Influence of socioeconomic factors on PM 2.5 pattern in China's megacities between 2013 and 2019

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Abstract

In the last decade, Chinese megacities have undergone rapid and massive urbanisation that resulted in rising $PM_{2.5}$ levels in megacities, which forced the government to implement stricter air quality guidelines to combat it. This study investigates the effectiveness of the five-year (2013–2017) air combat plan in reducing $PM_{2.5}$ in these megacities since they have achieved a certain level of urbanisation. The findings show that annual concentrations of $PM_{2.5}$ exceeded the World Health Organization (WHO) guideline value, and eight out of ten cities exceeded the national ambient air quality standard (NAAQS) guideline value. Although, on an annual level, a consistent downward trend was observed for $PM_{2.5}$ values among all cities starting from 2013, indicating positive policy feedback from guidelines. The cumulative rate of change in $PM_{2.5}$ concentrations from 2013 to 2019 indicated that the highest magnitude of the decrease occurred in Beijing and Chengdu (-59%). The Environmental Kuznets curve was observed for $PM_{2.5}$ with GDP and Industrial SO_2 emission. A negative relationship was observed between $PM_{2.5}$ and secondary industry share, while the contrary was observed between $PM_{2.5}$ and Industrial NO_2 emissions. Our data indicated that stricter sanctions and emission policies are needed to lower the $PM_{2.5}$ values in most of these megacities.

1. Introduction

Urbanisation has played a crucial role in improving the Chinese economy and the quality of life for its people since the government started implementing the policy in the early 1980s. It has led to a linear and exponential economic growth, accompanied by some of the largest human migrations in history (Han et al., 2014, Fang et al., 2015, Han et al., 2018). Nearly half of the Chinese population is speculated to migrate and stay in urban cities, leading to more cities constantly undergoing rapid development (Zund and Bettencourt, 2019). The urban population in China has increased by 300 million (1/5th of the Chinese population) from 2005 to 2018, indicating an exponential desire among Chinese residents to live in urban cities (Jizhe, 2020). Rapid urbanisation has led to a high standard of living in urban areas while, on the other way, led to high levels of $PM_{2.5}$ in the atmosphere, which is found at unhealthy levels in major Chinese cities (Han et al., 2014, Wang et al., 2016, Han et al., 2018, Luo et al., 2018). Even though the government has implemented measures and policies that help mitigate the $PM_{2.5}$ levels, multiple provincial and city-based studies have shown that the values are not constantly at healthy levels (Yang et al., 2018, Song et al., 2019, Yue et al., 2020).

There are significant differences among Chinese provinces and even great differences between the capital city and other cities in a developing country. Multiple studies have observed uneven economic development among regions, and the gap between rich and poor provinces is vast (Xu et al., 2019, Wang et al., 2021). The developed provinces are practically located in the southeastern coastal areas of China, such as Beijing, Shanghai, Jiangsu, and Zhejiang. In contrast, the poorer provinces in China are concentrated in the northwest and southwest regions, such as Guangxi, Yunnan, and Guizhou province, Qinghai Province, Gansu Province, to name a few.

Since gross domestic product (GDP) is a strong indicator of urbanisation, it indicates a massive migration from rural to urban areas. Even though there are multiple time-series studies on specific Chinese cities, time-series studies among major urbanised Chinese cities after the proposed guidelines coupled with GDP and population are also not well established (Luo et al., 2018, Wang et al., 2016, Zhou et al., 2018a, Liu et al., 2020a). It is commonly believed in the scientific community that different urban $PM_{2.5}$ and PM_{10} concentration levels among cities are highly attributable to the imbalance in the urbanisation progress (Han et al., 2014). One of the significant factors that influence urbanisation is the population of people living in urban cities and the transportation that these people use.

Anthropogenic activities are often the major contributor to a series of pollution episodes that causes heavy surface level pollution. Data from model simulation and satellite imagery suggest that $PM_{2.5}$ concentrations are higher in many regions of China than in other countries, mainly in urban areas (Jahn et al., 2013, Wang et al., 2013, Ming et al., 2017, Zhang et al., 2019, Sun et al., 2019). In 2013, the Chinese government established the five-year air combat plan named “Air pollution prevention and control action plan”, which proposed to reduce $PM_{2.5}$ in all the urban cities to a substantial level. This policy aims to achieve the National Ambient Air Quality Standard (NAAQS) (35 $\mu g/m^3$) and World Health Organization (WHO) (15 $\mu g/m^3$) guideline values. The issue remains that when compared with the 24hour- $PM_{2.5}$ values proposed by WHO, most urbanised Chinese cities still fail to reach those proposed targets (Cai et al., 2017, Li et al., 2022). The Chinese government has also implemented increasing the proportion of green spaces in most urbanised cities to mitigate the $PM_{2.5}$ pollution (Chen et al., 2016, Wang et al., 2019, Wang et al., 2020). Seasonal weather patterns and wind direction seem to significantly affect the fluctuation of values, resulting in most urban residents inhaling high levels of $PM_{2.5}$ (Ming et al., 2017, Mao et al., 2018). In terms of seasonality, previous studies showed that a higher concentration of $PM_{2.5}$ over cities was recorded during winter followed by spring, with the lowest recorded during the summer season (Wang et al., 2016, Zhan et al., 2018, He et al., 2021). Air pollution research in China about $PM_{2.5}$ has received extensive attention, including the analyses of spatiotemporal variation (Chen et al., 2016, Xu et al., 2017, Guan et al., 2017, Yang et al., 2018, Song et al., 2019, Sun et al., 2019, Wang et al., 2014), source apportionment (Zheng et al., 2005, Wang et al., 2013, Zhang et al., 2015, Li et al., 2018), chemical composition (Wen et al., 2016, Ming et al., 2017, Li et al., 2018) and health effects (Liu et al., 2017, Cao et al., 2018, Qi et al., 2018, Weber et al., 2016).

