The heterogeneous effects of socioeconomic determinants on $PM_{2.5}$ concentrations using a two-step panel quantile regression

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Abstract:

The haze pollution caused by high $PM_{2.5}$ concentrations has adverse health effects worldwide, especially in rapidly developing China. The influencing mechanism of $PM_{2.5}$ pollution is a complex process affected by both natural and anthropogenic factors. As meteorological conditions are uncontrollable, this study aims to investigate how anthropogenic factors affect the $PM_{2.5}$ concentration under high, medium and low emission levels. The distribution of socioeconomic variables is often non-normal, with important information hidden in the tail. By using balanced panel data of 273 Chinese cities from 2010 to 2016, two-step panel quantile regression is adopted to examine the cross-quantile heterogeneity of seven socioeconomic variables: economic growth, industrial structure, urbanization, foreign direct investment (FDI), population density, public transportation and energy consumption. The empirical results show that the relationships of $PM_{2.5}$ concentration with economic growth, urbanization, industrialization and FDI are heterogeneous. Compared with other variables, population density exerts the greatest positive effect on $PM_{2.5}$ pollution across all quantile cities. Moreover, the impact of GDP per capita on $PM_{2.5}$ concentration in the lower 25th quantile cities is stronger than those in the 25th-50th, 50th-75th and upper 75th quantile cities. The effects of FDI in the upper 75th and lower 25th quantile cities are higher than those in the 25th-50th and 50th-75th quantile cities, which supports the “pollution haven” hypothesis. The impact of industrial structure on $PM_{2.5}$ concentration in the upper 75th quantile cities is larger than those in the 0-25th, 25th-50th, and 50th-75th quantile cities. The heterogeneous effects of these socioeconomic determinants could assist policymakers in implementing differentiated policies that fit cities with different levels of air pollution.

Keywords: $PM_{2.5}$ concentrations; Spatiotemporal variations; Panel quantile regression, Prefecture-level cities

1. Introduction

Globally, outdoor air pollution characterized by atmospheric aerosols causes millions of premature deaths each year, predominantly in Asia. Fine particulate matter and carbonaceous particle emissions from residential energy use (such as heating or cooking) in China and India contribute significantly to this health hazard [1], while in the United States, emissions from electricity production and transportation are more important. Cities are centres of human economic and production activities. With the spread of urban spaces, air pollution has become one of the most important public health challenges worldwide.

As China is experiencing rapid urbanization and industrialization, its high energy consumption has been accompanied by a severe deterioration of air quality, and haze pollution has appeared frequently since 2013 [2, 3]. The highest daily mean concentration of fine particulate matter with a diameter less than 2.5 μm ($PM_{2.5}$) in Beijing, the capital of China, exceeds 500 μg/m^3 at times, while the 24-hour air quality guideline (AQG) for $PM_{2.5}$ concentration set by the World Health Organization (WHO) is 25 μg/m^3 [4]. In 2016, the population-weighted mean $PM_{2.5}$ concentration in Chinese cities was 61 μg/m^3, three times the global mean [5]. Overall, approximately 75.1% of Chinese cities fail to meet the annual AQGs suggested by the WHO. $PM_{2.5}$ and PM_{10} are the primary pollutants [6]. Fine particulate matter can be deposited in the airway or trachea, bronchus and alveoli by inhalation, which may lead to cardiopulmonary disease and reduce individual immunity [7]. Therefore, air pollution control is a major priority of the current Chinese government, and research on the spatiotemporal distributions and socioeconomic drivers of $PM_{2.5}$ pollution is particularly important. The Chinese government has made tremendous efforts to control and eliminate haze pollution. For instance, the State Council released the *Air Pollution Prevention and Control Action Plan* in 2013, which aimed to reduce the $PM_{2.5}$ concentration in cities at the prefecture level and above by more than 10% by 2017 relative to the 2012 level [8]. This plan set $PM_{2.5}$ targets for key regions and has been regarded as China's most influential environmental policy. In 2018, the State Council continued to promulgate the *Three-Year Action Plan* for tackling air pollution, following the expiration of the previous plan issued in 2013. The Three-Year Action Plan proposes to decrease the urban $PM_{2.5}$ concentration by at least 18% below the standard compared with 2015. Another notable change is that the Pearl River Delta, which was one of the three key regions in the previous action plan, is not included. Furthermore, the new Ministry of Ecology and Environment (MEE) was formally established for pollution-related functions, highlighting the importance of environmental affairs in China's policy management.

