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Changes in urban air quality during urbanization in China

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ABSTRACT

This paper primarily studies the air quality in China's cities during the urbanization stage. Using a cross-sectional data of 282 cities, we discuss the influencing factors and the existence of the Kuznets Curve for three air pollutants based on the EKC (Environmental Kuznets Curve) theory and the BMA (Bayesian Model Average) method. The results show that the concentration of SO_2 and PM_{10} presents the characteristics of an inverse-U shape. The urbanization process has a significant and negative effect on air pollutant concentration, which means that cities with higher urbanization rate tends to have lower air pollutant concentration. Population density, possession of civil motor vehicles, the proportion of secondary industry, and annual average temperature are the main influencing factors of air pollution. Based on these results, this paper suggests that China should speed up the "new" type urbanization process, constantly optimize the industrial structure, and promote the harmonious development of the economy and environment.

1. Introduction

Cities are the center of human politics, economy, and culture. Human activities and population are highly concentrated in cities, resulting in enormous energy demand and serious environmental pressure. China's urbanization process accelerated after the reforms and opening-up of the economy. In 1978, urbanization rate was only 17.92%, but exceeded 50% for the first time in 2011, reaching 51.27%. One goal of China's 13th Five-Year Plan is to promote the new-type urbanization and optimize its layout and form.

With the development of the urbanization process, urban population continues to increase, resulting in rising energy consumption (Jiang and Lin, 2012) and demand for urban infrastructure. Meanwhile, China is currently at a development level where industrialization is required. The energy structure is dominated by coal, and huge fossil energy consumption produces lots of pollutants, such as Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), and Particulate Matter.

China is facing serious urban air pollution problems. According to the "*2015 Environmental Status Bulletin*" released by the Ministry of Environmental Protection, only 73 (21.6%) out of 338 Chinese cities met the air quality standard. Fig. 1 shows the range of air pollutant concentration in 338 Chinese cities in 2015. According to the Ambient Air Quality Standards of China, 65% of the cities do not attain the Secondary Standards of PM_{10} (Particulate matter with particle size below 10 μm); 18.4% of the cities do not attain the Secondary Standards of NO_2; and 3.3% of the cities do not attain the Secondary Standards of SO_2.[1]

Air pollution seriously affects human health and life. According to data released by the World Health Organization in 2014, air pollution caused about 7 million deaths worldwide in 2012. This figure is almost one-eighth of total death. This fact confirms that air pollution is the world's largest environmental health risk. The "Global Burden of Disease Study 2010", published in "*The Lancet*" in 2012, reported that outdoor $PM_{2.5}$ pollution caused premature deaths of 1.2 million people in China in 2010 (Lim et al., 2012). Chen et al. (2013) evaluated the impact of air pollution on human health in China and found that China's annual premature death due to outdoor air pollution is between 350,000-400000 each year. According to the data released by the World Health Organization in

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[1] According to the Ambient Air Quality Standards of China, which announced in 2012 by Chinese Ministry of Environmental Protection, Secondary Standards area are the residential, commercial and traffic residents mixed area, cultural area, industrial area and rural areas. The Secondary Standards apply to Secondary Standards area. See Appendix A.

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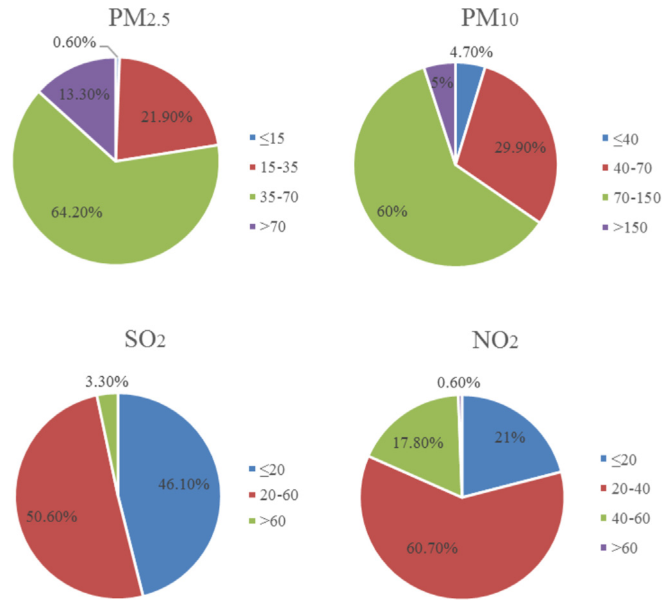

Fig. 1. The proportion of different pollutants concentrations in 338 Chinese cities in 2015.

2014 (Stewart and Wild, 2014), 2.2 million people died of cancer in China. This includes 600,000 people, about 27.3%, who died of lung cancer.

Air pollution also has a huge impact on urban architecture and environment. Excessive emission of SO_2 and NO_2 in the atmosphere results in acid rain in most parts of the country. The acid rain causes direct damage to the external walls of buildings and significantly reduces the life cycle of buildings and exposed machines. Air pollution also causes water pollution in rivers and lakes, which has a deleterious effect on the health of animals and plants.

The environmental problems caused by excessive concentration of the population through urbanization is serious. Scholars have different views on the relationship between urbanization and urban environment (see Fig. 2). Some scholars believe that urbanization process will aggravate urban environmental pollution. Human activities have an increasing impact on environment during the urbanization process (Song et al., 2015). Firstly, urbanization has changed human's way of life. People use natural resources to produce needed products, and emit lots of pollutants in the process (Bai et al., 2017). Secondly, the urbanization process has rigid demand for transportation and infrastructure construction, which will increase household energy consumption (Sun et al., 2014; Du et al., 2015a). Increasing energy consumption will produce lots of pollutants, eventually worsening the urban environment (Satterthwaite, 2009). Furthermore, the accumulation of population and the aggregation of industries caused by urbanization will also cause environment hazards (Li et al., 2012). Another viewpoint is that, firstly, the urbanization process will improve the efficiency of land use and energy consumption. Under the environmental regulation of the government, residents will reduce the direct combustion of fossil fuels, such as coal and oil (Sun et al., 2014; Gong and Lin, 2017), and increase the consumption of clean energy such as electricity (Damette et al., 2018; Du et al., 2015b), which will eventually reduce pollutants emission. Secondly, urbanization process can promote economic development (Yang et al., 2017; Jing, 2015). With the increase in income level, people have higher environmental standards, which can propel the government to strengthen urban greening and implement environmental policies. Additionally, with the agglomeration of the industry, cities can use more centralized treatment to deal with pollution emissions (Zeng and Zhao, 2009), which will effectively reduce air pollution.

