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Research article

Exploring the effect of economic and environment factors on PM2.5 concentration: A case study of the Beijing-Tianjin-Hebei region

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ABSTRACT

Air pollution, especially haze pollution is a serious environment problem that directly affects the sustainable development in China. Identifying the key factors affecting PM2.5 concentration and the interaction mechanism between them through quantitative analysis can greatly help a city devise PM2.5 pollution control strategy. Using the geographical detector model, we quantitative measured 13 cities in the Beijing-Tianjin-Hebei region's social factors and their interaction impacts on PM2.5 concentration in 2016. In the analysis process, factor analysis method is used to separate the factors preliminary. According to the results, the factors mainly divided into two categories, i.e. economic factor and environment factor. R&D ranks top in the studied cities in terms of factor detection results, presenting closely relationship between PM2.5 concentration and R&D. We also find the interaction between any two factors all enhance impact on PM2.5 concentration than any one alone. This study provided a scientific basic and guidance for measure the driving degree of social factors and their interaction effects.

1. Introduction

In recent years, China's economy and urbanization developed rapidly, and the achievements at the expense of the environment finally paid a painful price. Regional air pollution dominated by PM2.5 has become the most urgent and prominent environment problem in China (Zhou et al., 2016; Lelieveld and Fnais, 2015; Zhu et al., 2019; Zhang et al., 2020a, 2020b). Serious air pollution has aroused attentions at domestic and board largely. The main sources of PM2.5 are coal-fired power generation, industrial production, automobile exhaust, human activities. All of them discharge harmful factors and compounds enriched in particulate matter, which threaten air quality and atmospheric visibility. In 2013, the northern cities suffered severe haze pollution, disrupting the normal life of more than 80 million people, causing flight delays, highway closures, and serious respiratory diseases. Haze pollution is most severe in the Beijing-Tianjin-Hebei region (Wang et al., 2014; Song et al., 2020). According to the China Environmental Bulletin, air pollution representing with PM2.5 as the main pollutant accounts for 60% of the total pollution days (J.N Song et al., 2019). Therefore, controlling PM2.5 concentration is important for China to coordinate the contradiction between economic development and environmental pollution (Wang et al., 2014).

There are many factors related to air pollution, and only accurate understand the key factors can be targeted to provide a scientific basis for the treatment policy. The driving factors of PM2.5 concentration can be roughly divided into natural factors and social factors. Natural factors such as topography, wind speed and precipitation will affect the aggregation, transfer and diffusion of PM2.5, while PM2.5 pollution are formed by the emissions from the social factors (Ma et al., 2016). For the driving social factors of air pollution, domestic and foreign scholars mainly focus on urbanization and economic development. As for urbanization, some scholars think it can aggravate the air pollution. American environmental economist Grossman and Krueger (1995) used econometric methods proposed the hypothesis of Environmental Kuznets Curve (EKC), verifying the evolution rule of ecological environment quality in an inverted "U" shape along with urbanization with panel data of 42 developed cities. Wang et al. (2015) quantitatively measured the interaction between urbanization and ecological environment in Beijing-Tianjin-Hebei region by using physical coupling model, and obtained that population urbanization is one of the major factors

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influencing urbanization subsystem and ecological environment subsystem respectively. Yang and Zhang (2018) constructed a comprehensive index evaluation system in Beijing-Tianjin-Hebei region. Through this model companied with impulse response and variance analysis, they concluded the dynamic relationship between indexes. Han et al. (2014) used satellite data to study the impact of urbanization on urban PM2.5 concentrations. Their results indicated that there is a strong correlation between urban population and urban PM2.5 concentration. However, diametrically opposite view also existed. Based on the EKC (Environmental Kuznets Curve) theory and the BMA (Bayesian Mean Model) method, Lin and Zhu used cross-sectional data from 282 cities to find that the higher the urbanization level, the lower the concentration of urban air pollutants. Wang and Zhao (2018) also found that urbanization can slow down air pollution.

He et al. (2016) used EKC, with the panel data of 30 provinces and cities in China eastern region from 2001 to 2012, to study the relationship between air pollution and economic growth. Ma and Zhang and Li (2017) established a spatial environment Kuznets curve regression model and found that as GDP per capita continues to grow, pollution levels continue to rise. Zhou et al. (2018) used spatial regression and geographical detector technology to study the impact of economic and social development on China's urban PM2.5, found that their impact on PM2.5 concentration prominent. Zhang et al. (2019) used the log-mean index (LMDI) method to determine the key driving factors of PM2.5 concentration in 152 cities in eastern, central and western China. Studies have shown that economic output is one of the most important factors affect the change of PM2.5 concentration.

Tang et al. (2016) found that there is a significant positive correlation between FDI (Foreign Direct Investment) and haze pollution in China, with FDI increasing by 1% and China's haze pollution increasing by 0.0235%. However, Jiang et al. (2016) used the urban dataset of 150 Chinese cities in 2014 through the spatial econometric model to study the impact of foreign direct investment on China's air quality, and found that FDI improved China's air quality. There is also some research focus on technological innovation. Ehrlich and Holdren (1971) proposed an IPAT model, arguing that technological advances can slow down environmental pollution. Avik Sinha et al. (2019) used the Kuznets curve to analyze the relationship between environmental degradation and technological progress, and proposed sustainable development measures based on the analysis results.