Identifying and quantifying the socioeconomic determinants of urban $PM_{2.5}$ concentration changes could allow a better understanding of air quality problems and thus assist policymakers in implementing pollution mitigation strategies and health impact control. This study endeavours to assess how socioeconomic status affects urban $PM_{2.5}$ pollution, and the major influencing variables selected represent the current status of Chinese cities from various perspectives. Specifically, GDP per capita is regarded as the most important factor in almost all relevant articles, and regional economic gaps can be directly reflected by this common indicator. The "pollution haven" hypothesis holds that inward FDI leads to the deterioration of local environments [9]. However, bidirectional causality between these two phenomena has been investigated in some studies [10]. FDI is regarded to exert an uncertain impact on environmental pollution. Population density will stimulate living and production activities by continuously increasing rigid demand. Previous studies have found that air pollution is greater in more populated cities [11]. Energy activities in the industry sector are considered to play a key role in pollution discharge. Here, we assume that industrial structure increases $PM_{2.5}$ pollution. Total electricity consumption is used to specify energy consumption. The expected direction here is positive because the greater the electricity consumption, the greater the power supply and the more $PM_{2.5}$ emissions will be emitted by coal-fired power plants. The built-up area refers to the area that has been developed and constructed with basic municipal public facilities. Cities with larger built-up areas are often first-tier cities with a larger population base, and these cities are more likely to be polluted. The number of buses per ten thousand people represents the level of public transport in a city. The number of buses will have a certain substitution effect on private cars, and we expect that this factor will exert an inhibitory effect on $PM_{2.5}$ pollution. In summary, there are two main reasons why these socioeconomic factors are chosen as explanatory variables. The first is theoretical relevance; economy, industrialization and urbanization are closely related to urban air pollution to varying degrees and are often regarded as the explanatory variables of environmental pollution in the existing literature [12]. Second, only the availability and consistency of data can ensure the smooth progress of empirical research. Based on the available statistical data of 273 prefecture-level cities in China from 2010 to 2016, we quantitatively investigate how the impacts of these variables change across cities in the lower 10th, 25th-50th, 50th-75th, 75th-90th, and upper 90th quantiles. Table 1 summarizes the variables used in this study and the expected relationship with $PM_{2.5}$ pollution in accordance with existing studies.

Table 1 Definition of socioeconomic variables

Variable	Definition	Unit of measurement	Expected direction
GDP	GDP per capita	yuan	+
SI	The proportion of added value of secondary industry in GDP	percent	+
PUC	The proportion of urban construction land in urban areas	percent	+
FDI	Proportion of FDI in GDP	percent	−
PD	Population density	people/km^2	+
BUS	The number of buses per ten thousand people	number/10000 person	−
EL	Total electricity consumption	10000 kwh	+

The main novelties and contributions of this research are as follows. This study investigates cross-quantile heterogeneous effects of anthropogenic factors on urban $PM_{2.5}$ concentrations under different emission levels, further enriching the research perspective on the variation rule of factor coefficients. Compared with most of the literature, which solely emphasizes the average effect, a more comprehensive assessment of the relationship between socioeconomic factors and $PM_{2.5}$ pollution is carried out by taking into account the specific disparities between cities. Specifically, a two-step quantile regression approach is applied to reveal the extent to which the relationship between socioeconomic factors and $PM_{2.5}$ pollution changes across different levels. Compared with the traditional OLS method, this approach can capture the heterogeneous effects exerted by socioeconomic factors on different emission quantiles by presenting the full picture of the conditional distribution. The remainder of the paper is arranged as follows. Section 2 succinctly reviews the existing related literature on the relationship between socioeconomic and $PM_{2.5}$ pollution. Section 3 describes the applied method as well as the corresponding data. Section 4 presents the empirical results and discussion. Conclusions and countermeasures are discussed in Section 5. Table A1 shows the abbreviation summary.

2. Literature review

Different meteorological conditions lead to different distributions of fine particles in the air and thus affect haze pollution [13, 14]. Temperature, precipitation, wind speed and other meteorological conditions have a combined effect on fine particulate matter. For example, wind transports suspended particulate matter in the atmosphere parallel to surrounding cities and dilutes air pollutants. The higher the wind speed, the better the air quality of a city. When precipitation reaches a certain level, haze particles in the air will be washed away. The heat island effect makes the temperature of a city higher than that of the suburbs, and various suspended particulate matter will absorb a large amount of longwave heat radiation and accumulate over the city, thus increasing the possibility of haze pollution.