Similarly, multiple $PM_{2.5}$ studies have analysed social and economic factors to investigate the impact of urbanisation and anthropogenic activities (Luo et al., 2018, Zhou et al., 2018b, Zhou et al., 2018a, Wang et al., 2021). A common denominator that stands out from all these studies is that the cities with less total area tend to have lower $PM_{2.5}$ concentrations (Xu et al., 2019, Liu et al., 2020b). However, urban population size and GDP might have a positive linear relationship based on the geographical location (Luo et al., 2018) or fit the Environmental Kuznets Curve (EKC) (Zhao et al., 2019). The EKC is a hypothesis that could be applied to understand the relationship between economic development and environmental pollutants with an inverted U-shaped curve (Grossman and Krueger, 1995). The environmental Kuznets curve hypothesises that a country or city’s economic development initially

increases environmental pollutants, but after achieving a certain level of economic growth, the country or city begins to improve its relationship with the environment, which will be evident through the decreasing levels of environmental pollutants. We found that only few studies have specifically focused on long term relationships between socioeconomic variables and $PM_{2.5}$ pollution on a city level in China.

Our study addresses the lack of knowledge by accessing ground-based monitoring datasets from 2013 to 2019. In China, we studied ten megacities (Beijing, Tianjin, Chengdu, Chongqing, Hangzhou, Guangzhou, Shanghai, Shenzhen, Suzhou and Wuhan) based on their population, population density, GDP, Industrial emissions, Green area and Secondary industry share. We want to point out that the Chinese government started recording and publishing ground-based $PM_{2.5}$ concentrations only in 2013, challenging long-term monitoring. We implemented the rate of change from 2013 to 2017 to understand the impact of the "China air pollution combat plan" and from 2013 to 2019 to observe whether the changes were retained after 2017. We performed regression models to identify the socioeconomic factors influencing $PM_{2.5}$ from 2013 to 2019. The findings from our study have the potential to understand the impact of the socioeconomic factors driving $PM_{2.5}$ in these Chinese megacities and attempt to produce a quantitative explanation of their relationship.

2. Study Area, Data, And Methodology

Study area

The geographical locations of the ten megacities are shown in Fig. 1. Most studies have indicated that these cities are known for their high $PM_{2.5}$ concentrations, which exceed the WHO and NAAQS (Chan and Yao, 2008, Peng et al., 2016, Zhou et al., 2018b). Regarding long-term concentration, $PM_{2.5}$ in the selected cities were previously associated with rapid urbanisation (Luo et al., 2018, Zhou et al., 2018b).

Particulate matter data

The study utilised $PM_{2.5}$ data from respective cities monitoring stations. The acquired $PM_{2.5}$ data covered the period between January 2013 and December 2019 for all the cities. All the data can be accessed through China's national urban air quality real-time publishing platform (http://106.37.208.233:20035) provided by the government of the People's Republic of China.

Socioeconomic data

Previous studies have used many socio-economic factors to examine the impact of urban development or human activities on air pollutants (Zhao et al., 2019, Shi et al., 2020, Wang et al., 2021). Based on previous studies and considering data availability of $PM_{2.5}$, we selected five types of factors: 1) Total population, green area, and gross domestic product (GDP), which can reflect the degree of urban development; 2) population density representing the intensity of human activity; 3) industrial activities

measured by the share of secondary industry and industrial SO_2 and NO_2 emissions. Data for most of these factors were obtained from the Chinese national and regional statistical yearbook.

Statistical methodology

Daily $PM_{2.5}$ concentrations values from 2013 to 2019 were analysed at seasonal and annual scales to assess the variations of the ten megacities. Only seasonal and annual means were used to compare and calculate this study. Since all of these cities have four distinctive climatic seasons, we decided to follow the northern hemisphere seasonal pattern for the analyses, and these include Winter (December-January-February), Spring (March-April-May), and Summer (June-July-August) and Autumn (September-October-November).

Rate of Change

The present study employed two rates of change scenarios; 1) to assess cumulative changes and 2) the influence of a five-year air pollution policy. In order to understand the effect of the five-year air pollution policy, we studied the rate of change from 2013 to 2017, while the cumulative rate of change was studied from 2013 to 2019. For an easy understanding of the changes, we computed relative percentages as shown in Eq. 1;

$$\mathrm{Relativechange}(\%) = ((\delta\_\mathrm{j} - \delta\_\mathrm{i}) / \delta\_\mathrm{i})\mathrm{X}100\%$$

1

Where: δ is the concentration of the pollutant during the selected years i and j.