In terms of research methods, IDA (Index Decomposition Analysis) and SDA (Structure Decomposition Analysis) are two common model used to energy demand、energy intensity and carbon emission driving factor decomposition. Guan et al. used a structure decomposition analysis (SDA) method to study the impact of socioeconomic drivers on China's primary PM2.5 emissions. Wei and Ma (2015) constructed a computable general equilibrium model to study the optimal policy for energy structure adjustment and haze governance in China. Leng et al. (2015) used typical metrological analysis methods to study the effect of foreign direct investment on haze pollution. Compared to them, the method used in this paper have some significant advantages. First, no assumption or restriction is required with respect to dependent and independent variables. Second, it can examine the interactive influence of two independent variables on dependent variable (Zhang and Zhao, 2018). According to the analysis results, we could know that whether two driving factors were independent in influencing PM2.5 concentration, whether they enhanced or weakened one another when taken together.

Many previous studies have rarely studied the effects of social factors and their interactions on PM2.5 concentration specially. Social factors are the formation factors of PM2.5, their impact on PM.5 concentration is the most critical (Ma et al., 2016; Ding et al., 2019a, 2019b). This paper selected 13 cities in the Beijing-Tianjin-Hebei region as the research area, taking PM2.5 concentration as the research object. We select per GDP energy consumption, AFI, GDP per capita, per capita consumption expenditure, urbanization rate, and R&D full-time equivalent of industrial enterprises above designated size as research factors. Factor analysis method separates the factors into two categories preliminary. The data is superimposed and discretized by ArcGIS technology, and then the geographic detector software is used to quantitatively analyze the contribution and interaction of each factors under the two categories. Finally, based on the research results, scientific and reasonable PM2.5 concentration control measures are proposed. The research is beneficial to quantitatively understand the influence of social factors of PM2.5 concentration in Beijing-Tianjin-Hebei region and its interaction mechanism.

2. Methods

2.1. Selection of social factors

Previous studies have shown that various social factors have different effects on PM2.5 concentration changes (Bai et al., 2019). Social factors are interrelated, which will have a coupling effect on PM2.5 concentration changes. Coupling, as a physics concept, refers to the phenomenon that two (or more than two) systems or forms of motion interact with each other through various interactions (Zhou, 2003).

The social factors affecting the concentration of PM2.5 are numerous and complex. In this study, the selection of an indicator is made against the following considerations: (I) The indicator should be relevant to the corresponding theme. (II) The indicator can be measured by the available data. (III) The selected indicators should avoid overlapping, double-counting and correlation between indicators. Drawing on the existing research results and considering the availability of data, energy consumption per unit of GDP (PGDP), Actual use of foreign investment (AFI), GDP per capita (AGDP), per capita consumption expenditure (AE), urbanization rate (UR), forest coverage (FP), and R&D full-time equivalent (RT) are chosen to be the research objects of social factors. The energy consumption per unit of GDP in social factors reflects the energy utilization of economic development (Zhang, 2008). The Actual use of foreign investment reflects the degree of trade openness. The GDP per capita reflects the economic growth (Li and Huang, 2018). The per capita consumption expenditure reflects the consumption of the residents (Song et al., 2019). The urbanization rate reflects the urbanization situation. Forest coverage reflects the state of the ecological environment (Yang and Zhang, 2018). Researchers' full-time equivalents reflect the state of science and technology development (Yuan and Zhang, 2019).

2.1.1. Energy consumption per unit of GDP

Energy consumption per unit of GDP is used to measure energy consumption condition. In the current stage of development, the Chinese economy reflects relatively obvious industrial characteristics, making it consume more energy per unit of GDP production. Energy consumption per unit of GDP is also an important indicator reflecting energy efficiency (Lin and Liu, 2010). Reducing energy consumption per unit of GDP and improving energy efficiency to avoid energy waste is conducive to sustainable development.

2.1.2. Actual use of foreign investment

Here we use the Actual use of foreign investment to measure trade openness (Zhang and Li.,2017). Hao et al. have found that FDI is one of the important explanatory variables. Among the existing research results, FDI has two opposing theories on the direction of environmental pollution. The "pollution halo" hypothesis believed that FDI can improve environmental pollution through advanced technology (e.g., Hoffmann et al., 2005; He, 2016). The "pollution haven" hypothesis believed that FDI will bring the transfer of high-pollution industries and increase environmental pollution (e.g., Keller and Levinson,2002; Eskeland and Harrison, 2003).

2.1.3. GDP per capita

GDP per capita is an indicator represents the level of economic development. According to previous research, GDP per capita is an important indicator affecting environmental quality (Li et al., 2016). GDP per capita can represent the stage of economic development in which an economy is roughly located, while different stages of economic development mean different characteristics of energy consumption (Lin and Liu, 2010). The level of GDP per capita is an important factor affecting haze, and it is also the focus of scholars' research.

2.1.4. Per capita consumption expenditure

Per capita consumption expenditures reflect residents' consumption condition. Previous studies have found that PM2.5 concentrations are higher in cities with higher consumption levels, because the higher the consumption level, the more household cars and household appliances are in the area (Jiang et al., 2016). As a result, the atmosphere suffers a lot of pollution. Vries and Ferrarini found that rising level of domestic consumption are related to air pollution in both advanced and emerging economies. Compared with GDP per capita, per capita consumption expenditure reflects the impact of people's use of household appliances in their daily lives to environment. While GDP per capita reflects the impact of the production of household appliances to environment.

2.1.5. Urbanization rate

The urbanization rate can reflect the process of urbanization. The results of Wang et al. (2015) showed that there is an extremely complex interaction relationship between urbanization and ecological environment. Since 1980, the coordination degree of urbanization and ecological environment in Beijing-Tianjin-Hebei region changed as S-shaped curve, and the coordination type transferred from serious uncoordinated-urbanization hindered development to advanced coordination - ecological environment lag type (Wang et al., 2015). At present, China's population is highly mobile, and there is a big gap between the registered and resident population (Yang et al., 2015). Due to polluted gas emissions are closely related to local social, economic and energy activities, estimation of urbanization rate should use the resident population, instead of the registered population.