The actual situations in China is peculiar. Since the reform and opening-up, the pace of urbanization has increased rapidly, but the urbanization process significantly varies across cities (In 2014, the lowest is 26.65%, and the highest is 100%). Other changes caused by urbanization were also obvious. Firstly, urbanization has enhanced population aggregation. The urban population density was 255.68 person/square kilometers in 2012 but increased to 268.89 person/square kilometer in 2015. The difference among the cities is greater (Between 5.77 and 2501.14 person/square kilometers in 2015). Secondly, the increase in urbanization has also augmented the demand for transportation. In 2012, the population of civil vehicles in China was 109 million but increased to 162 million in 2015. Thirdly, government investment in pollution control has also been increasing (711.4 billion Yuan in 2012 and increased to 880.63 billion Yuan in 2015). Finally, air pollutants emission in China is concerning. It is imperative to know that in 2012, SO_2, NO_2, and smoke (powder) dust emissions were 21.17, 23.37, and 12.36 million

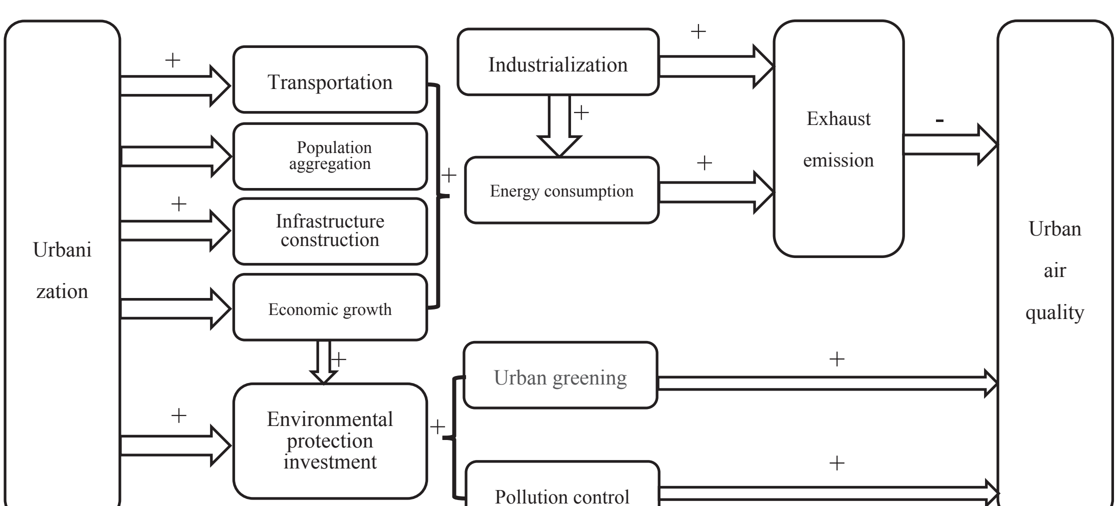

Fig. 2. The main mechanisms and paths of urbanization on urban air quality in China.

tonnes, respectively. In 2015, they are 18.59, 18.51 and 15.38 million tonnes respectively (SO_2 and NO_2 emissions have decreased significantly).

Based on this, the paper analyzes the influencing factors of different air pollutants using the BMA (Bayesian Model Average) method. The existing literature has shown that urbanization is an important factor affecting environmental quality and that the impact of the current process of urbanization on air quality in China is worthy of discussion. This paper decomposes urbanization into detailed index and analyzes the impact of urban variables, such as population density, transportation, and urban greening on urban air quality. At the same time, we analyze the impact of urbanization on air quality in general, which has important significance for Chinese cities to promote urbanization construction and implement environmental policy.

The advantage of BMA is that it can solve the problem of model uncertainty. For different air pollutants, the major influencing factors are not exactly the same. SO_2 and NO_2 are mainly from industrial emissions and automobile exhaust, and straw burning will also emit NO_2. The source of particulate matter is extensive, including industrial activities, automobile exhaust, construction projects, and related chemical reactions.

Compared with previous studies, this article has two contributions. Firstly, based on the EKC theory, this paper analyzes the three major pollutants that affect air quality during the urbanization process. We also discuss the mechanism of urbanization, that is, we explore ways through which urbanization affects air quality, which is conducive for making specific policy recommendations. Secondly, to the best of our knowledge, this paper pioneers the use of BMA model in analyzing air pollutants in Chinese cities and finds that the influencing factors of different pollutants are not the same. This has certain significance for implementing different air pollution control measures in different regions.

In the second section of this paper, we review the existing literature on environmental pollution, BMA model and the EKC (Environmental Kuznets Curve) theory. We introduce the BMA method and EKC in the third section. The fourth section consists of source and description of the data used in this paper. In the fifth part, we examine the existence of EKC for different air pollutants, and based on the EKC theory and BMA method, we investigate the main influencing factors of these three pollutants. The last section concludes the paper with some policy recommendations.

2. Related literature

Sustainable development requires a coordinated development of the economy, society, resources, and environment. The most influential economic growth and environmental pollution research is the EKC, which was proposed by American scholars Grossman and Krueger (1991). Since then, scholars have studied the relationship between economic growth and environmental pollution. Shafik and Bandyopadhyay (1992) explored the relationship between environmental quality and economic growth by analyzing the environmental transformation model of countries with different income levels. Selden and Song (1994) used cross-regional panel data to validate the relationship between economic growth and particulate matter, NO_2, and other four kinds of pollutants and determine if it is in line with the EKC hypothesis. The results showed that the four pollutants and per capita GDP show an inverted U-shaped relationship. Other scholars such as Jones and Manuelli (2000), Brock and Taylor (2005), Al-Mulali and Ozturk (2016) also used different models to verify the existence of the EKC relationship between economic growth and environmental pollution. In the wake of declining environmental quality in China, many scholars studied the relationship between environmental pollution and economic growth in China. It is worth noting that these scholars mainly used national or provincial environmental pollution data for related analysis (Jalil and Mahmud, 2009; Llorca and Meunie, 2009). Kaneko et al. (2013) used non-parametric method and China's provincial panel data from 1992 to 2003 to test the EKC relationship between income and water pollution. Wang et al. (2016a) used Beijing data from 1990 to 2014 to study the relationship between environmental pollution and economic development. Other scholars (Ho et al., 2013; Yin et al., 2015; Wang et al., 2016b) also discussed the relationship between economic growth and environmental pollution in China.