Regression analysis

The Ordinary Least Squares regression was carried out in two steps: First, the study explored the relationship between the socioeconomic factors and $PM_{2.5}$ concentration using scatterplots. Secondly, an ordinary least squares (OLS) regression analysis was performed using $PM_{2.5}$ concentration as the dependent variable and socioeconomic factors as independent variables.

A mathematical representation of linear regression is as follows.

$$Y = X\alpha + \epsilon$$

2

where Y is the dependent variable ($PM_{2.5}$), X is the explanatory variable (socioeconomic factors), α is the regression coefficient, and ε is the random error.

All these statistical analyses were performed using SPSS™ 24.

3. Results And Discussion

3.1 Spatio-temporal variation and rate of change of $PM_{2.5}$ concentration

The seasonal and annual variation of $PM_{2.5}$ is shown in Figs. 2 and 3. The average $PM_{2.5}$ concentrations in ten megacities revealed a decreasing trend from 2013 to 2019. The annually averaged concentration of $PM_{2.5}$ among the megacities ranged from 28.2 to 96 μg/m^3, with most cities exceeding the new NAAQS (35 μg/m^3) of China and the World Health Organization air quality guideline (10 μg/m^3). From Fig. 3, it can be observed that the $PM_{2.5}$ concentration is generally higher in the cities located in the northern region than those observed in the southern region and are lower in the coastal regions than in the inland regions. This suggests that different control strategies should be implemented by considering the geographical location, local/regional emissions and meteorological factors. A U-shaped pattern could be observed for most cities with distinctive seasonal weather patterns, with winter highest and summer lowest (Fig. 2).

These results are consistent with the study conducted by Gao et al. (2020). Moreover, intense emissions of transportation and coal burning in winter were also important factors (Ming et al., 2017, Mao et al., 2018, Sun et al., 2019). High levels of $PM_{2.5}$ concentration during winter could be due to coal and fossil fuel burning to supplement heat during cold conditions (Liu et al., 2020b). The significant decrease in $PM_{2.5}$ during summer could be associated with reduced anthropogenic emissions such as fossil fuel and biomass burning for domestic heating (Lin et al., 2018, Li et al., 2018, Zhao et al., 2021). The U-shaped seasonal variation could also be influenced by meteorological conditions, including low mixing heights and high atmospheric stability in winter, which did not favour particle diffusion. For instance, Zhao et al. (2013) investigated the visibility and $PM_{2.5}$ in Northeast China and concluded that wind speed was the essential meteorological factor influencing $PM_{2.5}$ concentration.

It can be noted from Fig. 4 that the decrease in $PM_{2.5}$, industrial SO_2 and NO_2 emissions coincides with the Chinese government's five-year plan (2013–2017) for air combat policy. From 2013 to 2019, Beijing, Tianjin, Suzhou, Wuhan and Chengdu had the most reduction (≥ 50%) in $PM_{2.5}$ concentration; cities with a ≥ 50% from 2013 to 2017 include Beijing and Tianjin, Suzhou and Chengdu. The present findings are inconsistent with other studies investigating post-2013 air pollution (Cai et al., 2017, Sun et al., 2019, Zhang et al., 2019, He et al., 2021). These reductions are due to stricter policies implemented to limit industrial emissions (Xu et al., 2019, Wang et al., 2021). Such reductions in $PM_{2.5}$ reflect the regional mitigation efforts implemented through a clean-heating policy to reduce the city's reliance on coal and fossil fuel burning for long-term heating (Li et al., 2022). For instance, at the start of 2017, governments in North China implemented a strict ban on dispersed coal usage (Li et al., 2018, Gao et al., 2018).

3.2 Relationship and impact of socioeconomic factors on the level of $PM_{2.5}$ concentration

$PM_{2.5}$ concentrations from the megacities were significantly related to many socioeconomic factors (Fig. 5). These factors included the population, GDP, secondary industry share and Industrial NO_2 emissions. An inverse U-shaped relationship was observed between $PM_{2.5}$ concentration with GDP and Industrial SO_2 emission (no significance), supporting the classical Environmental Kuznets curve (EKC) hypothesis. In contrast, we observed a U-shaped relationship between $PM_{2.5}$ concentrations and Green area (no significance) and Secondary industry share. We observed a non-linear relationship between $PM_{2.5}$ concentration and population density (no significance) but failed to fit an inverse U-shaped curve. This result has rarely been found in other studies since population density has always supported the EKC hypothesis or linear relationship in Chinese cities (Xu et al., 2019, Zhao et al., 2019, Wang et al., 2021). An inverted U-shaped EKC relationship was observed between $PM_{2.5}$ and GDP, similar to other studies (Shi et al., 2019, Wang et al., 2021), with the turning point of EKC at ~ 12,000 Hundred million Yuan.