2.1.6. Forest coverage

Forest coverage reflects the ecological environment of the city. Ji et al. (2013) showed that plant absorption is an effective way to purify air for it has a significant effect on reducing atmospheric particulate matter and improving air quality. When the forest coverage rate increases, the block adsorption capacity of particulate matter is also enhanced.

2.1.7. R&D full-time equivalent of industrial enterprise above designed size

R&D full-time equivalent of industrial enterprise above designed size can reflect technological developments in industrial enterprises. The innovation of energy saving and emission reduction technology is undoubtedly an important way to control environmental pollution. Avik et al. (2020) stressed on the need to use modern technology to achieve its objectives. Zhou et al. analyzed the inter-provincial panel data of China from 1995 to 2012 and found that the development of science and technology is of great significance to the mitigation of pollution.

From Fig. 1, we can see that the R&D full-time equivalent of industrial enterprise above designed size in 2016 have big difference. The Tianjin has the biggest invest in technology among enterprises, Beijing followed it. Remaining 11 cities in Hebei province also exist big differences. Shijiazhuang up to 20745 man-years while Zhangjiakou as low as 1269 man-years.

2.2. Research area

This paper selects the Beijing-Tianjin-Hebei region as the research area, because this region is a developed area of China's heavy industry, the most typical and serious area of extreme air pollution. The results of Shao et al. showed that the Beijing-Tianjin-Hebei region is the core area of the PM2.5 high-emission "club" and can be regarded as the "main battlefield". As the economic and political center of the country, serious air pollution has become a shackle to the rapid economic and social development of the region, and the control of PM2.5 concentration in air pollutants has become a top priority. The short-term behavior of "slogan and sport" cannot effectively control the increase of PM2.5 and the occurrence of haze weather. Joint prevention and control measures in the Beijing-Tianjin-Hebei region are imperative. It is necessary to make long-term unremitting efforts to fundamentally solve the problem of regional environmental pollution and maintain the sustainable development of society (Wang et al., 2014). Therefore, it is obvious to study the factors affecting the concentration of PM2.5 and the interaction between them is of great significance to the healthy development of the Beijing-Tianjin-Hebei region in the future.

As shown in Fig. 2, the annual average PM2.5 concentration of 9 cities in the 13 chosen cities are higher than the national average concentration with 47 μg/m^3. The annual average PM2.5 concentration in Hengshui, Cangzhou, Tianjin, Langfang are more than 70 μg/m^3 (see Fig. 3).

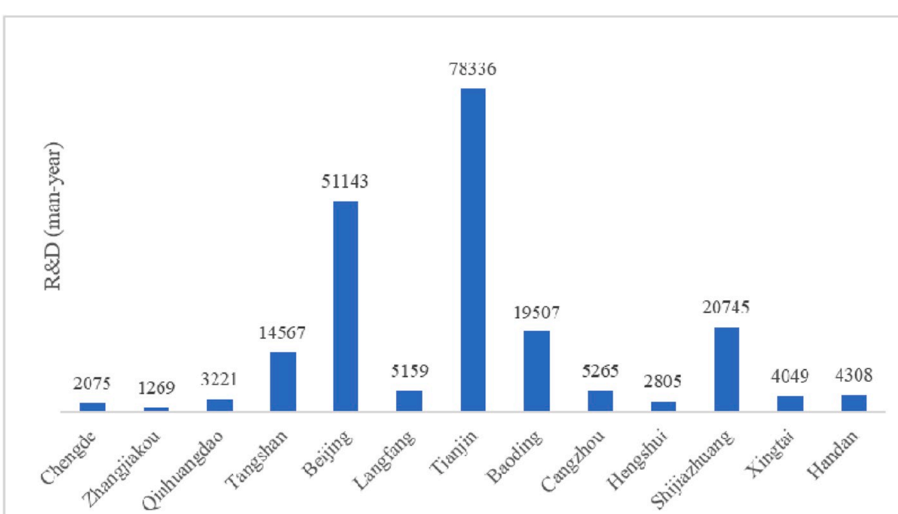

Fig. 1. R&D full-time equivalent of industrial enterprise above designed size in 2016.

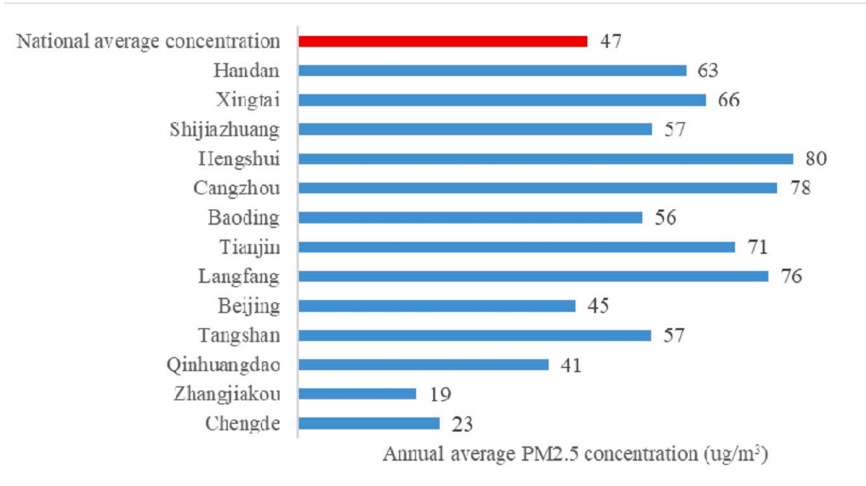

Fig. 2. Annual average PM2.5 concentration in Beijing-Tianjin-Hebei cities in 2016.

