( I \) is the sample number (years considered in this research). The first component is extracted by

\[
t_1 = \frac{E_0 E_1^T F_0}{|E_0 F_0|}
\]

(5)

where

\[
E_0 = \left[ x_{ij} - \text{mean}(x_{ij}) \right]_{n \times 3}
\]

(6)

and

\[
F_0 = \left[ y_i - \text{mean}(y) \right]_{n \times 1}
\]

(7)

The residual matrix and vector are written as \( E_1 \) and \( F_1 \), respectively, with \( t_1 \) as the independent variable to explain \( E_0 \) and \( F_0 \). The second component \( t_2 \) is extracted by Eq. (5) by replacing \( E_0 \) and \( F_0 \) with \( E_1 \) and \( F_1 \). Additional components are obtained by using the same method.

The number of components introduced into the final equation is not “the more, the better.” The cross-validity indicator (Wang, et al., 2005) can ascertain the optimal component number. Suppose the \( m \) components are selected to be introduced into the final equation by the cross-validity indicator. The following equation is obtained by the OLS algorithm:

\[
\hat{P}_0 = n_1 t_1 + n_2 t_2 + \ldots + n_m t_m
\]

(8)

The estimated parameters of Eq. (2) can be obtained from Eq. (8) by using the inverse operation of component extraction.

The component extraction process provides that the contribution of the \( i \)th sample to the estimated equation should be written as follows:

\[
T_i^2 = \frac{1}{(I-1)} \sum_{k=1}^{m} \frac{\varepsilon_k^2}{\text{var}(\varepsilon_k)}
\]

(9)

If a sample contribution is large, then this sample should be considered an outlier because it greatly affects the estimated parameters. Tracy et al. (1992) adopted an \( F \) statistic to recognize the outlier. The authors concluded that when

\[
T_i^2 \geq \frac{m(I-1)}{I(I-m)} F_{m, I-m}(m, l-m)
\]

(10)

the \( i \)th sample should be considered an outlier with a confidence of \( 1 - \alpha \). Specifically, when only two components \( m = 2 \) are present, Eq. (11) can be written as follows:

\[
\left( \frac{t_1^2}{s_1^2} + \frac{t_2^2}{s_2^2} \right) \geq \frac{2(l-1)(l-2)}{l(l-1-2)} F_{2, l-2}
\]

(11)

If \( t_1 \) and \( t_2 \) are regarded as two axes, then the border of the outlier is an ellipse. The samples located outside the ellipse are outliers.

3.3. Entropy evaluation algorithm

In Eq. (2), an indicator \( I \) is needed to measure the pollution emission level. In this research, this emission level is the comprehensive evaluation results of the emission data of all considered pollution sources.

The emission proportion of the \( j \)th \((j = 1, 2, \ldots, n) \) pollution source in the \( i \)th year is first calculated.

\[
r_{ij} = \frac{z_{ij}}{\sum_{j=1}^{n} z_{ij}}
\]

(12)

where \( z \) is the pollution emission.

The entropy of the \( j \)th indicator is as follows:

\[
H_j = -\frac{1}{\ln I} \sum_{i=1}^{I} r_{ij} \times \ln r_{ij}
\]

(13)

The evaluation weight of the \( j \)th indicator is as follows:

\[
w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} H_j}
\]

(14)

In this manner, the pollution level of the \( i \)th year is as follows:

\[
P_i = \sum_{j=1}^{n} w_j r_{ij}
\]

(15)

3.4. Hybrid trend extrapolation model

Let \( z_{ij}^{(0)} \) be the observation time series of an independent variable in Eq. (2) \((P, A, \text{or } T)\). This model uses an iterative equation to fit and forecast the trend of this time series. Specifically,
\[
\begin{align*}
\phi_{i+1}^{(0)} &= \lambda_1 \phi_i^{(0)} + \lambda_2 i + \lambda_3 \\
\phi_i^{(1)} &= \phi_i^{(0)} + \lambda_4
\end{align*}
\]

(16)

The parameters of Eq. (16) are estimated by

\[
\Lambda = [\lambda_1 \quad \lambda_2 \quad \lambda_3] = (A' A)^{-1} A' B
\]

(17)

and

\[
\lambda_i = \frac{1}{1 + \sum_{j=1}^{l-1} \lambda_j^3} \left[ \sum_{q=1}^{l-1} g_{i1}^{(q)} - \sum_{q=1}^{l-1} q \lambda_j^{q-1} - \lambda_j \phi_i^{(0)} \right] \lambda_i^{(1)}
\]