Research on emission–growth–renewables has focused attention on the potential impact of various socioeconomic activities on pollutant emissions from an energy-related perspective [15, 16]. A large body of scholarly literature has explored the complex relationship between $PM_{2.5}$ concentrations and economic and social development, but the different effects of different variables are still unclear. The most commonly used methods in previous studies include econometric analysis [17, 18], spatial econometrics modelling [19-22], remote sensing techniques [23], autoregressive distributed lag approach (ARDL) [24], input-output models [25-27], and geographically weighted regression (GWR) [28, 29]. Table 2 lists representative studies of socioeconomic factors affecting $PM_{2.5}$ pollution using different methods in the past five years. The expected relationships between different socioeconomic factors and pollution are indicated by the symbol "+," representing positive, and "–", representing negative.

Table 2 Representative literature on socioeconomic factors of $PM_{2.5}$ pollution

Sources	Socioeconomic factors	Methods	Data
Liu et al. (2019) [17]	economic development (U-shaped), industrial structure (+), road density (+), built-up area (mixed); FDI (+), population density (no effect)	panel regression model	panel data of 287 cities
Wang et al. (2017) [18]	urban area (+), urban population (+), share of secondary industry (+), population density (+)	linear regression	cross-sectional data of 190 cities
Zhou et al. (2018) [19]	population density (+), industrial structure (+), industrial dust (+), road density (+), trade openness (no effect), electricity consumption (no effect)	spatial regression model	cross-sectional data of 190 cities

Hao and Liu (2016) [20]	GDP per capita (U-shaped), vehicle population (+), secondary industry (+)	spatial lag model spatial error model	cross-sectional data of 73 cities
Jiang et al. (2018) [32]	industrial activities (+), city sizes (+), residents' activities (+)	structural equation model	panel data of 135 cities
Cheng et al. (2017) [33]	economic development (U-shaped), secondary industry, population density (+), energy intensity (+), industrial structure (+), traffic intensity (+), central heating (+), FDI (no effect)	dynamic spatial panel model	panel data of 285 cities
Zhang et al. (2019) [34]	emission intensity (−), energy intensity (−), economic output (+), population (+)	Logarithmic Mean Divisia Index	panel data of 152 cities

Specifically, through an analysis of $PM_{2.5}$ concentration datasets of 945 monitoring stations in 190 cities, Wang et al. (2017) found marked seasonal variation of $PM_{2.5}$ concentrations at the city level, with the highest concentration in winter. Population density in part is responsible for the differences in $PM_{2.5}$ concentrations among Chinese cities. Energy-intensive industries promote the economic development of most cities and have a positive impact on $PM_{2.5}$ concentrations. Furthermore, the hypothesis of an inverted U-shaped relationship between $PM_{2.5}$ concentrations and the level of economic development has been strongly supported [18]. Similarly, using data from China's urban monitoring stations, Zhou et al. (2018) investigated the effects of population density, industrial structure, industrial dust, road density and economic growth on $PM_{2.5}$ concentrations [19]. Based on panel data of Chinese cities from 2001 to 2012, Cheng et al. (2017) used dynamic spatial panel models to find the sources of air pollution. The results indicated that secondary industry, energy structure, population growth and traffic intensity have driving effects on haze pollution [22]. Given the possible heterogeneous distribution of $PM_{2.5}$ concentrations in space and time, Dong et al. (2019) developed a geographically and temporally weighted regression (GTWR) model to identify and investigate the influence of eleven variables on $PM_{2.5}$ concentrations. The results showed that the effects of various factors are volatile. Transportation and construction are the main sources of haze pollution and should be the major targets for pollution mitigation [30]. In addition to major pollutants such as $PM_{2.5}$ and PM_{10}, the spatial pattern and spatial agglomeration of air quality have received increased attention. Ye et al. (2018) utilized the Comprehensive Air Quality Index (CAQI) to explore the spatial distribution patterns of six pollutants (PM, PM, SO, NO, CO, O) in 338 Chinese cities and adopted the spatial autocorrelation method to detect the spatial agglomeration type [31]. Similarly, Xu et al. (2019) used the Air Pollution Index (API) and Air Quality Index (AQI) to examine the socioeconomic factors driving the observed spatiotemporal variations in air quality. API is calculated based on SO_2, NO_2 and PM_{10}, while AQI is calculated using six atmospheric pollutants, i.e., SO_2, NO_2, PM_{10}, $PM_{2.5}$, CO and O_3. Car ownership, energy consumption and secondary industry have been empirically confirmed to be important factors affecting air quality [21].