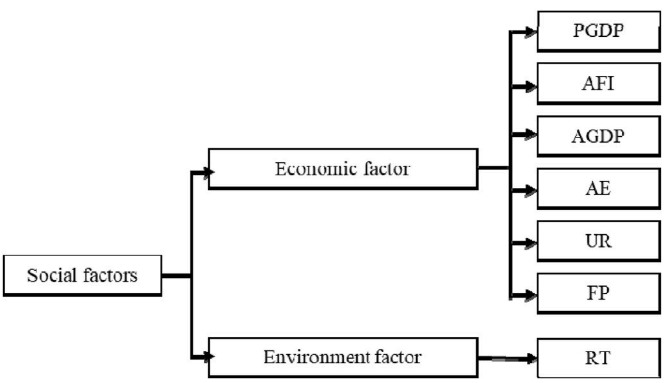

Fig. 3. Factor analysis results.

2.3. Data and data sources

The selection factors are shown in Table 1. All data are from China Statistical Yearbook, Hebei Economic Yearbook, Beijing Statistical Yearbook, Tianjin Statistical Yearbook and related city statistical yearbooks. PM2.5 concentration data was obtained from CNEC's Urban Air Quality Monitoring Station and all data were from 2016 (see Table 2).

2.4. Factor analysis

The basic idea of factor analysis is to synthesize the original variables into common factors and special factors. The number of factors less than the number of original variables, and then the original variables are explained by factors. Usually we set $X = (x_1, \cdots, x_p)^{'}$ to be an observable

Table 1
Summary statistics of variables.

Number	Factors	Unit	Symbols
X1	Energy consumption per unit of GDP	Tons of standard coal	PGDP
X2	Actual use of foreign investment	Ten thousand dollars	AFI
X3	GDP per capita	yuan	AGDP
X4	Per capita consumption expenditure	yuan	AE
X5	Urbanization rate	%	UR
X6	Forest coverage	%	FP
X7	R&D full-time equivalent of industrial enterprises above designated size	Man-year	R&D

Table 2
Interaction categories of two factors and the interaction relationship.

Description	Interaction
$q(X1 \cap X2) < Min(q(X1), q(X2))$	Weaken; univariate
$Min(q(X1), q(X2)) < q(X1 \cap X2) < Max(q(X1), q(X2))$	Weaken; univariate
$q(X1 \cap X2) > Max(q(X1), q(X2))$	Enhance, bivariate
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinearly enhance

random vector. For decoupling index, $E(x) = \mu$, The common factor vector $F = (F_1, \cdots, F_m)^{'}$ is an unobservable random vector. $E(F) = 0$, $D(F) = I_m$, Special factor vector $\varepsilon = (\varepsilon_1, \cdots, \varepsilon_p)^{'}$, $E(\varepsilon) = 0$, $D(\varepsilon) = diag(\sigma_1^2, \cdots, \sigma_p^2) \overset{def}{\Rightarrow} D$ (diagonal matrix), Common factors and special factors are not related. The orthogonal factor model is:

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + \varepsilon_1, \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + \varepsilon_2, \\ \cdots\cdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}X_m + \varepsilon_p, \end{cases} \tag{1}$$

Where F indicates a common factor and $\varepsilon$is a special factor.

The common factor $F_1, \cdots, F_m$generally works for every component X_i, while the special factor ε_i only works for a specific X_i. Not related between common factors and between common and special factors. The matrix $A = (a_{ij})_{p \times m}$in the model is a matrix of coefficients to be estimated, called the factor load matrix.

2.5. Geographical detector method

The geographical detector method is a novel spatial statistical analysis method developed by Wang et al. (2010), which can be used to study the spatial differentiation of the dominant driving factors and the interaction between factors. The basic principle of the geographical detector method is that the study area is divided into several sub-areas. If the sum of the variances of the sub-areas is smaller than the total variance of the area, the area is considered to have spatial differentiation. If the spatial distribution of the two subjects tends to be consistent, the statistical correlation is considered to exist (Wang and Xu, 2017). The q statistic can be used to measure the extent of a factor explains the interpreted variable. The statistic q value of the interaction factor can reflect the degree of interpretation of the interpretative variable by the interaction of the factors. The geographical detector consists of four detectors: the factor detector, the interaction detector, the risk detector, and the ecological detector. This paper mainly uses factor detector and interaction detector.

The method can be applied in different fields such as natural sciences, social sciences, and environmental pollution. It does not require linear assumptions, has an elegant form, and has clear meanings. It is an extension of the traditional cross-interaction measurement model. Before using the geographical detector method, the data should be discretized. The grid-based and spatial superposition analysis of the data requires the use of professional spatial analysis software such as ArcGIS10.3.

2.5.1. Factor detector

The factor detector quantifies the effect of the selection factor on the interpreted variable through the $q$statistic (Wang et al., 2010).

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{2}$$

Where $h(1, \cdots, L)$ is the number of subregions of factor X; N represents the total number of spatial units (in this study, cities) over the entire study area; N_h represents the number of samples in subregion h; $\sigma$and σ_h represents the total variance and variance of samples in subregion h, respectively.

The value of q is in the range [0,1]. The greater the value of q, the stronger the explanatory power of the factors.

2.5.2. Interaction detector

Interaction detector is used to detect whether the interpretation enhanced or weakened when the two factors are combined, or the interpretation of these factors is independent of each other. Calculate the values of the two factors X1 and X2 for PM2.5 concentration separately. Compare the values of $q(X1)$ and $q(X2)$ with the interaction value of $q(X1 \cap X2)$. The comparison results can be divided into five categories.

3. Analysis and conclusion

3.1. Factor analysis results

From the test results in Table 3, the assumption that the variables are independent of each other can be rejected, that is, there is a strong correlation between the variables. From the obtained KMO value of 0.696, it is suitable to use the factor analysis model to explore and analyze the impact factor.