Urbanization is an important index to measure urban development. Many scholars have researched the relationship between urbanization and environmental quality. Effiong (2017) argued that urbanization process can reduce environmental pollution. Li and Zhou (2017) found that increase in urbanization rate can improve air quality. However, opposing views were advanced by Fathi et al. (2014) and Fang et al. (2015). Some scholars realized that there is an inverted U- shaped relationship between urbanization and pollution (Du and Feng, 2013; Wang et al., 2014; Shahbaz et al., 2016). Other scholars including Satterthwaite (2009) argued that urbanization is not the direct cause of environmental pollution, but the increasing urban population and urban consumption caused by urbanization are the root causes of environmental pollution. Han et al. (2014) analyzed the relationship between urbanization and $PM_{2.5}$ concentration, and found a significant impact of urbanization on $PM_{2.5}$ concentration. Urban transport infrastructure investment also has an impact on air quality. Sun et al. (2018) analyzed the impact of transport infrastructure investment on urban air quality. The results showed that transport infrastructure investment generally improves air quality, but the long-term and short-term impacts are different. In the short term, traffic congestion caused by transport infrastructure investment will lead to more pollutant emissions. In the long run, transport infrastructure investment can improve the road network and reduce congestion, thereby reducing pollutant emissions.

Many scholars have evaluated the main factors that affect environmental quality. Cuhadaroglu and Demirci (1997) explored the effects of meteorological factors on air pollutants using multiple linear regression analysis. The study found a moderate relationship between SO_2 concentration and meteorological factors in some months. Jänicke et al. (1989), by examining the correlation between industrial structure and environmental pollution in 31 industrialized countries, showed that the effects of industrial structure on environmental quality exhibit different results across countries. Antweiler et al. (2001) analyzed three effects of foreign trade on environmental quality through a pollution-demand model. The results showed that foreign trade affects pollution emissions mainly through scale effect and technology effect. Based on the EKC theory, Park and Lee (2011) analyzed the air pollution status in different regions of Korea. The results showed that the EKC curves are different in different regions, and energy consumption is the most important factor that affects air pollution. Hao and Liu (2016), based on the data on $PM_{2.5}$ concentration and air quality index of 73 cities in China, used the Spatial Lag and Spatial Error Models to empirically investigate the influencing factors of $PM_{2.5}$ concentration. Xu and Lin (2018) used panel data and STIRPAT models to examine the key driving factors of $PM_{2.5}$ emissions at the regional level in China. The results showed that the impacts of urbanization on $PM_{2.5}$ emission are different in different regions. Li et al. (2017) analyzed the air pollution in Beijing using the extended IPAT model and found that emission intensity is the most important factor affecting air pollution. Based on these results, the authors proposed that government regulation and related policies play a central role in improving air quality. Spatial econometric models were adopted by Ma et al. (2016) to analyze the spatial correlation of $PM_{2.5}$ air pollution. The results showed that economic, social and technological factors have a spillover effect on air pollution. Therefore, the author proposed that in order to improve China's air pollution problems, industrial transfer should be carried out.

The previous literature showed that a number of studies have analyzed the main factors affecting air quality. Considering data accessibility, many research studies use the pollutant emissions index (Sun et al., 2018; Wu et al., 2018). Currently, more researchers have been applying the air pollutant concentration indexes (Xu and Lin, 2018; Ma et al., 2016; Hao and Liu, 2016), because these indexes have closed relationship with human health. This paper uses three representative indexes of air pollution; that is, the annual average concentration of SO_2, NO_2, and PM_{10}. The reasons for the choice of these indexes are as follows. Firstly, there is a serious smog pollution in China, and the SO_2、NO_2 and PM_{10} are the main smog pollutants. Secondly, SO_2 and NO_2 and PM_{10} are the main pollutants in exhaust emissions. The analysis of the influencing factors of these three pollutants can promote targeted emission reduction policies for different pollutants. Moreover, we use the BMA method to study the influencing factors of the three air pollutants in Chinese cities, which has some theoretical significance.

The BMA method was first proposed by Leamer (1978). BMA sets the prior probability for all single models including all possible explanatory variables and calculates the posterior probability of all possible variables by Bayesian analysis. The importance or significance of the variables is sorted by posterior inclusion probability (PIP). Since the BMA method takes into account the uncertainty of model selection, it is widely used in various fields. Raftery et al. (1997) provided a detailed explanation of the BMA approach. Magnus et al. (2010) compared BMA and weighted-average least squares methods, pointing out the advantages and disadvantages of both approaches. Cogley and Sargent (2005) used the model average method and established a new inflation model. Moral-Benito (2012) based on the BMA method, established a country-specific panel of economic growth model to determine the main factors of economic growth. Jacobson and Karlsson (2004) predicted inflation in Sweden using the BMA method. They further verified the effectiveness of the BMA method by testing the predictability of the model. Rodríguez et al. (2016) employed the BMA method to investigate the relationship between air pollution and urban structure in 249 European cities.

3. Models and methods

3.1. Environmental Kuznets curve (EKC)

One of the theories that study the relationship between environmental pollution and economic growth is the EKC. The EKC is proposed by American scholars Grossman and Krueger (1991). They found that there is an inverted U-shaped relationship between economic growth and environmental pollution. When the level of economic development is low, the level of pollution is relatively low, and as growth progresses, pollution level increases. However, when the economy develops to a certain stage, i.e., reaching an inflection point, a further increase in income will gradually improve environmental quality. Considering the existence of EKC relationship for urban air pollutants in China, we choose the quadratic equation of per capita GDP as an explanatory variable. The model is expressed as:

$$\ln(Pollution_i) = \alpha + \beta_1 \ln(PCGDP) + \beta_2[\ln(PCGDP)]^2 + \varepsilon \tag{1}$$

where $Pollution_i$ represent the average annual concentration of SO_2, NO_2, and PM_{10} respectively, $PCGDP$ represents per capita GDP. When $\beta_1 > 0$ and $\beta_2 < 0$, we could determine that air pollutants appear to have the characteristics of EKC.