Unlike most scholars, Liu et al. (2019) considered that the versatility of cities affects the degree of environmental pollution. Hence, to compare the varied effects of natural and anthropogenic factors on $PM_{2.5}$ concentrations at different income levels, 287 Chinese cities were categorized into three groups according to income levels [17]. The results showed that in terms of meteorological factors, climate conditions such as precipitation, wind speed, relative humidity and temperature must be taken into account in urban construction and planning practices. In terms of anthropogenic factors, road density is the decisive factor. GDP per capita, industrial structure and FDI will increase $PM_{2.5}$ concentrations. Among these factors, FDI contributes more to $PM_{2.5}$ concentrations in low-income cities. The present study is similar to the above research to some extent, but it differs from that of Liu et al. (2019), who divided cities into groups for general regression analysis. Our study considers that the impact of variables on cities at different levels of $PM_{2.5}$ concentrations is heterogeneous; thus, quantile panel regression can more precisely compare this stratified heterogeneity. Overall, the primary contributions of this study are twofold. First, several studies have used the traditional OLS method to investigate the average effect of socioeconomic factors on $PM_{2.5}$ concentrations, despite the tremendous heterogeneity in different cities, which may undermine the explanatory power of the model for disparate factors. Second, research at the provincial level or higher has been thorough, but cities or urban agglomerations are the basic units where environmental policies are implemented. Consequently, studies of the mechanism of air pollution at the city level remain desperately needed.

3. Methodology and model specification

3.1. Panel quantile regression

Due to the tremendous heterogeneity of urban modalities in China [14], the relationships between multiple socioeconomic factors and $PM_{2.5}$ levels are likely to vary across quantiles. In this regard, it is inadequate to model the mean value. We are interested in predicting not the average $PM_{2.5}$ level of a particular group of cities but rather what kinds of cities are likely to experience the highest $PM_{2.5}$ levels. Ordinary least squares (OLS) is a statistical tool used to describe the relationship between a set of independent variables and a dependent variable. OLS estimates the mean value of dependent variables for independent variables at a given level. However, this approach is parametric and usually relies on assumptions that are often not satisfied [35]. Previous studies traditionally use OLS to identify predictor variables for $PM_{2.5}$ concentration, but this approach can address only the question of how, on average, the predictor variables affect the level of $PM_{2.5}$ concentration and cannot answer whether a predictor variable has a different weight in cities with low $PM_{2.5}$ levels than in cities with average $PM_{2.5}$ levels. A more comprehensive picture of the different effects of the independent variables on dependent variables can be obtained by panel quantile regression. This method makes no assumptions about the distribution of residuals, and it has a distinct advantage for detecting variation effects [36].

In the context of the above debate, this study aims to empirically examine how the economic and social development of cities affect $PM_{2.5}$ pollution. Economic and social factors, such as energy structure, urban area, population density, and economic level, can adequately represent the development status and differences among cities, but not every factor has a significant impact on $PM_{2.5}$ pollution in a statistical sense. The "socioeconomic determinants" used here include the effective factors that may slow $PM_{2.5}$ pollution as determined by modelling. Based on previous research and data availability, we select the possible influencing factors of $PM_{2.5}$ concentrations — the effect of GDP per capita (GDP), proportion of added value of secondary industry in GDP (SI), proportion of urban construction land in urban areas (PUC), proportion of FDI in GDP (FDI), population density (FD), number of buses (BUS) and total electricity consumption (EL) — and analyse these factors across 273 Chinese cities using panel quantile regression (see Table 2).