We found a slightly negative relationship between $PM_{2.5}$ and GDP, suggesting that economic development may or may not worsen the air quality in the megacities, which was also observed by (Zhou et al., 2018b). However, given the annual reduction of $PM_{2.5}$ in all megacities, we believe the deterioration of $PM_{2.5}$ is highly unlikely, and we hope that the Chinese government maintains a stable and sustainable economic growth which does not worsen air pollution levels. Our study also observed a contrasting relationship between $PM_{2.5}$ and secondary industry share compared with most studies that supported the EKC hypothesis (Zhou et al., 2018b, Zhao et al., 2019). Since our study looks at megacities that reached a potential saturation in population density with negligible increases every year, it would explain the non-linear relationship between $PM_{2.5}$ concentration and population density (Zhang and Cao, 2015, Luo et al., 2018). Cities with higher population density usually consume more energy and have higher emissions, but given the government's recent "green movement", we observed a U-shaped relationship between green area and $PM_{2.5}$, which indicates a reduction in densification. The reduction could help mitigate the city's air pollution (Zhao et al., 2021). Our study shows that in megacities with near-saturated population density, more importance should be given to creating green areas to mitigate $PM_{2.5}$ levels in the atmosphere. The industrial structure is considered by the government and researchers as a critical factor when it comes to impacting air pollution. Our data on the relationship between $PM_{2.5}$ and secondary industry share differed from several studies; we observed a negative, almost linear (U-shaped) relationship (Liu et al., 2020b, Fan et al., 2020, Shi et al., 2020). Industrial NO_2 emissions had a significant positive relationship with $PM_{2.5,}$ but it did not fulfil the EKC hypothesis, whereas the exact opposite was observed for Industrial SO_2 emissions. Wang et al. (2021) observed a positive relationship between Industrial NO_2 emissions and $PM_{2.5,}$ citing clean air policy implemented by the Chinese government in 2013 has helped set emission standards for industries. Several studies have also noted that Industrial SO_2 and NO_2 emissions have started reducing in cities, transitioning to greener technologies (Li et al., 2022, Ye et al., 2018). Given that the Industrial NO_2 emissions are still positively correlated with PM2.5, the government needs to implement stricter guidelines to minimise these emissions in the future. The OLS regression co-efficient showed that all variables, except for Industrial SO_2 emission, green area and

population density, were significantly related to $PM_{2.5}$. Among all the variables, Secondary industry share was the most important predictor, indicated by the standard coefficients, and Industrial NO_2 emissions were the second most important predictor (Table 1).

Table 1
Coefficients of the OLS regression model.

	Regression Coefficient
Constant value	5.567** (3.249)
ln (Population)	-0.229* (-2.692)
ln (Population density)	-0.084 (-1.795)
ln (GDP)	-0.147** (-2.812)
ln (Secondary industry share)	-0.505** (-3.252)
ln (Green area)	-0.041 (-0.145)
ln (Industrial SO_2)	-0.022 (-0.275)
ln (Industrial NO_2)	0.286** (2.687)
N	70
Adjusted R^2	0.551

Note: Values in brackets are the t values. *: $p < 0.05$, **: $p < 0.01$.

In China, economic development in more developed cities, such as the megacities in the BTH, YRD and PRD regions, may rely on tertiary industries (e.g., wholesale and retail Businesses, finance and real Estate) compared to cities from the Jing-Jin-Ji region which are known for their secondary industries. Furthermore, cities, such as Beijing, with better economic development, may have already experienced

severe air pollution, which has resulted in them paying more attention and investing more resources in air pollution control in recent years. Consequently, these cities may have lower PM2.5 concentrations.

Conclusion

$PM_{2.5}$ pollution is recognised as a severe problem in major Chinese cities. The study results indicate that implementing air quality guidelines has reduced the $PM_{2.5}$ levels in several cities by over 50% annually from 2013 to 2019. Even though some cities still average more than the target NAAQS and WHO guidelines, it can be observed that is there a consistent annual downward trajectory for $PM_{2.5}$ values. In addition, $PM_{2.5}$ mass concentrations revealed notable seasonal variability, with the highest $PM_{2.5}$ level occurring during the winter and the lowest during the summer. Shenzhen and Guangzhou (coastal cities) seem to have the cleanest air compared with other cities, indicating potential coastal influence. Seasonal variations were found to conform to a U-shaped curve, and the rate of change showed that $PM_{2.5}$ concentration levels in the megacities had decreased massively due to the five-year air pollution combat plan complemented by the Chinese government.

Declarations

Ethics approval

Not applicable

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Consent to participate

Not applicable

Consent to publish

Not applicable

Authors contribution

The following are individual contributions: M.N, & A.R: conceptualisation, formal writing, and original draft preparation. H.B & Z.C: Data curation, methodology, visualization. B.A, and A.R and C.G: writing-review and editing, investigation. Z.C & B.W: Validation. B.A: Funding.

Declaration of competing interest

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

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Availability of data and material

All data generated or analysed during this study are included in this published article (and its supplementary information files).