3.2. Bayesian model averaging (BMA) method

Model uncertainty is a common phenomenon in the process of econometric modeling. This problem is mainly derived from two aspects: variable selection and variable measurement. According to economic theory, we can usually determine that a model contains a particular variable, but most variables are included or excluded arbitrarily (Magnus et al., 2010). Secondly, using different measures for the same variable often results in different or even contradictory conclusions. Take different air pollutants as an example. The influencing factors of air pollutants are complicated, and researchers are often unable to determine which of the variables to be introduced into the model, especially the three different air pollutants considered in this paper. Therefore, in the previous literature, different scholars often use different explanatory variables when constructing econometric models. The BMA method can effectively solve the above problems.

Following Magnus et al. (2010), consider the linear regression model:

$$Y = \alpha + \beta X + \gamma Z + \varepsilon, \quad \varepsilon \sim N\left(0, \delta^2\right) \tag{2}$$

where $Y(n \times 1)$ represents the dependent variable, $X(n \times k_1)$ and $Z(n \times k_2)$ represent the explanatory variables, ε is the error vector, α is the intercept, β and γ are unknown parameter vector. We assume that $k_1 \geq 1$, $k_2 \geq 1$, and the column of (X, Z) is full rank. It is further assumed that the error vector $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots \varepsilon_n)$ is $IID \sim N(0, \delta^2)$.

In the linear regression model described above, X depicts the explanatory variables for all models, which is sometimes called core variable because X contain important factors that influence Y according to economic theory. For different linear models, Z represents the unique explanatory variables in different models and are called auxiliary variables. In general, the types and numbers of explanatory variables in Z are not the same. We make a distinction between X and Z because we are sure that the model must contain X. However, we cannot determine which auxiliary variables to be included in the model. When the auxiliary variables in the model are different, the regression coefficients of X are not the same, therefore, the choice of variables in Z becomes critical.

There are k_2 explanatory variables in matrix Z, and alternative linear models reach 2^{k_2}. Assuming $M = \{M_1, M_2, \cdots, M_K\}$ is the model space which contain all models , where $K = 2^{k_2}$. Then for any model $M_i \in M$:

$$Y = \alpha + \beta X + \gamma_i Z_i + \varepsilon \tag{3}$$

where , Z_i is a subset of Z, γ_i is a subvector of γ.

We assume the single model is normal linear model , then the likelihood of model M_i is given by:

$$p\left(y|\alpha, \beta, \gamma_i, \sigma^2, M_i\right) \propto \left(\sigma^2\right)^{-n/2}\left\{\exp\left[-\frac{1}{2\sigma^2}(Y - \alpha - \beta X - \gamma_i Z_i)'(Y - \alpha - \beta X - \gamma_i Z_i)\right]\right\} \tag{4}$$

Before we implement the BMA method, there is need to set the prior distribution of parameters and models. The first is the priori distribution of parameters. Following O'Hagan (1994) and Magnus et al. (2010), the distribution of the coefficient is assumed as follows:

$$p\left(\sigma^2\middle|M_i\right)\propto\sigma^{-2},\quad p(\beta|\sigma^2,M_i)\propto 1,\quad \gamma_i|\beta,\sigma^2,M\sim N\left(0,\sigma^2V_i\right).$$

According to Zellner (1986), the V_i is a g-priors and defined as a positive definite matrix $V_i = g_iZ_i'WZ_i$, where, $W = I_n - X(X'X)^{-1}X'$.

As for the distribution of g_i, following the information standard of Fernandez et al. (2001), the g_i is chosen as $g_i = 1/\max(n,k_2^2)$.

Secondly, for the prior distribution of single model M_i, under the condition of lack of prior information, we assume it follows a uniform distribution $p(M_i) = 2^{-k_2}$. For more details about BMA method, see Magnus et al. (2010).

The BMA method takes PIP (Posterior Inclusion Probability) as weight, and uses PIP as a criterion for the choice of explanatory variables, which can effectively improve the explanatory power of the model. Raftery et al. (1997) pointed out that the linear BMA model is superior to other traditional stepwise regression models for selecting the "real" model. Compared with a linear model, the BMA method has the advantage of dealing with the variable selection problem by considering the uncertainty of the model. Madigan and Raftery (1994) pointed out that under the Logarithmic Scoring criterion, the results of weighted average prediction of the BMA model is better than the results of all the single models. By using the BMA method, all possible single model can be averaged in advance, and the PIP (Posterior Inclusion Probability) of the explanatory variables is calculated by setting the prior probabilities of single models. The importance of the explanatory variables is sorted by the PIP. It can avoid information deviation which is caused by the artificial selection of the explanatory variables.

In this paper, there are three dependent variables; annual average concentrations of SO_2, NO_2 and PM_{10}. The core variables are per capita GDP, the square of per capita GDP and urbanization rate, and a total of ten auxiliary variables, which will be described in Section 4.

4. Data description

In 2012, the State Council of the People's Republic of China issued the New Standard for environmental air quality, and gradually implemented it in various cities. In 2013 and 2014, only a section of Chinese cities which implemented the New Standard published their air pollution data. This paper uses the annual data of 282 Chinese cities in year 2012. The reasons are: firstly, we consider the availability and consistency of data; secondly, from Tables 2 and 3, the standard deviation of most variables is higher, indicating a big difference between the cities. Furthermore, relative to the 12 explanatory variables considered in this paper, 282 cities is a large sample to ensure reliable estimation results. So the selection of the 282 cities in 2012 is a good choice in terms of analyzing the impact of influencing variables on air pollution. Cross section data is also widely used in recent environmental analysis (Galeotti et al., 2006; Rodríguez et al., 2016). Based on relevant research studies on environmental economics, we construct an econometric model with 12 explanatory variables. Table 1 depicts the data sources. Some missing data are supplemented through interpolation.