(18)

where \( A = \begin{bmatrix} z_1^{(0)} & 1 & 1 \\ z_2^{(0)} & 2 & 1 \\ \vdots & \vdots & \vdots \\ z_{l-1}^{(0)} & l-1 & 1 \end{bmatrix}, \ B = \begin{bmatrix} z_1^{(0)} \\ z_2^{(0)} \\ \vdots \\ z_{l-1}^{(0)} \end{bmatrix} \), and \( z_i^{(1)} = \sum_{q=1}^{l} z_i^{(q)}. \)

3.5. Data selection

Eq. (2) indicates that certain data, such as pollution level (I), population (P), wealth (A), and technological level (T) of the BTH region are needed. In this research, industrial waste gas emissions (unit: trillion meter), SO2 emissions (unit: million tons), and soot emissions (unit: million tons) were selected as the basic indicators used to evaluate the pollution level. These emissions are the major source of air particulates in the BTH region. As most of these particulates are inorganic matter, and normally 10–10 μm across, the health status of population in this region is seriously threatened. These pollution-related data were released by the National Bureau of Statistics (2018b). The population data were selected from the China Statistical Yearbook (National Bureau of Statistics, 2018a). This research used the GDP per capita to reflect the wealth of the BTH region. The GDP data were derived from the Beijing Statistical Yearbook (Beijing Municipal Bureau of Statistics, 2018), Tianjin Statistical Yearbook (Tianjin Municipal Bureau of Statistics, 2018), and Hebei Economic Yearbook (Hebei Provincial Bureau of Statistics, 2018). The price fluctuations can change the GDP values and further affect the fitting and forecasting results; thus, all GDP data were adjusted to real GDP by using the GDP price index (the price index of year 2003 is 1) (National Bureau of Statistics, 2018a). This research used fossil energy intensity (fossil energy consumption per unit of real GDP) to measure the technological level.

At the end of year 2002, China implemented market-oriented reforms to its electric power industry. Accordingly, the energy market greatly changed in the next year. Considering that the latest available data are from 2017, the timespan of sample collection covered 2003–2017. Table 1 lists the aforementioned data used in this research.

4. Results

4.1. Pollution emission level

The emission data in Table 1 were first preprocessed using Eq. (12) to measure the pollution emission level of each year. Thereafter, the entropy evaluation weight of each indicator was obtained using Eqs. (13) and (14). The calculation results manifested that the weights of industrial waste gas, SO2, and soot (dust) emissions are 0.691, 0.109, and 0.200, respectively. The pollution emission level of each year was obtained through Eq. (15) by using these weights and the preprocessed emission data. Table 2 lists the results.

The contribution of each indicator to the pollution emission level for each year was calculated using the evaluation weights and the preprocessed emission data listed in Table 2. Fig. 1 shows these results.

4.2. Relationship fitting equation

Data in Tables 1 and 2 were used to construct the independent matrix X and dependent vector Y to estimate the parameters of Eq. (2). The components were then extracted one by one by using Eq. (5).
Table 3 illustrates the first three components and their cross-validity results to ascertain the optimal component number (Wang, et al., 2005).

The values of cross-validity decrease one by one, and the one larger than 0.0975 is the criterion that a component should be introduced into the final equation (Wang, et al., 2005). Accordingly, the parameters of Eq. (2) were calculated using $t_1$ and $t_2$. The estimated equation is as follows:

$$
\ln I = -9.409 + 1.314 \ln P + 0.963 \ln A + 0.865 \ln T
$$

(19)

where $I$ is the fitting result to the pollution emission level and hence has no unit. The units of $P$, $A$, and $T$ are million, million yuan per capita, and ton standard coal equivalent per million yuan, respectively.

Table 3 shows that two components are enough for the parameter estimation of Eq. (2). The outlier distributions for different confidence levels are drawn in Fig. 2, with $t_1$ and $t_2$ as two axes.

4.3. Trend fitting for the basic indicators

Eq. (16) was used for the trend fitting of population, real GDP, and fossil energy consumption based on the statistics listed in Table 1. This task is performed to forecast the pollution emission level of the BTH region by using Eq. (19). After the parameter estimation process was introduced in Eqs. (17) and (18), the results listed in Table 4 were obtained.

The fitting and forecasting results of population, real GDP, and fossil energy consumption were calculated by using the estimated parameters listed in Table 4 for Eq. (16). Considering that social and economic development has large uncertainty, this research only forecasted the developmental results of the above-mentioned indicators before 2025.

These results indicated that the fitting and forecasting results of pollution emission level were also obtained using Eq. (19). Fig. 3 shows the forecasting results of population (million), real GDP (trillion yuan), fossil energy consumption (million tons of standard coal equivalent), and air pollution emission level.