To this end, we follow the theoretical Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model proposed by Dietz and Rosa (1997) [37], which considers environmental impact and neo-classical growth. The STIRPAT model is derived from the following basic environmental impact:

$$I = aP^b A^c T^d e \tag{1}$$

where I, P, A and T (IPAT) represent environmental impact, population size, per capita economic activity and technology, respectively. For the convenience of estimation and hypothesis testing, Eq. (1) can be converted to linear logarithmic form as follows:

$$\ln I = a + b(\ln P) + c(\ln A) + d(\ln T) + e \tag{2}$$

Therefore, the multivariate framework in the study is as follows:

$$PM2.5_{i,t} = f\left(\, GDP_{i,t}, SI_{i,t}, PUC_{i,t}, FDI_{i,t}, PD_{i,t}, BUS_{i,t}, EL_{i,t}\right),$$

where $t = 1, 2, \ldots, T$ and $i = 1, 2, \ldots, N$ stand for time period and cross-section (cities), respectively. In the energy and environment areas, the data often have a distinct peak or fat tails [35, 38]. In this situation, quantile regression can provide more robust estimation results [39, 40]. To account for impact effects and unobserved individual heterogeneity, we consider the following model:

$$\begin{aligned} Q_{PM2.5_{i,t}}(\tau|\cdot) = {} & \alpha_{1,\tau} GDP_{i,t} + \alpha_{2,\tau} SI_{i,t} + \alpha_{3,\tau} PUC_{i,t} + \alpha_{4,\tau} FDI_{i,t} + \alpha_{5,\tau} PD_{i,t} \\ & + \alpha_{6,\tau} BUS_{i,t} + \alpha_{7,\tau} EL_{i,t} + \beta_i, \\ & i = 1, \ldots, N, t = 1, \ldots, T \end{aligned} \tag{3}$$

The main problem in the estimation of Model (3) is unobserved individual heterogeneity. To control for unobserved heterogeneity, we consider a two-step panel quantile method proposed by Canay (2011) [41]. This approach considers the fixed effect as a pure location shifter. The first step is to apply the standard panel model with a fixed effect:

$$y_{i,t} = \boldsymbol{x}_{i,t}^T \cdot \beta + u_i + \epsilon_{i,t} \tag{4}$$

where u_i is the unobserved fixed effect. Then, we can subtract the fixed effect obtained in (4) from the response variable:

$$\hat{y}_{i,t} = y_{i,t} - \hat{u}_i \tag{5}$$

From Eq. (5), we can obtain the $\widehat{PM2.5}_{i,t}$ free of the influence of unobserved heterogeneity. Then, the quantile regression estimator introduced by Koenker and Bassett Jr (1978) can be applied to estimate our model [40] as follows:

$$\underset{\alpha}{\operatorname{argmin}} \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T} w_k \rho_{\tau_k}\{\widehat{PM2.5}_{i,t} - \alpha_{1,\tau} GDP_{i,t} - \alpha_{2,\tau} SI_{i,t} - \alpha_{3,\tau} PUC_{i,t} - \alpha_{4,\tau} FDI_{i,t} - \alpha_{5,\tau} PD_{i,t} - \alpha_{6,\tau} BUS_{i,t} - \alpha_{7,\tau} EL_{i,t}\}$$

$$i = 1, \ldots, N, t = 1, \ldots, T \quad (6)$$

where $\rho_\tau(y) = \mathrm{y}(\tau - \mathbf{1}_{y<0})$ is the traditional check function, $\mathbf{1}_A$ is the indicator function of set A, K is the index for quantiles, and $w_k = 1/K$ is the weight on the k-th quantile, which controls the proportion of different quantile levels in this estimation [42].

3.2. Data source and description

For the purpose of this study, a balanced dataset covering a total of 273 Chinese cities, including 269 prefecture-level cities and four municipalities, for the period of 2010 to 2016 was used. Specifically, $PM_{2.5}$ concentrations were obtained by decomposing the global average concentration grid data detected by satellite into the annual average specific values of Chinese cities, which are released by the Socioeconomic Data and Application Center at Columbia University [43]. The other socioeconomic variables, including GDP per capita (GDP), proportion of added value of secondary industry in GDP (SI), proportion of urban construction land in urban areas (PUC), proportion of FDI in GDP (FDI), population density (FD), number of buses (BUS) and total electricity consumption (EL) were collected from the China City Statistical Yearbook and China Regional Economic Statistical Yearbook. For the convenience of estimation and expressing large numbers, all variables were converted to logarithmic form in this study. Tables 1 and 3 present the definitions of the socioeconomic variables in this model and the summary statistics of all variables, respectively. As shown in Table 3, the skewness of the seven variables is not equal to 0, which indicates that the variables are asymmetric. The positive kurtosis values indicate that the distributions of seven variables have fatter tails, while the negative kurtosis value indicates that the distribution of GDP has thinner tails. Furthermore, the Jarque-Bera tests clearly show that all series depart from normality.