From Tables 4 and 5, among the 7 variables, we can see that the characteristic roots of the first two factors$F_1$and F_2 are more than 1. The highest feature root is $F_1$with 4.623, followed by $F_2$with 1.097. The cumulative variance contribution rate of the first two factors is 81.71%, indicating that the explanatory power of the basic model is sufficient. The variance contribution rates of F_1 and F_2 are 66.04% and 15.67% respectively, and the influence of the latter factors gradually decreases, so it is appropriate to select two factors.

Extraction method: principal component analysis.

Rotation method: varimax with Kaiser normalization.

Table 6 show the energy consumption per unit of GDP (−0.755), actual utilized foreign capital (0.864), GDP per capita (0.778), per capita consumption expenditure (0.962), urban population share (0.911), and R&D full-time equivalent (0.756) has a higher load onF_1 , so it is named as economic factor. F_2 has a higher load on forest coverage (0.96), which is named as environment factor.

From the factor analysis, selected factors mainly cover economic and environment two aspects. This gives us a clearer understanding of the research objects.

Table 3
KMO and Bartlett sphericity test.

KMO sampling suitability measure	Bartlett sphericity test		
	Approximate chi-square distribution	df	Sig.
0.696	81.274	21	.000

3.2. Geographical detector analysis results

3.2.1. Factor detection results

The results of the factor detector showed that the effects of economic factors on the concentration of PM2.5 in Beijing-Tianjin-Hebei were: R&D full-time equivalent (0.646), energy consumption per unit of GDP (0.456), GDP per capita (0.299), urban population share (0.269), per capita consumption expenditure (0.267), Actual use of foreign investment (0.167). The impact of forest cover on eco-environmental factors is (0.556).

From the results, it can be seen R&D full-time equivalent of industrial enterprise above designed size of the economic factor has the greatest influence on the PM2.5 concentration. It reflects the increasingly significant effect of the technological development level on the environment, also means that the role technology played in controlling the PM2.5 concentration process is very important. The Beijing-Tianjin-Hebei region is a developed area of science and technology. Science and technology as the primary productive force should be the first impetus to protect the environment. The fundamental way to solve environmental problems such as air pollution lies in the advancement of science and technology (Cheng, 1989) . Environmental problems are accompanied by advances in science and technology, and they also need to be addressed through advances in science and technology. The fundamental reason for the low utilization of resources and energy in China is that science and technology are not advanced. Therefore, technological advancement makes it possible for enterprises to adopt clean production technology to produce less pollutants. It is extremely necessary to rely on science and technology as the focus of the entire environmental protection work and to develop environmental protection industries.

The Beijing-Tianjin-Hebei region is an industrially developed area, and pollutant emissions have always remained at a high level. The energy consumption per unit of GDP ranks second among the economic factors affecting the concentration of PM2.5. It reflects the impact of economic development energy consumption on the concentration of PM2.5 is significant. The higher the energy consumption per unit of GDP, the more energy is wasted, resulting in a large amount of valuable energy not being converted into energy required for production, but discharged into the atmosphere in the form of harmful substances such as smoke and carcinogens to increase air pollution. The scale of China's economic development has been expanding at a rapid rate of nearly 10%, and the consumption level of fossils has been rising. Adjusting the industrial structure and transforming the industrial development mode is not only the starting point for the future reduction of energy consumption per unit of GDP in the Beijing-Tianjin-Hebei region, but also the key to control the PM2.5 concentration.

The GDP per capita of economic factors is also an important factor, which reflects the impact of economic development on PM2.5 concentration. The high-input, high-pollution economic development model in the Beijing-Tianjin-Hebei region has brought high GDP while also paying a painful environmental cost. Economic development at the expense of the environment is not advisable. The road of sustainable development is the only way. The influence of the Urbanization rate on the change of PM2.5 concentration should not be ignored. On the one hand, the rapid advancement of urbanization has brought about the accumulation of capital, labor, technology and other factors and the increase in consumer demand, which has promoted the development of production and economic growth, also brought about an increase in environmental protection investment. On the other hand, urbanization is accompanied by an increase in the rigidity of energy consumption demand, which has led to rapid growth in energy consumption and

Table 4
Total variance explained by principal component analysis (1).

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative%	Total	%of variance	Cumulative%
1	4.623	66.041	66.041	4.623	66.041	66.041
2	1.097	15.669	81.710	1.097	15.669	81.710
3	.507	7.242	88.953			
4	.477	6.820	95.773			
5	.259	3.699	99.472			
6	.023	.334	99.806			
7	.014	.194	100.000			

Table 5
Total variance explained by principal component analysis (2).

Component	Rotation sums of squared loadings	Component	Rotation sums of squared loadings
	Total	% of variance	Cumulative
1	4.251	60.734	60.734
2	1.468	20.977	81.710
3			
4			
5			
6			
7			

Table 6
Rotated component matrix.

	Component	
	1	2
PGDP	-.755	.151
AFI	.864	.156
AGDP	.778	-.156
AE	.962	-.217
UR	.911	-.298
FP	-.064	.960
RT	.756	-.583

pollutant emissions. In short, the dialectical relationship between urbanization and air pollution is the unity of opposites (Yang and Zhang, 2018). The effect of actual use of foreign investment on economic factors is minimal, and correspondingly it represents the effect of openness on PM2.5 concentration changes. A large influx of foreign capital, on the one hand, puts pressure on China's environment, but on the other hand, foreign companies bring advanced "clean" production technology to reduce the level of environmental pollution. Therefore, the Actual use of foreign investment is an important factor affecting China's environmental pollution, and is also an important factor driving the change of PM2.5 concentration.