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Figures

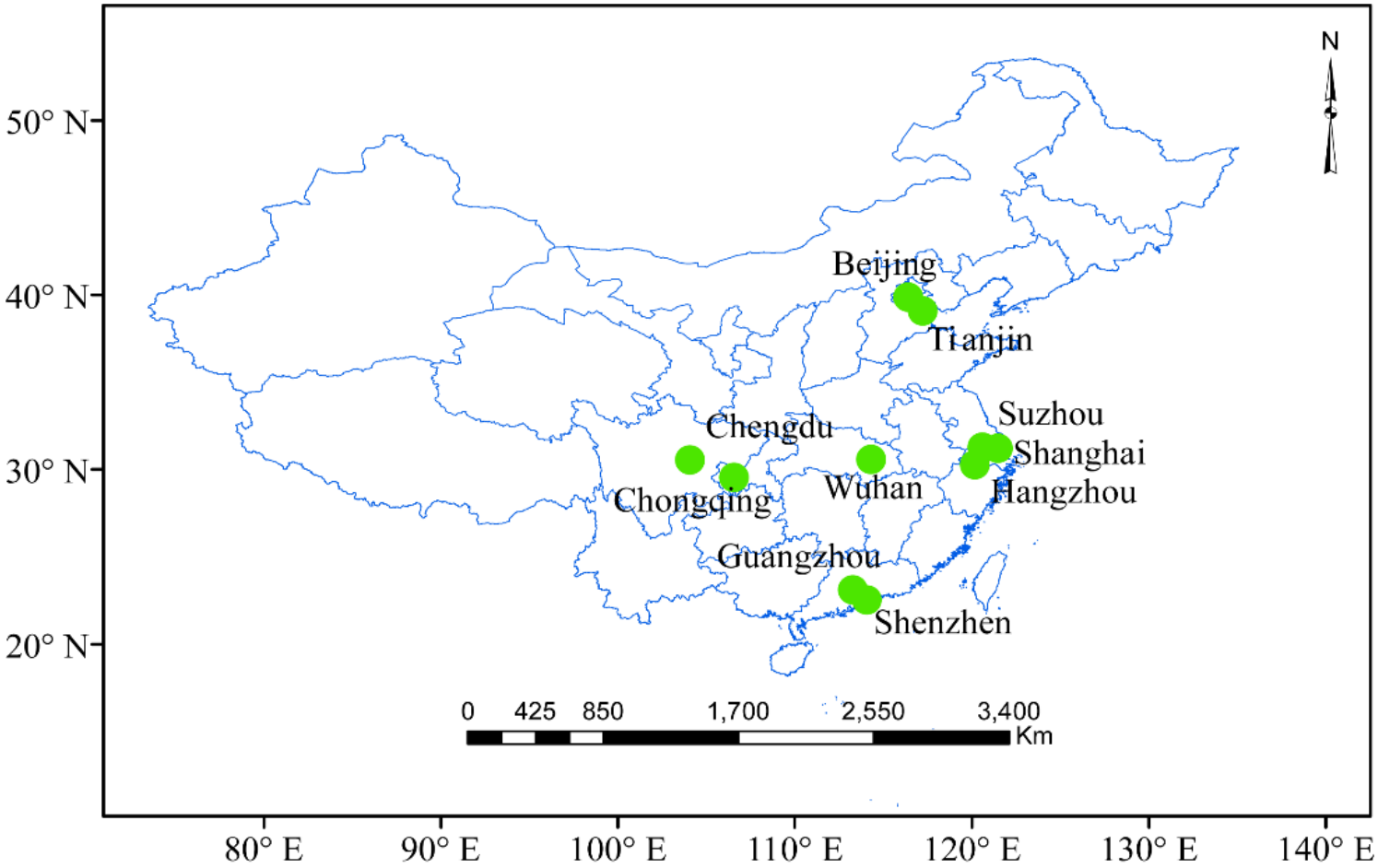

Figure 1

Spatial distribution of the selected cities used in this study

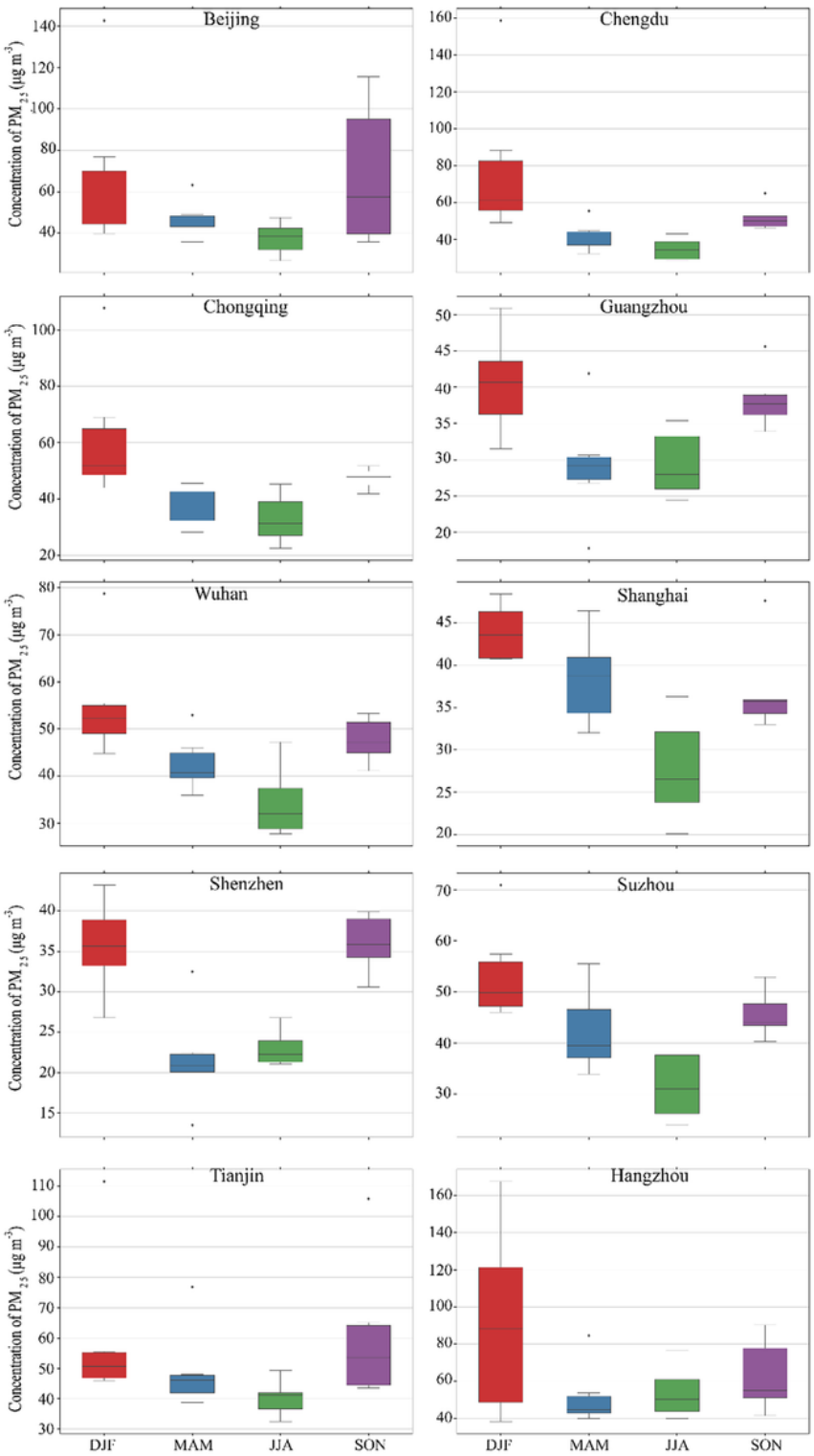

Figure 2

Seasonal PM2.5 concentrations for selected cities. The seasons are defined as follow: Spring as March to May (MAM), summer as June to August (JJA), fall as September to November (SON), and winter as December to February (DJF). The boxes show interquartile range, horizontal lines represent the median, while the whiskers extent to the minimum/maximum value within 1.5 interquartile range of the

lower/upper quantile. The crosses denote the outliers outside the 1.5 interquartile range of the upper/lower quartile.