Table 3 The summary statistics of all variables (in logarithmic form)

Variables	$PM_{2.5}$	GDP	SI	PUC	FDI	PD	BUS	EL

Minimum	1.5433	8.6179	2.7014	-3.9120	-8.9176	1.6194	-1.1394	9.1854
Maximum	4.4599	12.4861	4.4970	4.5766	3.0131	8.6932	4.7052	16.5142
Q1(.25)	3.1808	10.1770	3.7795	0.9802	-0.6636	5.2522	1.4294	12.2823
Q3(.75)	3.8949	10.9673	4.0183	2.4911	0.9381	6.4526	2.3442	13.7826
Mean	3.4941	10.5779	3.8763	1.6836	0.0356	5.7947	1.8449	13.0686
Stdev	0.4984	0.5721	0.2310	1.0922	1.2628	0.9371	0.7200	1.1417
Skewness	-0.6824	0.1086	-1.3492	-0.3322	-1.1123	-0.7325	-0.3830	0.1191
Kurtosis	0.6083	-0.1226	3.5430	0.1854	2.4306	1.7512	0.8668	0.2726
Jarque-Bera	0.0000	0.0863	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: the definition of GDP, SI, PUC, FDI, FD, BUS and EL is shown in Table 1.

3.3. Spatial distribution of annual $PM_{2.5}$ concentrations

In this study, $PM_{2.5}$ concentrations were divided into six intervals: 0-10 μg/m^3, 10-25 μg/m^3, 25-40 μg/m^3, 40-55 μg/m^3, 55-70 μg/m^3, and above 70 μg/m^3. Fig. 1 shows the $PM_{2.5}$ levels in 273 Chinese cities in 2010, 2013 and 2016. The red part represents the city with the worst $PM_{2.5}$ level, dark green represents the city with the lowest $PM_{2.5}$ level, and the other colours correspond to different concentration ranges (see Fig. 1). In 2010, the average annual $PM_{2.5}$ concentration ranged from 5.02 μg/m^3 to 74.81 μg/m^3. The cities with the best air quality were located in Gansu, Xinjiang, Inner Mongolia, Yunnan and other central or western provinces. The cities with orange colour on the map showed a significant trend of change. In 2010, the number of cities within the 40-55 μg/m^3 level was 53, which became 46 in 2013 and decreased to 38 in 2016. Similarly, the number of cities within the 55-70 μg/m^3 level gradually decreased in the past six years. Moreover, in 2010, there were 13 cities with an average annual concentration of $PM_{2.5}$ concentration exceeding 70 μg/m^3, and the number of such cities increased to 16 in 2013, including Cangzhou, Xingtai, Langfang, Hengshui, Jinan, Jining, Tai'an, Dezhou, Binzhou, Heze, Kaifeng, Hebi, Puyang, Xuchang and Tianjin. In 2016, $PM_{2.5}$ pollution was alleviated, and more green cities appeared on the map. This finding indicates that cities in China suffered serious $PM_{2.5}$ pollution in 2013, particularly cities in northern China, including Hebei Province and Shandong Province. This reduction may be the preliminary effect of various measures related to pollution control introduced by the government. In summary, the $PM_{2.5}$ concentration shows aggregation and diffusion effects to a certain extent, and the unknown coupling relationship between $PM_{2.5}$ pollution and urban development characteristics remains to be investigated.