Among the environment factor, the impact of forest coverage on PM2.5 concentration changes very large, which also indicates that increasing vegetation coverage is an effective measure to control PM2.5 concentration. Forests not only help to retain water but also absorb harmful particles in the air to reduce pollution and purify the air. The vegetation coverage rate in Tianjin and Handan City in the Beijing-Tianjin-Hebei region is still at a low level. It is an important task to do a good job in afforestation and increase forest coverage.

3.2.2. Interaction detection results

Table 7 presents the results of the $q$statistics of the interaction effects formed by the superposition of the seven driving factors. From the results, it is known that the change in PM2.5 concentration is a result of a combination of various factors. In the interaction mechanism using social interaction factor to influence the changes of PM2.5 concentration,

Table 7
Rotated component matrix.

	X1	X2	X3	X4	X5	X6	X7
X1	0.456						
X2	0.586	0.167					
X4	0.653	0.433	0.313	0.267			
X5	0.709	0.536	0.358	0.358	0.269		
X6	0.741	0.706	0.714	0.714	0.598	0.556	
X7	0.662	0.728	0.707	0.707	0.696	0.734	0.646

the social factors are mainly synergistic. This shows that the influence of urbanization, economic development level and technological development level in the Beijing-Tianjin-Hebei region on PM2.5 concentration is closely intertwined. The interaction detection results show that the seven factors of the study work together to enhance the explanatory power of PM2.5 concentration. Most of the co-factors have a decisive power greater than 0.5 or even 0.7. The unit GDP energy consumption and forest coverage rate are determined to be 0.74. The forest coverage rate and R&D full-time equivalent of industrial enterprise above designed size are determined to be 0.73. The Actual use of foreign investment and R&D full-time equivalent of industrial enterprise above designed size interaction up to 0.72. That is, the combined effect of these three groups of factors can explain the change in PM2.5 concentration by 70%. It shows that the correlation between PM2.5 concentration and

Table 8
Interaction between economic factors.

C	A + B	Conclusion	Interpretation
$X1 \cap X3 = 0.698$	$> Max(X1(0.456), X3(0.299))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X1 \cap X4 = 0..653$	$> Max(X1(0.456), X4(0.267))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X1 \cap X5 = 0..709$	$> Max(X1(0.456), X5(0.269))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X2 \cap X5 = 0..536$	$> Max(X2(0.167), X5(0.269))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X2 \cap X7 = 0..728$	$> Max(X2(0.167), X7(0.646))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X3 \cap X7 = 0..707$	$> \max(X3(0.299), X7(0.646))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X4 \cap X7 = 0..714$	$> \max(X4(0.267), X7(0.646))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X5 \cap X7 = 0..696$	$> Max(X4(0.269), X7(0.646))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate

Note: Due to the excessive number of economic factor interactions, only some of the interaction results are listed above.

social factors are higher.

Available from Table 8, in the interaction of economic factors, the interaction between energy consumption per unit GDP and GDP per capita is as high as 0.698, which enhances the effect of PM2.5 concentration changes. They reflect the energy consumption of economic development and the level of economic development, which indicates that the relationship between economic development and energy consumption is well coordinated, and the transformation of high-energy economic development mode is the key to controlling the concentration of PM2.5. The energy consumption per unit of GDP and the Urbanization rate also enhance each other's influence on PM2.5 concentration, which reflects the interaction between economic development energy consumption and urbanization level. The effect of interaction between R&D full-time equivalent and other economic factors on PM2.5 concentration about 0.65–0.7. It also shows that science and technology involve all aspects of economic, also meaning the factors contained in economic factors are closely related (see Table 9).

It can be seen from Table 8 that the interaction between the forest cover rate and the factors contained in the economic factors all at a high level. Among them, the forest coverage rate and R&D full-time equivalent of industrial enterprise above designed size interaction are as high as 0.734, which is the most influential.

Based on the above results, the interaction between economic factors and economic factors and eco-environment factors ultimately increases the effect of each other on PM2.5 concentration. This also shows that a one-size-fits-all approach to environmental governance is not feasible in the long-term governance process.

3.3. Robustness test

In order to prove that the results are robust, this paper select the data of 2015, 2014, 2013 to do deep research. The results of the factor analysis in three years show the selected seven factors classified into two factors. It shows the factor analysis model is robust. It also indicates that the PM2.5 concentration driving factors cover two aspects in recent years. And in these years, science and technology all at the first importance. It shows the importance to impulse enterprises invest more for technology research.

4. Conclusions and policy implication

4.1. Conclusion

In this study, factor analysis model was used to reduce the dimension of the factors affecting the concentration of PM2.5 in Beijing-Tianjin-Hebei to obtain two factors, which made the relationship between factors affecting PM2.5 concentration clearer, also beneficial to the atmospheric protection measures more targeted. The factor analysis results show that the selected factors mainly cover economic and environment two aspects. Through the geographical detector method, the driving factors are ordered by the value of q statistic, the dominant driving factors are detected and identified, and the spatial superposition interaction effects of the factors are analyzed. The results show that among the selected seven driving factors, it can be integrated into two factors: economic factor and eco-environmental factor. These two factors form a first-level indicator.

Among the economic factors, the most influential effect is the R&D full-time equivalent reflecting the level of scientific and technological development, followed by the unit GDP energy consumption reflecting the energy consumption of economic development and the GDP per capita reflecting the economic development, reflecting the residents' life. Others follow as the level of per capita consumption expenditure, the Urbanization rate reflecting the urbanization process, and finally is the actual utilization of foreign capital reflecting the degree of trade openness. In the results of the interaction analysis, the factors involved in the economic factors enhance the influence to PM2.5 concentration changes. The influence of the interaction to PM2.5 concentration between R&D full-time equivalent of industrial enterprise above designed size and others at a higher level, which also indicates that science and technology are the key points to future PM2.5 concentration.