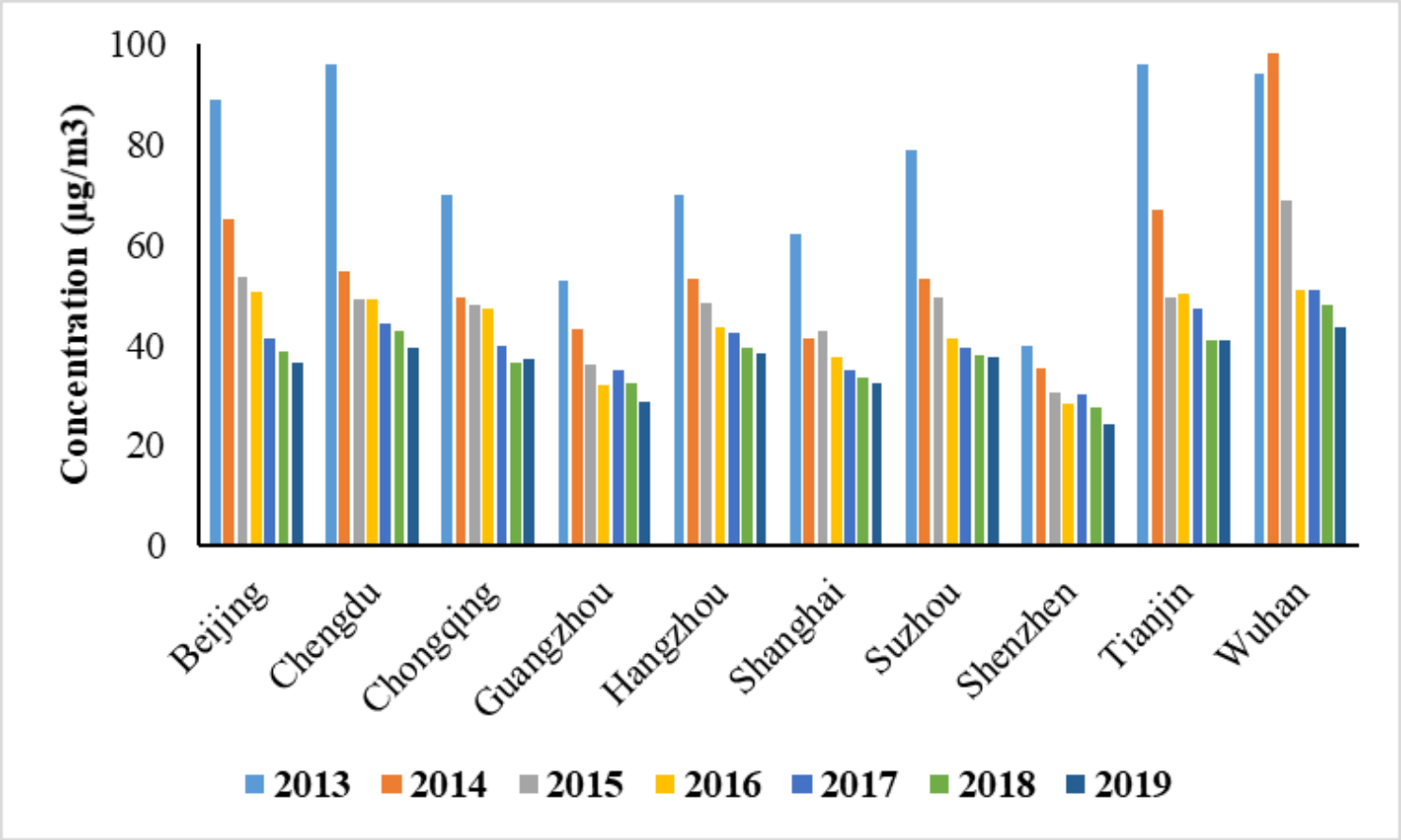

Figure 3

Annual $PM_{2.5}$ concentration over ten mega cities of China

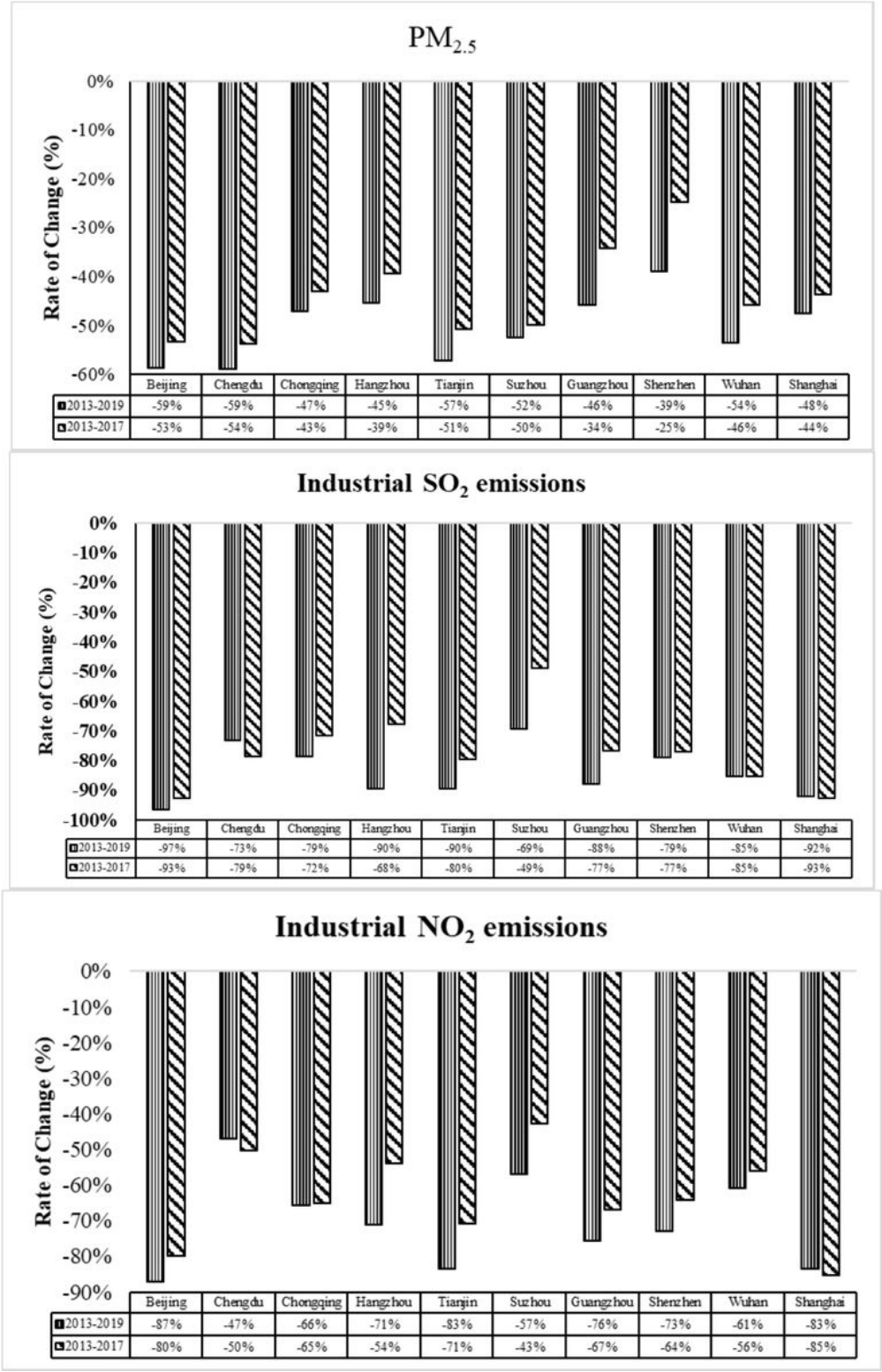

Figure 4

Rate of change of $PM_{2.5}$ concentration, Industrial SO_2 and NO_2 emissions over ten mega cities of China from 2013-2019 and 2013-2017.