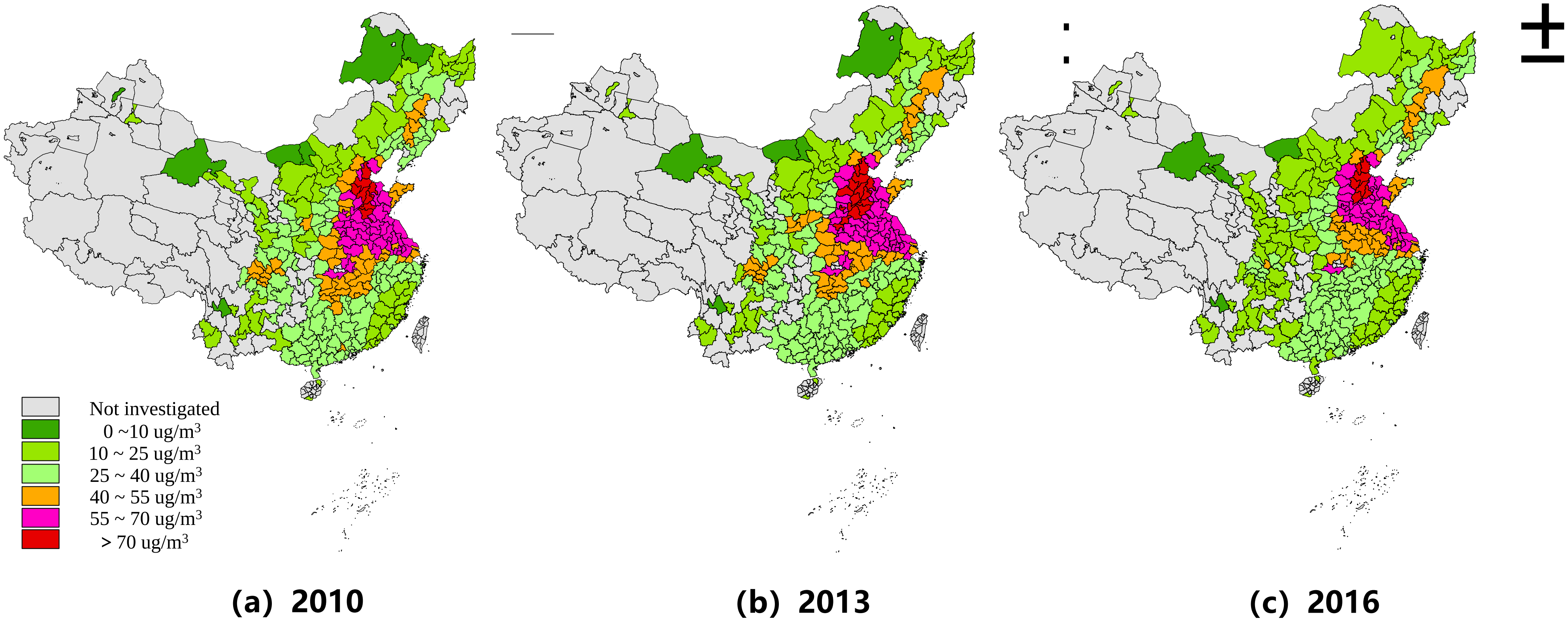


Fig. 1. The spatial distribution of the $PM_{2.5}$ concentration in Chinese cities (2010, 2013, 2016)

4. Empirical findings and analysis

4.1. Panel unit root test

The stationarity test is a key step in the process of economic data analysis. Certain nonstationary economic time series often show a common trend of variation, but they are not necessarily related to each other. In such cases, the regression results are likely to become a pseudo-regression [43]. The unit root test is the method most commonly used to detect whether a series of data is stationary. If a sequence has no unit roots, it is characterized as stationary and mean reversion; moreover, the absence of a unit root implies that the sequence has a finite variance independent of time. Conversely, if a sequence features a unit root, it is characterized as nonstationary. In addition, the variance of the sequence is time dependent and is permanently affected by random shocks. In this regard, before rigorous empirical investigation with panel quantile regression models, we first investigate the order of integration of the considered variables of the study by using the Levin-Lin-Chu (LLC), Fisher-ADF and Fisher-PP tests. Table 4 shows the results of the panel unit root tests for all variables, which indicate that the null hypothesis of the existence of a unit root can be strongly rejected for all variables at the 1% significance level, meaning that the variables are stationary and can be used in the subsequent empirical analysis.