4.1. Air pollution variables

Air pollution data includes the annual average concentrations of SO_2, NO_2, and PM_{10}. According to the statistics of Ministry of Environmental Protection of China, particulate matter was the primary pollutant in Chinese cities, for more than 90% of the total number of days in 2012. The main sources of air pollutants are the emissions of human production process, various types of motor vehicle exhaust emissions (including SO_2 , NO_2 and other pollutants), and the emission of industrial dust (industrial SO_2 and industrial NO_2). Table 2 describes the statistical analysis of the three air pollutants in 282 Chinese cities.

Table 1
Date sources.

Variables	Data sources
Average annual SO_2 concentration (SO_2)	*2012 China Environmental Quality Report*
Average annual NO_2 concentration (NO_2)	
Average annual PM_{10} concentration (PM_{10})	
Population density (PD)	CEIC China Database[a]
Green coverage rate of built-up area (GCR)	*2013 China Statistical Yearbook*
Foreign direct investment (FDI)	*2013 China City Statistical Yearbook*
The proportion of secondary industry (SI)	
The proportion of primary industry (PI)	
Possession of civil motor vehicles (CMV)	
Investment in fixed assets (FAI)	
Total land area of administrative region (UA)	
Export dependence (ED)	
Per capita GDP (PCGDP)	
Urbanization rate (Urb)	2013 Statistical Yearbook of Chinese provinces
Temperature (T)	Annual Statistical Bulletin of Chinese provinces and cities

[a] CEIC economic data company is an authoritative provider of Asian economic research information (https://insights.ceicdata.com/).

4.2. Explanatory variables

There are many variables that can affect air quality. With reference to previous literature and theories of environmental economics, this paper selects the following twelve explanatory variables.

4.2.1. Core variables

(1) Per capita GDP (PCGDP). The most influential research on the relationship between environmental pollution and income levels is the EKC theory. The EKC theory is widely used in environmental analysis in the existing literature, such as studies on air pollutant, water pollutant and CO_2 emissions. The commonly used expression is quadratic form, so this paper uses PCGDP and the square of PCGDP as core variables to explore the relationship between environmental quality and income level.

(2) Urbanization rate (Urb). This paper takes the proportion of urban population to total population as the urbanization rate. The most obvious changes in urbanization process are the aggregation of population and changes in consumption patterns. The demand for energy grows fast and rigorously during urbanization process. For a populous country like China, there is a close relationship between urbanization and environment pollution. Therefore, this paper chooses urbanization rate as a core variable to study the impact of urbanization on air quality.

4.2.2. Auxiliary variables

(1) Economic development variables. Economic development variables include foreign direct investment (FDI), fixed asset investment (FAI) and exports dependence (ED). In this paper, we use the actual utilization of foreign capital represented by FDI. There are two different views concerning the impact of FDI on environmental quality. Some scholars believe that FDI can bring about technological progress for the host country

Table 2
Summary statistics of pollution variables.

Variables	Obs	Mean	Std. Dev.	Min	Max
SO_2 (ug/m^3)	282	32.81	14.07	4	87
NO_2 (ug/m^3)	282	29.04	10.40	5	68
PM_{10} (ug/m^3)	282	75.10	19.25	21	145

through technology transfer. It is also believed that FDI can bring transfer of experience and knowhow to improve environmental pollution through technological dispersion, and eventually improve environmental quality in the host country (Eastin and Zeng, 2009). Others suggested that FDI transfer from countries with high environmental quality standards to countries with lower standards would lead to a deteriorating trend of environmental quality in the host country (Chichilnisky, 1994).

For fixed asset investment, the government faces double pressure between economic growth and environmental pollution and makes decisions between investment in fixed assets and investment in environmental pollution. When government pursues rapid economic growth and investment in fixed assets, it will inevitably lead to investment in environmental pollution, and massive investment in fixed assets may weaken environmental protection. Nevertheless, the pressure of environmental pollution conversely forces the government to increase investment in environmental protection.

Export dependence represents the ratio of total export to total GDP. It is considered to investigate the impact of foreign trade on environmental quality. There is no consensus about the impact of foreign trade on air quality. Some argue that freer trade can improve environmental quality (Antweiler and Taylor, 1998). However, the pollution hypothesis theory states that environmental pollution-intensive industries will be transferred to countries with lower environmental quality standards through foreign trade, which will worsen pollution in these countries.

(2) Industrial structure variables. The industrial structure variables adopted in this paper include the proportion of primary industry (PI) and the proportion of secondary industry (SI). China has entered the mid- and post-industrialization stage; and the proportion of the secondary industry is high and also differs in terms of industrial structure. Among the 282 Chinese cities, the lowest proportion of the secondary industries in 2012 accounted for 17.1%, while the highest accounted for up to 87.96%. Intensive industrial production process causes pollutant emissions. The hypothesis of industrial structure

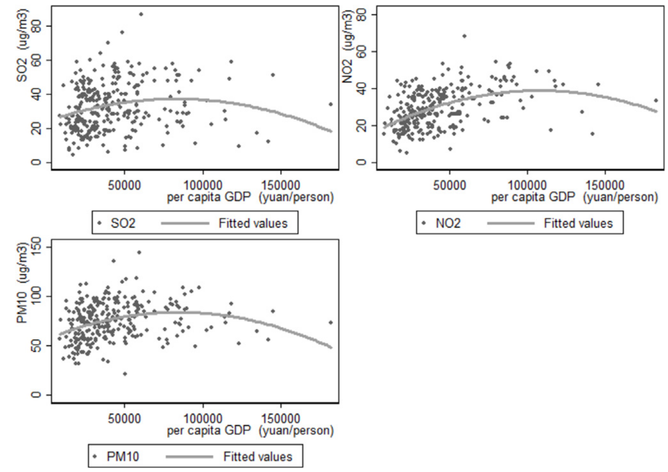

Fig. 3. Display of the relationship between three pollutants and income per capita in scatter plots and nonlinear fitting graphs.

changes shows that human society will change from agriculture-based low-polluting society to an industry-oriented high-polluting society, and finally transform to a service-oriented low-polluting society in the future.