The interaction effects on the concentration of PM2.5 in the Beijing-Tianjin-Hebei region between economic factors and environment factor have also increased, indicating that economic and ecological environment interact and complement each other.

Table 9
Interaction between economic factors and eco-environmental factor.

C	A + B	Conclusion	Interpretation
$X6 \cap X1 = 0.741$	$> Max(X6(0.556), X1(0.456))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X6 \cap X2 = 0.706$	$> Max(X6(0.556), X2(0.167))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X6 \cap X3 = 0.714$	$> Max(X6(0.556), X3(0.299))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X6 \cap X4 =$ 0..711	$> Max(X6(0.556), X4(0.267))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X6 \cap X5 =$ 0..598	$> Max(X6(0.556), X5(0.269))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate
$X6 \cap X7 =$ 0..734	$> \max(X6(0.556), X7(0.646))$	$C > Max(q(X1), q(X2))$	Enhance and bivariate

4.2. Policy recommendations

From the analysis results, it can be concluded that R&D are the key factor influencing PM2.5 pollution in recent years. Thus, based upon the findings above, some policy recommendations are proposed as follows.

China's science and technology are booming, and technology in all fields has a place in the world. Correspondingly, the development of science and technology in environmental protection should follow the pace of social development and increase investment in environmental protection research. It requires insist on independent innovation and equip it with all system, mechanism and cultural conditions. In the process of globalization, it is necessary to explore the systems and cultures that are suitable for China's manufacturing progress and technological innovation, finally build a most competitive innovation culture and atmosphere. Measures towards technology innovation need to be explored. The construction of intellectual property system is important. The government should promote the establishment of a joint technology innovation mechanism between enterprises and universities, and promote the integration of "political-enterprise-school". The government also needs to encourage the agglomeration of industries. It can bring the effects of regional technology innovation agglomeration.

In order to decrease energy consumption per unit of GDP, it's necessary to develop clean energy and improve energy efficiency. The government should encourage the formation of a diverse, safe, clean and efficient energy supply and consumption system, as well as the application and popularization of green energy such as wind and solar energy. The Beijing-Tianjin-Hebei region should continue to implement measures such as peak restrictions and license plate number limit, improve the convenience of public transport facilities, rationally plan public transport routes, encourage and attract residents to low-carbon travel. To avoid the pollution effect of FDI, it requires China government to formulate strict environmental access system, make selective use of foreign capital, realize the mutual complement and mutual promotion of domestic capital and foreign capital, and achieve the harmonious development of economy and environment.

Increasing the greening rate can protect the environment and improve the living environment of residents in the Beijing-Tianjin-Hebei region. Improving forest coverage should be a long-term measure for the Beijing-Tianjin-Hebei region, especially in Tianjin and Handan, where vegetation coverage is relatively low. Greening the land can effectively cope with global warming, adsorb toxic particles, which has a profound positive impact on the human environment.

Credit author statement

Wenqi Wu, rewrite the paper. Ming Zhang, provide the idea. Yueting Ding, write the paper.