5. Discussion

5.1. Pollution emission level decomposition

Fig. 1 demonstrates that industrial waste gas emissions have always played a decisive role during the changes of the pollution emission level. This notion implies that a major policy direction to mitigate air pollution in the BTH region is to reduce industrial waste gas emissions. Compared with this emission indicator, the impact of soot (dust) emissions is significantly smaller but still larger than that of $SO_2$ emissions. In fact, according to Table 1, different the other two pollution emission indicators, $SO_2$ emissions in this region presents a decreasing trend. This result is mainly because of the adjustment of energy consumption structure (decrease of coal share), popularization of desulfurization equipment (especially for the coal-fired units), and limitation to some heavily-polluting industries (cutting backward capacity of steel, cement, and some other enterprises).

Fig. 1 also shows that the pollution emission levels of years 2008 and 2012 are lower than those of their neighbors. The relatively less pollution emissions in year 2008 can be explained by some temporary policies implemented to support the Olympic Games in Beijing. The Chinese government regarded this event as a unique opportunity to showcase the image of the nation. Thus, many measures were taken in the BTH region to mitigate the air pollution in 2008. For instance, the

| Component | Vector | Cross-validity |
|-----------|--------|---------------|
| $t_1$     | $[-3.45, -2.8, -1.38, -0.99, -0.54, -0.23, 0.06, 0.73, 1.37, 1.42, 1.42, 1.21, 1.09, 1.09, 0.99]^T$ | - |
| $t_2$     | $[0.67, 0.76, -0.67, -0.84, -0.89, -0.39, -0.59, -0.51, -0.5, -0.16, 0.17, 0.57, 0.66, 0.77, 0.95]^T$ | 0.110 |
| $t_3$     | $[0.28, -0.48, -0.05, 0.17, 0.16, -0.33, 0.21, 0.24, -0.19, -0.26, -0.28, -0.13, 0.21, 0.23, 0.24]^T$ | -0.511 |
odd–even rule was initiated to reduce vehicle exhaust. Vehicles with license plates ending in odd numbers were banned from the roads on even-numbered calendar days, and those with plates ending in even numbers were banned from the roads on odd-numbered days (Wang et al., 2009). Industrial production was also controlled to improve air quality. The top 10 heavily polluting industrial factories were shut down. Environmental inspection activities were frequently conducted in energy-intensive companies. The Chinese government mandated that the construction projects should reduce the dust.

The changes of the building material production greatly contributed to the improvement of the air conditions in year 2012. The BTH region, especially the Hebei Province, is one of the important building material bases of China. In the early 2010s, the production of rolled steel and cement in Hebei Province accounted for 21.70% and 5.92% of the country’s total production average, respectively (Hebei Provincial Bureau of Statistics, 2018; National Bureau of Statistics, 2018a). The steel and cement industries are important air pollution sources and greatly responsible for the haze in this region (Fan et al., 2019). In 2012, numerous products backlogged, and the price continuously declined because of the overcapacity of the cement industry and the relative recession of the construction industry. In this year, the profits of the entire industry reduced by greater than 40%. The cement production of Hebei Province decreased from 140.93 (2011) to 128.10 million tons (2012), with a decrease rate of 9.10% due to this macroenvironment (Hebei Provincial Bureau of Statistics, 2018). The steel industry, which produces another major building material, also suffered. The growth speed of most steel-related products slowed down in year 2012.

The above-mentioned change of the production situation induced less pollution emissions and then led to relatively enhanced air conditions. The high pollution emission level after 2013 can be mainly explained by the recovery of the above-mentioned building material industries. Hebei is presently implementing the plan of cutting capacity in six industries, namely, steel, cement, plate glass, coal, coke, and thermal power (State Council, 2019). The air quality of the BTH region is expected to improve in the near future due to these measures.

5.2. Outlier analysis

The figure presents that 2003 and 2004 are considered outliers with a confidence of 80%. When the confidence decreases to 60%, 2017 also becomes an outlier, and 2006 nears the border of the outlier.

At the end of 2002, severe acute respiratory syndrome broke out in China. The epidemic situations reached a peak in the middle of year 2003, and its reverberations lasted until the next year. The BTH region, which was the hard-hit area, implemented strict measures to prevent the spread of the epidemic. Schools, shopping malls, and some factories were temporarily closed. The transportation and tourist industries were badly hit. At that time, the ways of production and living were greatly changed and then rendered the positions of these two samples outside the ellipse.

As previously introduced, the BTH region develops large-scale building material industries, especially steel production in Hebei Province. During 2005–2007, with the rapid development of China’s real estate and infrastructure projects, these industries were prosperous. In 2006, Hebei produced 18.06% of China’s rolled steel. However, this share accounted for only 15.81% in 2004 (Hebei Provincial Bureau of Statistics, 2018; National Bureau of Statistics, 2018a). The abnormal development of building material industries in 2006 consumed a large amount of fossil energy, emitted substantial pollutants, and made the location of that year near the border of the outlier.