(3) Urban variables. Urban variables include urban population density (PD), green coverage rate of built-up area (GCR), annual average temperature (Tem), total land area of administrative region (UA) and urban possession of civil motor vehicles (CMV). With the continuous improvement in urbanization in China, urban resident population and floating population will grow at a high rate, resulting in severe population pressure in the cities. In 2015, there were 13 cities in China with population of more than 10 million. The increase in urban population has a great impact on urban air quality. Firstly, the increase in urban population brings an urgent demand for traffic and transportation. Secondly, it increases the demand for energy consumption, commodity consumption and public infrastructure.

The city's annual average temperature reflects the urban climate condition. There is a large difference in temperature between the southern and northern parts of China. The northern part of China is very cold during the winter; hence, it needs to burn lots of coal for heating, leading to release of more exhaust gas into the environment. In contrast, the temperature is relatively warmer in the south, especially in the coastal areas of southeastern part of China, where there is higher annual temperature and relatively low level

Table 3
Summary statistics of explanatory variables.

Variable	Unit	Obs	Mean	Std.Dev.	Min	Max
PCGDP	Yuan	282	43,132.88	26,450.88	8157	182,680
Urb	%	282	51.79	15.26	21.61	100
PD	Person/Square Kilometres	282	429.20	334.20	5.10	2581.78
GCR	%	282	39.09	7.76	2.98	82.32
FDI	Million Dollar	281	859.24	1962.51	0	15,185
SI	%	282	51.38	10.31	17.1	87.96
PI	%	282	19.95	8.13	0.05	49.89
CMV	Thousand	280	413.46	544.45	15.77	4957
FAI	Million Yuan	282	124,692.60	128,188.10	9334.88	938,000.10
ED	%	282	11.28	18.23	0.01	132.27
Tem	Degrees	282	14.51	5.39	−2.8	27.5
UA	Square Kilometres	282	16,562.50	21,965.63	1200	253,000

Table 4
Estimation results of environmental Kuznets curve.

	$\ln(SO_2)$	$\ln(NO_2)$	$\ln(PM_{10})$
ln(PCGDP)	3.910***	0.875	2.295***
	(2.60)	(0.79)	(2.80)
$[\ln(PCGDP)]^2$	−0.178**	−0.0269	−0.102***
	(-2.50)	(-0.51)	(-2.63)
_cons	−17.99**	−2.925	−8.530**
	(-2.27)	(-0.50)	(-1.97)
N	282	282	282

Note: t-statistics in parentheses.
*p < 0.1, **p < 0.05, ***p < 0.01.

Table 5
BMA results and the poster inclusion probability of auxiliary variables.

Auxiliary variables	$\ln(SO_2)$	$\ln(NO_2)$	$\ln(PM_{10})$
ln(PD)	0.80	0.74	0.54
ln(GCR)	–	–	–
ln(FDI)	–	–	–
ln(SI)	1.00	0.98	1.00
ln(PI)	–	–	–
ln(CMV)	0.92	0.86	0.77
ln(FAI)	–	0.50	0.92
ln(ED)	0.99	–	–
ln(Tem)	0.86	0.75	1.00
ln(UA)	–	–	–

Note:“-”represents PIP<0.5.

of environmental pollution. We, therefore, consider temperature as an important factor affecting air quality, and is included as an auxiliary variable.

Table 3 depicts the summary statistics of the explanatory variables. The correlation coefficients between the respective variables can be seen in Appendix B. As expected, urbanization rate is positively correlated with per capita GDP.

5. Empirical analysis

5.1. Environmental Kuznets curve (EKC)

Firstly, we consider whether the urban air pollution is in accordance with the characteristics of EKC. The simple EKC describes the relationship between the concentration of environmental pollutants and per capita income. We have a scatter analysis for the three pollutants and per capita GDP. It displays non-linear fitting graphs. The results are shown in Fig. 3.

It seems that the fitting results of all the three pollutants display an inverted U-shaped curve feature. Meanwhile, most of the cities were on the left side of the curve in 2012. To further explore the EKC feature of these three pollutants, based on EKC hypothesis of equation (1), we conducted a regression analysis for the pollutants and the results are shown in Table 4.

According to the regression results in Table 4, the coefficient of PCGDP is positive, while that of the square of PCGDP is negative in the SO_2 and PM_{10} regression results. This indicates that SO_2 and PM_{10} satisfy the environmental Kuznets curve characteristics. That is, it has an inverted U curve and an inflection point. Howbeit, the coefficients of PCGDP and the square of PCGDP in the NO_2 regression results are not significant.

5.2. Bayesian model average (BMA) results

5.2.1. Poster inclusion probability of auxiliary variables

Under the linear model assumption, ten auxiliary variables raise the number of alternative models to 2^{10}. Table 5 is the posterior inclusion probability (PIP) of the auxiliary variables for different pollutants. An auxiliary variable has a higher reliable explanation power if it has a higher PIP. According to Raftery (1995), the optimal model should contain auxiliary variables with PIP greater or equal to 0.5. From the results of Table 5, the auxiliary variables with PIP greater or equal to 0.5 are similar across pollutants. Population density (PD), the proportion of the secondary industry (SI), the possession of civil motor vehicles (CMV) and annual average temperature (Tem) have a PIP greater than 0.5 for each pollutant. The difference is that export dependence (ED) is selected with a PIP of 0.99 for SO_2, and fixed asset investment (FAI) is selected with a PIP of 0.5 and 0.92 for NO_2 and PM_{10} respectively.

Another difference is that the PIP differs across pollutants (see Fig. 4). Population density has a PIP of 0.80, 0.74 and 0.54 for SO_2, NO_2 and PM_{10} respectively, implying that population density has a higher explanatory power for SO_2. The proportion of the secondary industry has a higher PIP and is equal to 1.00, 0.98 and 1.00 for the three pollutants respectively. These are realistic conclusions in the sense that the industrial processes are the major sources of air