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References

Avik, S., Tuhin, S., Rafel, A., 2020. Interplay between technology innovation and environmental quality: formulating the SDG policies for next 11 economics. J. Clean. Prod. 242, 1–12.
Bai, L., Jiang, L., Yang, D.Y., Liu, Y.B., 2019. Quantifying the spatial heterogeneity influences of natural and socioeconomic factors and their interactions on air pollution using the geographical detector method: a case study of the Yangtze River Economic Belt, China. J. Clean. Prod. 232, 692–704.
Ding, Y.T., Zhang, M., Chen, S., Wang, W.W., Nie, R., 2019a. The environmental Kuznets curve for PM2.5 pollution in Beijing-Tianjin-Hebei region of China: a spatial panel data approach. J. Clean. Prod. 220, 984–994.
Ding, Y.T., Zhang, M., Qian, X.Y., Li, C.R., Chen, S., Wang, W.W., 2019b. Using the geographical detector technique to explore the impact of socioeconomic factors on PM2.5 concentrations in China. J. Clean. Prod. 211, 1480–1490.
Ehrlich, P.R., Holdren, J.P., 1971. Impact of population growth. Science 171 (3977), 1212–1217.
Eskeland, G.S., Harrison, A.E., 2003. Moving to greener pastures? Multinationals and the pollution haven hypothesis. J. Dev. Econ. 70, 1–23.
Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110, 353–377.
Han, L.J., Zhou, W.Q., Li, W.F., Li, L., 2014. Impact of urbanization level on urban air quality: a case of fine particles (PM2.5) in Chinese cities. Environ. Pollut. 194, 163–170.
He, F., M, D.D., Zhu, L.Y., 2016. Study on Environmental Kuznets Curve of haze pollution in China—an empirical analysis based on panel data of the sample of Chinese 30 provinces during 2001 -2012. Soft Sci. 30 (4), 37–40.
Hoffmann, R., Lee, C.G., Ramasamy, B., Yeung, M., 2005. FDI and pollution: a granger causality test using panel data. J. Int. Dev. 17, 311–317.
He, J., 2016. Pollution haven hypothesis and environmental impacts of foreign direct investment: the case of industrial emission of sulfur dioxide in Chinese provinces. He,J., 2006 Ecol. Econ. 60, 228–245.
Jiang, L., Folmer, H., Ji, M., Tang, J., 2016. Energy efficiency in the Chinese provinces: a fixed effects stochastic frontier spatial Durbin error panel analysis. Ann. Reg. Sci. 58, 301–319.
Ji, J., Wang, G., Du, X.L., Jin, C., Yang, H.L., Liu, J., Yang, Q.L., Tchouopou, L.J., Li, J., Chang, C.T., 2013. Evaluation of adsorbing haze PM2.5 fine particulate matters with plants in Beijing-Tianjin-Hebei region in China. Sci. China Life Sci. 43, 694–699.
Lelieveld, J., Evans, J.S., Fnais, M., et al., 2015. The contribution of outdoor air pollution sources to premature mortality on a global scale. Nature 525, 367–371.
Leng, Y.L., Xian, G.M., Du, S.Z., 2015. Foreign direct investment and haze pollution: an empirical analysis based on provincial panel data. J. Int Trade. 12, 74–84.
Li, W.D., Huang, X., 2018. Emprical study on the social and economic influence factors of Beijing's haze. J. Capital University of Econ and Business 20, 58–68.
Lin, B.Q., Liu, X.Y., 2010. China' s carbon dioxide emissions under the urbanization process: influence factors and abatement policies. Econ. Res. J. 8, 66–78.
Li, T., Wang, Y., Zhao, D., 2016. Environmental Kuznets curve in China: new evidence from dynamic panel analysis. Energy Pol. 91, 138–147.
Ma, X.Q., Liu, Z., Zhao, X.Y., Tian, L.H., Wang, T., 2016. The spatial and temporal variation of haze and its relativity in the Beijing-Tianjin-Hebei region. Areal Res and Dev 35, 134–138.
Song, J.N., W, B., F K, Y, W., 2019. Unraveling economic and environment implications of cutting overcapacity of industries: a city-level empirical simulation with input-output approach. J. Clean. Prod. 222, 722–732.
Song, Y., Li, Z.R., Yang, T.T., Xia, Q., 2020. Does the expansion of the joint prevention and control area improve the air quality?—evidence from China's Jing-Jin-Ji region and surrounding areas. Sci. Total Environ. 706, 136034.
Tang, D., Li, L., Yang, Y., 2016. Spatial econometric model analysis of foreign direct investment and haze pollution in China. Pol. J. Environ. Stud. 25, 317–324.
Wang, Y.S., Zhang, J.K., Wang, L.L., et al., 2014. Researching significance, status and expectation of haze in Beijing-Tianjin-Hebeiregion. Adv. Earth Sci. 29, 388–396.
Wang, S., Fang, C., Wang, Y., 2015. Quantitative investigation of the interactive coupling relationship between urbanization and eco-environment. Acta Ecol. Sin. 35, 2244–2254.
Wei, W.X., Ma, X.L., 2015. Optimal policy for energy structure adjustment and haze governance in China. China Popul. Resour. Environ. 25, 6–14.
Wang, J.F., Xu, C.D., 2017. Geodetector: principal and prospective. Acta Geograplica Sin 1, 116–134.
Wang, J.F., Li, X.H., Christakos, G., Liao, Y.L., Zhang, T., Gu, X., Zheng, X.Y., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. Int. J. Geogr. Inf. Sci. 24, 107–127.
Wang, Y., Zhao, T., 2018. Impacts of urbanization-related factors on CO 2 emissions: evidence from China's three regions with varied urbanization levels. Atmos. Pollut. Res. 9, 15–26.
Yang, H., Zhang, L., 2018. An empirical study of the impact of evolution of industrial structure and urbanization on air quality in Beijing-Tianjin-Hebei region. China Popul, Resour Environ 28, 111–119.
Yang, X., Fu, L., Ding, D., 2015. Issues on regional CO2 emission peak measurement: taking beijing as an example. China Popul, Resour Environ. 25, 39–44.
Yuan, B.L., Zhang, Y., 2019. Flexible environment policy, technological innovation and sustainable development of China' industry: the moderating effect of environment regulatory enforcement. J. Clean. Prod. 243, 1–17.
Zhang, M., Li, M., 2017. Study on the regional difference in the relationship among haze pollution, economic growth and environmental regulation from the perspective of spatial gravitational effect. China Popul, Resour Environ. 27, 23–34.
Zhang, M., Sun, X.R., Wang, W.W., 2020a. Study on the effect of environmental regulations and industrial structure on haze pollution in China from the dual perspective of independence and linkage. J. Clean. Prod. 256, 120748.
Zhang, X.P., 2008. Regional disparities in energy consumption intensity in China and determining factors. Resour. Sci. 30, 883–889.
Zhang, Y., Shuai, C.Y., Bian, J., Chen, X., Wu, Y., Shen, L.Y., 2019. Socioeconomic factors of PM2.5 concentrations in 152 Chinese cities: decomposition analysis using LMDI. J. Clean. Prod. 218, 96–107.
Zhang, X.L., Zhao, Y., 2018. Identification of the driving factors' influences on regional energy-related carbon emissions in China based on geographical detector method. Environ. Sci. Pollut. Res. 25, 9626–9635.
Zhou, H., 2003. Modern Chinese Dictionary. Guangming Daily Press.
Zhou, L., Wu, J.J., Jia, R.J., Liang, N., Zhang, F.Y., Ni, Y., Liu, M., 2016. Investigation of temporal-spatial characteristics and underlying risk factors of PM2.5 pollution in Beijing-Tianjin-Hebei Area. Res of Environ Sci 29, 483–493.
Zhou, C.S., Chen, J., Wang, S.J., 2018. Examining the effects of socioeconomic development on fine particulate matter (PM2.5) in China's cities using spatial regression and the geographical detector technique. Sci. Total Environ. 619–620, 436–445.
Zhu, B.Z., Jiang, M.X., Zhang, S.F., et al., 2019. Resource and Environment Economic Complex System: Models and Applications. Science Press, Beijing.