The outlier of 2017 can be explained by the closing down of backward production facilities. There were once many small steel and cement factories in the BTH region. Because of the outdated technology and lacking pollution-control devices, most of these factories are illegal, and their emitted pollutants are not recorded in the statistics. To

| Table 4 |
|-----------------|-----------------|
| Indicator       | Estimated parameters $\lambda_1$–$\lambda_4$ |
| Population      | $[0.964, 0.010, 5.010, -0.035]$ |
| Real GDP        | $[0.919, -0.005, 0.266, -0.005]$ |
| Fossil energy consumption | $[0.932, -2.189, 49.560, -0.695]$ |

When using these parameters for trend fitting, $i = 1$ in Eq. (16) refers to year 2003.
mitigate the environment pollution, governments in the BTH region closed many of them and replaced with large and legal factories. As a result, the pollution emission level in this period is higher than the expectation and year 2017 is identified as an outlier (Fig. 2).

5.3. Pollution forecasting analysis

Fig. 3(a) shows that the growth trend of population in the BTH region closes to a linear curve. Specifically, the growth rate of population in this region gradually decreases. However, the future population growth rate in the BTH region is still expected to be higher than the mean level of that of the country because of the population conditions. During the time span of this research (2003–2017), the population growth rate of China is 7.57%. For the BTH region, this indicator is as high as 21.78%, and Beijing, Tianjin, Hebei are 49.11%, 54.01%, and 11.09%, respectively (National Bureau of Statistics, 2018a). Affected by the strict population-limitation and non-capital function alleviation policies, Beijing's population scale is expected to remain stable in the future (Tong et al., 2020). Different from Beijing, Tianjin is encouraging the population immigration and trying to prosper its economy by this (Shi, 2019). As to Hebei, benefit from the “universal two-child” policy (Zeng and Hesketh, 2016), it population is growing rapidly. As a result, the population in the BTH region will further increase faster than the country’s level, although its growth rate will slow down. Eq. (19) indicates that pollution emissions in the BTH region is very sensitive to the population growth. Compare with other regions in China, population factor will be a more important driver for the pollution emission growth. Accordingly, controlling population growth is a major policy direction in the BTH region to mitigate air pollution.

In contrast to the curves of population, those of real GDP and fossil energy consumption reach a peak and then decrease during 2003–2025. Specifically, the curve of real GDP increases to 2.32 trillion yuan in 2017 and then slowly decreases. Fossil energy consumption reaches a peak in 2014 and then decreases with a steep trend. Given this, the improvement of air quality in the BTH region is attributed to the reduction in fossil energy use. This is obviously the immediate cause. Besides, the slowing down of economic development also contributes to air quality improvement.

Fig. 3(d) shows that the fitting curve of pollution emission level reaches a peak in 2015 and then gradually decreases. The economic transformation is a slow process, and the unexpected changes in social and policy conditions affect pollution emissions. Accordingly, the future decrease will present a fluctuating and slow trend. Generally, the pollution emissions will decrease to the level of 2007 in 2025. This notion implies that the recent improvement of air quality is the inevitable result of social and economic development, not the short-term effect of some environment-related policies.
6. Conclusion

In this research, a STIRPAT model was used to fit and forecast the air pollution emissions in the BTH region. By using the entropy evaluation method to measure the pollution emission level, the PLS algorithm to estimate the STIRPAT equation parameters, and the hybrid trend extrapolation equations to forecast the STIRPAT explanatory variables, the following conclusions were drawn:

(1). Fitting curve to pollution emission trend in the BTH region reached a peak in 2015 and then decreased in a fluctuating and slow process. This implies that the recent improvement of air quality is the inevitable result of social and economic development, not the short-term effect of some environment-related policies. The pollution emissions in 2025 will decrease to the level of 2007.

(2). Industrial waste gas emissions have always played a decisive role during the changes of the pollution emission level. The impact of soot (dust) emissions is significantly smaller but still larger than that of the SO2 emissions. The contribution shares are 69.07%, 19.99%, and 10.94%.

(3). The slowing down of the economic development in the future will contribute to air quality improvement. However, the rapid growth of population in Hebei and Tianjin would hinder such improvement.

(4). The development of building material industries, especially the steel and cement sectors in Hebei Province, should be monitored to ensure the steady improvement of air quality.

CRediT authorship contribution statement

Ming Meng: Conceptualization, Methodology, Software, Writing - review & editing. Jin Zhou: Data curation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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