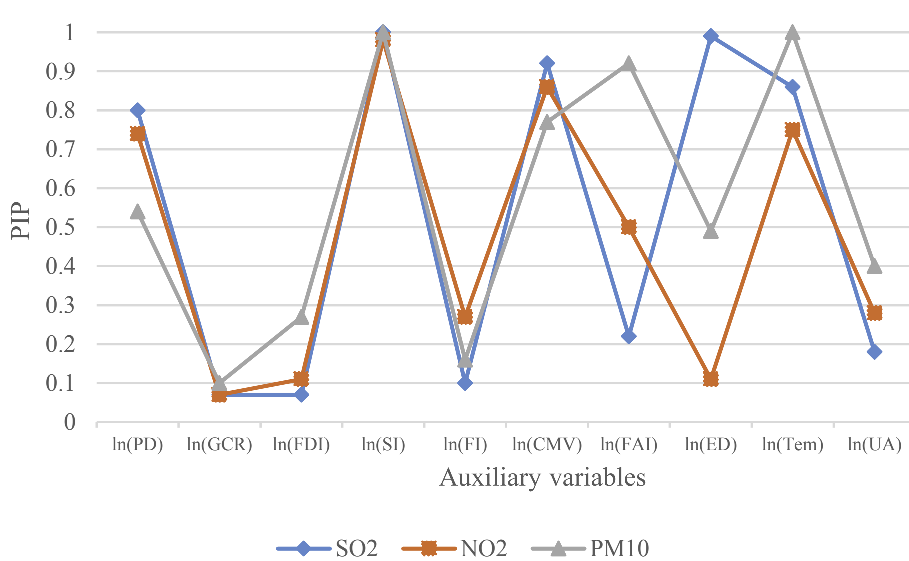

Fig. 4. BMA result and the poster inclusion probability of auxiliary variables.

Table 6
Ordinary Least Squares estimation results.

	$\ln(SO_2)$	$\ln(NO_2)$	$\ln(PM_{10})$
ln(PCGDP)	3.631***	−0.225	1.641**
	(2.66)	(-0.23)	(2.24)
$[(\ln(PCGDP)]^2$	−0.167***	0.0149	−0.0768**
	(-2.61)	(0.32)	(-2.23)
ln(Urb)	−0.339**	−0.0562	−0.163**
	(-2.36)	(-0.54)	(-2.10)
ln(PD)	0.123***	0.111***	0.0515**
	(3.17)	(3.89)	(2.42)
ln(SI)	0.775***	0.412***	0.339***
	(5.44)	(3.96)	(4.36)
ln(CMV)	0.174***	0.116***	0.0731***
	(5.10)	(3.22)	(2.72)
ln(ED)	−0.0891***		
	(-3.98)		
ln(Tem)	−0.211**	−0.135***	−0.225***
	(-3.16)	(-2.88)	(-6.43)
ln(FAI)		0.0823*	0.0654*
		(1.80)	(1.92)
_cons	−18.97***	0.741	−6.015
	(-2.66)	(0.15)	(-1.58)
N	279	279	279

Note: t statistics in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

pollutants in China. The population of civil motor vehicles has a PIP of 0.92, 0.86 and 0.77 for the three pollutants respectively. This is because sulfur oxide, nitrogen oxides, and particulates are the main components of automobile exhaust.

Temperature is one of the most significant differences between Southern and Northern China. The weather is colder in the northern part of China during winter and requires more coal-fired heating. Obviously, there will be emission of pollution gases than in the southern part. Research has revealed that coal-fired heating is the main cause of serious haze in winter in northern China (Li et al., 2016). Therefore, it is reasonable for "temperature" to have a higher explanatory power for $PM_{10,}$ with a PIP of 1.00.

Surprisingly, green coverage rate (GCR), foreign direct investment (FDI), the proportion of the primary industry (PI) and the total land area of administrative region (UA) are not selected for any of the pollutants, implying that the aforementioned variables have weak explanatory power for the three pollutants.

5.2.2. Ordinary least squares estimation results

In order to investigate the influence of economic growth and urbanization on the three pollutants, we establish the ordinary linear regression model based on the EKC theory as follows:

$$\ln(Pollution_s) = \alpha + \beta_1 \ln(PCGDP) + \beta_2[\ln(PCGDP)]^2 + \beta_3 \ln(Urb) + \gamma \ln(Auxiliary\ variables) + \varepsilon \quad (5)$$

The auxiliary variables consist of explanatory variables with PIP greater than or equal to 0.5. We estimate equation (5) using OLS (Ordinary Least Square) method and the results are reported in Table 6.

The OLS estimation results analyze the relationship between the three pollutants and their influencing factors. Firstly, there is an inverted U-shaped curve for SO_2 and PM_{10}, which indicates that SO_2 and PM_{10} support the EKC hypothesis. However, most of the cities are currently on the left side of the Kuznets curve and have not reached the turning point.

Secondly, urbanization rate (Urb) is highly significant and negatively correlated with SO_2 and PM_{10}, indicating that higher urbanization rate is associated with a lower concentration of SO_2 and PM_{10}. A one percent increase in urbanization rate leads to a 0.339% and 0.163% decrease in the concentration of SO_2 and PM_{10} respectively. Some urban variables, such as population density (PD) and the population of civil motor vehicles (CMV), are highly significant and positively correlated with the three pollutants. In specifics, a one percent increase in population density will lead to an increase in the concentration of SO_2, $NO_{2,}$ and PM_{10} by 0.123%, 0.111% and 0.052% respectively. Moreover, a one percent increase in the population of civil motor vehicles will lead to an increase in the concentration of SO_2, $NO_{2,}$ and PM_{10} by 0.174%, 0.116%, and 0.073% respectively.

Thirdly, as expected, the proportion of the secondary industry (SI) has a positive effect on the concentration of SO_2, $NO_{2,}$ and PM_{10}. A one percent increase in the SI increases the three pollutants by 0.775%, 0.412%, and 0.339% respectively. Finally, annual average temperature (Tem) is negatively correlated with the three pollutants. A one percent increase in temperature is found to be associated with 0.211%, 0.135% and 0.225% decrease in the three pollutants. This is consistent with our previous analysis. The cities with lower average temperature will burn larger amounts of coal and other fuels for heating during winter, and emit lots of air pollutants, eventually increasing air pollutants concentration. The results also show a positive and significant relationship between fixed assets investment (FAI) and PM_{10}, FAI and NO_2.