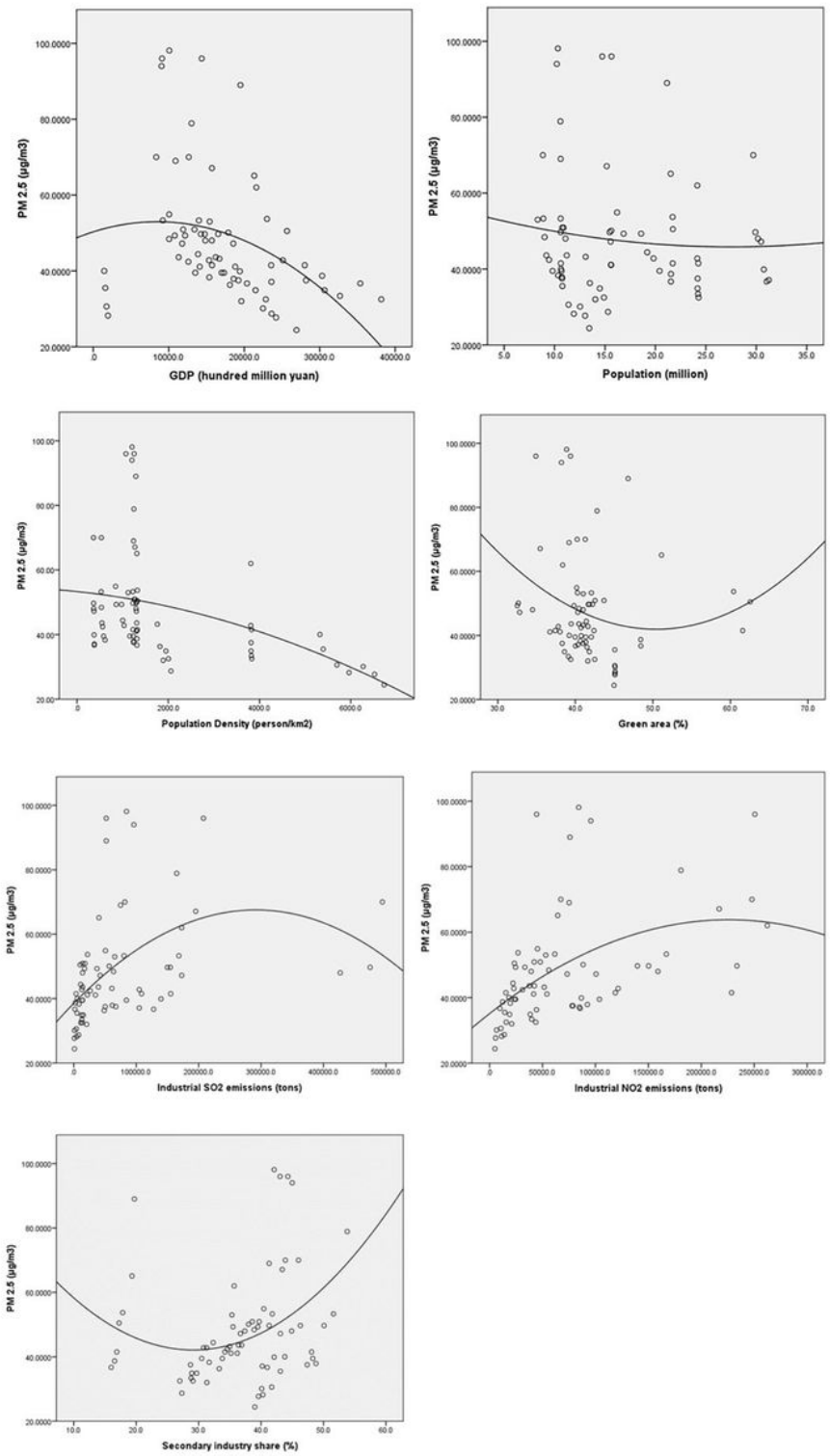

Figure 5

The scatterplots of $PM_{2.5}$ concentrations from 2013-to 2019 and socioeconomic factors. The black lines on the scatterplots indicate the fitting curve of the relationship between $PM_{2.5}$ concentration and socioeconomic factors of study cities according to the OLS regression model.