5.2.3. Discussion

From the BMA and OLS regression results, the urban variables (population density, possession of civil motor vehicles, fixed assets investment) and industry variables (the proportion of second industries) have a good explanatory power for the three pollutants. The increase in these variables will lead to higher pollutant concentrations. However, the overall index (urbanization rate) is negatively related to SO_2 and PM_{10}, indicating that cities with high urbanization rate tend to have lower pollutant concentrations. It seems that this conclusion is not consistent with reality. The current situation is that air pollution in China, such as fog and haze, appears to be increasing with the urbanization process. This view has also been supported by some scholars, but these scholars did not consider the following factors when analyzing air pollution. Firstly, China's fog and haze shows obviously seasonal change characteristics，and normally occur in cold winter, mainly in northern China (Guo et al., 2017). The winter in northern China is colder and requires fuel for heating. The pollutants emitted by burning fossil fuel are the main causes of smog (Yuan et al., 2015). Additionally, the wind speed is lower and the relative humidity is higher in winter, which further aggravates the accumulation of air pollutants. Secondly, China is now in the middle and late stages of industrialization, where industrial pollution is the main source of pollutants (Xu and Lin, 2016; Cheng et al., 2017). For example, in 2012, the total SO_2 emissions was 21.18 million tonnes, including 19.12 million tonnes (90.28%) from industrial sources; while total NO_2 emission was 23.38 million tonnes, of which industrial emission was 16.58 million tonnes (70.93%). Thirdly, the concentrated population, which resulted from a high urbanization rate, have obviously resulted in pollution. However, environmental protection investment is currently increasing, especially in the cities with higher urbanization rate. In these cities, developed economy and high income levels make environmental protection investment possible. Effective environmental protection and regulation can effectively improve the urban eco-efficiency (Wang et al., 2014). Therefore, the increase in urbanization rate, and its association with lower pollutant seems to be consistent with reality.

6. Conclusions and policy recommendations

Based on the BMA (Bayesian model average) method and the EKC (Environmental Kuznets Curve) hypothesis, this paper investigates whether air pollutants satisfy the Kuznets curve hypothesis, and discusses the main factors influencing urban air quality in China during the urbanization stage. The main conclusions are as follows: (1) the Kuznets test results show that SO_2 and PM_{10} are in accordance with the characteristics of the EKC. (2) Urbanization rate is highly significant and negatively correlated with SO_2 and PM_{10}. Other variables, such as population density, population of civil motor vehicles, the proportion of secondary industry, and annual average temperature, are the main influencing factors explaining changes in air pollution. (3) Another important conclusion drawn from the BMA method is that the major influencing factors of different air pollutants are not exactly the same. Therefore, each pollutant should be analyzed separately.

China's urbanization and industrialization process has a significant effect on urban air quality, so protecting urban air quality as well as keeping a stable economic growth are key issues to be considered. Based on our analysis, this paper propose the following policy recommendations:

The first is accelerating the “new” urbanization process. The “new” urbanization must be a radiation development from the central city to the small surrounding towns. It is necessary to promote a coordinated development of large cities and small towns. There is need to increase the construction of rural infrastructure, narrow the income gap between urban and rural residents, and plan the development of urban and rural areas as a whole.

The second is the improvement in urban public transportation system. Improved and well-managed transportation system plays a certain role in the replacement of private vehicles. Large and medium-sized cities should speed up the construction of urban rail transit. A convenient and feasible transportation network will alleviate people's dependence on private cars and eventually reduce emissions from cars. Meanwhile, there is need to promote the use of clean energy for heating in China's northern cities. A gradual increase in the proportion of gas heating, electric heating, renewable energy heating should be promoted in accordance with residents' ability to pay.

The third is the strengthening of pollution control and improving environmental legislation. The air pollution problem is closely related to human health. Government needs to take pollution control as an emergency issue. Investment in pollution mitigation is necessary for environmental protection. It is also necessary to strengthen urban greening. A green environment, to some extent, can reduce pollutant concentration. Furthermore, a perfect environmental legislation needs to be established. For high pollution and high energy consuming enterprises, the government should strictly limit the total amount of pollutant emission and also formulate strict penalty for environmental pollution.

The fourth is the optimization and upgrading of the industrial structure. Since the economic reform, China has made great efforts to develop the heavy industry and speed up the industrialization process. The rapid development of the secondary industry has caused serious environmental problems. Currently, many Chinese cities are not only facing severe air pollution but also suffering from water contamination and other pollution problems. In order to promote the optimization and upgrading of the industrial structure, there is the need to change the concept of development from the traditional viewpoints to sustainable development. Cities should adapt to the change in the demand structure, focus on the development of modern industrial system, enhance the level of industrial technology, and promote a coordinated development of the three industries.

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Appendix A. Ambient air quality standards of China

Pollutant	Averaging time	Level		Unit
		Primary standards	Secondary standards	
SO_2	Annual	20	60	ug/m^3
	24-h	50	150	
	1-h	150	500	
NO_2	Annual	40	40	ug/m^3
	24-h	80	80	
	1-h	200	200	
PM_{10}	Annual	40	70	ug/m^3
	24-h	50	150	

Data sources: Ministry of Environmental Protection of the People's Republic of China (http://kjs.mep.gov.cn/).

Appendix B. Correlation coefficient matrix

	PCGDP	Urb	PD	GCR	FDI	SI	PI	CMV	FAI	ED	TEM	UA
PCGDP	1											
Urb	0.7628*	1										
PD	0.137	0.1734*	1									
GCR	0.3112*	0.2838*	0.1356	1								
FDI	0.5834*	0.5237*	0.4925*	0.2612*	1							
SI	0.3824*	0.1663*	0.1006	0.1691*	0.0322	1						
PI	−0.7636*	−0.7269*	−0.2862*	−0.2492*	−0.4930*	−0.3140*	1					
CMV	0.4270*	0.3149*	0.4610*	0.1749*	0.6626*	−0.0519	−0.4734*	1				
FAI	0.5270*	0.3664*	0.4525*	0.1583*	0.7063*	0.0949	−0.4241*	0.8350*	1			
ED	0.3892*	0.4404*	0.4619*	0.2680*	0.5876*	−0.019	−0.3587*	0.4293*	0.4202*	1		
Tem	−0.0565	−0.075	0.5434*	0.1109	0.1608*	0.1106	−0.0908	0.1624*	0.1817*	0.2870*	1	
UA	−0.3062*	−0.3865*	−0.6837*	−0.1392	−0.2477*	−0.2495*	0.4325*	0.05	0.0469	−0.2576*	−0.3511*	1

Note: *p < 0.01.

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