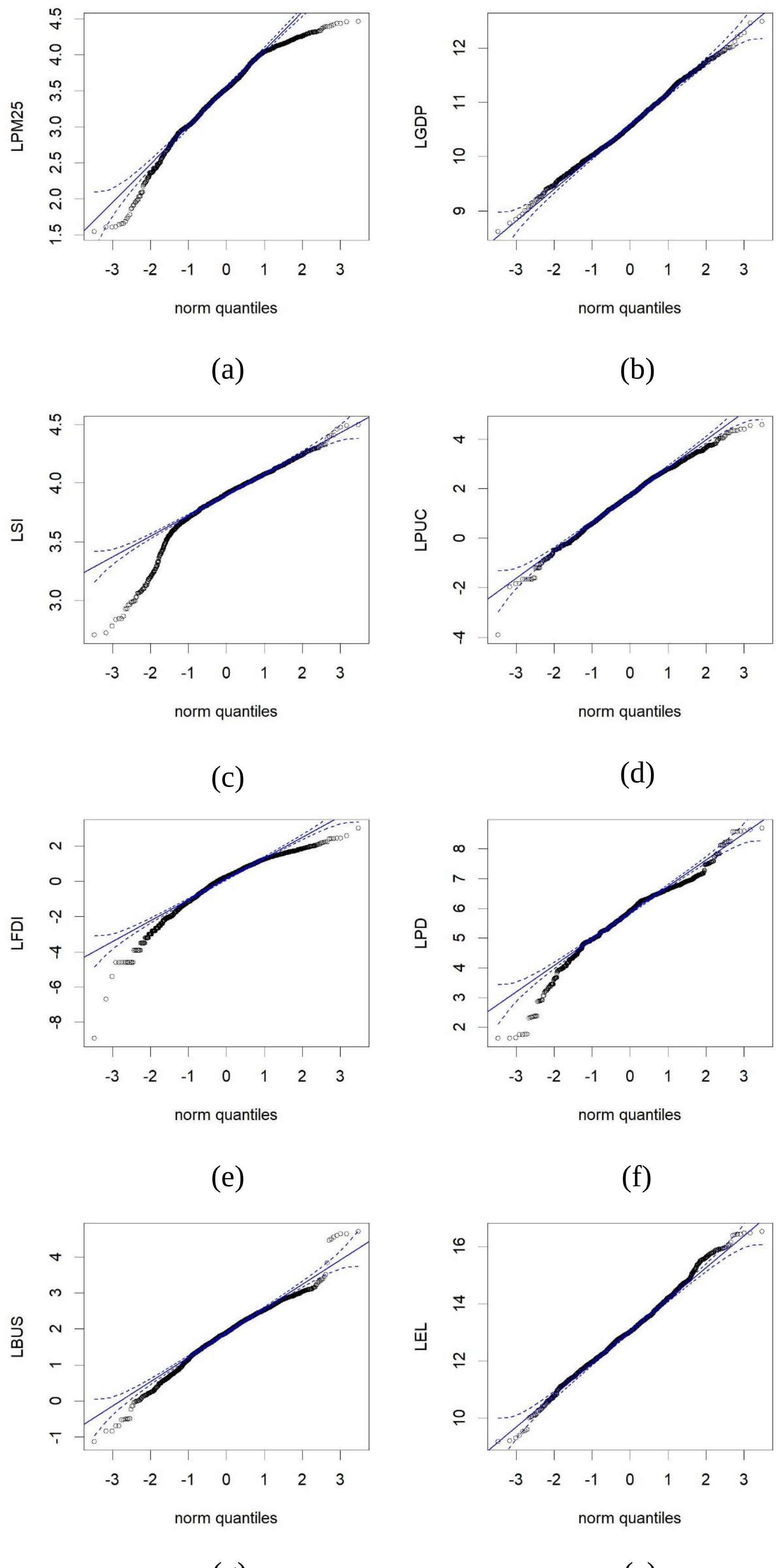
Table 4 Results of panel unit root tests

Variable	$PM_{2.5}$	GDP	SI	PUC	FDI	PD	BUS	EL
LLC	-1300***	-130.00***	-13.62***	-190.0***	-510***	-27.55***	-11.99***	-98.43***
Fisher-ADF	64.49***	78.43***	44.92***	85.90***	92.37***	98.26***	93.60***	106.79***
Fisher-PP	25.18***	143.42***	34.99***	47.49***	76.43***	40.11***	35.87***	40.14***

Note: * indicates the parameter is significant at the 10% level, ** indicates the parameter is significant at the 5% level, *** indicates the parameter is significant at the 1% level.

4.2. Normal distribution test

A normal distribution is the most common continuous probability distribution in real life. Thus, it is often regarded in natural and social sciences as the basic assumption for distributing unknown random variables. The normality assessment of sample data is a prerequisite for regression analysis. If the sample data are not normally distributed, then the quantile regression will make the estimated results more robust than the results of the OLS method. There are two main methods used to assess normality: graphical and numerical methods. For the graphical method, the frequency distribution (histogram), stem-and-leaf plot, box plot, probability-probability plot (P-P plot), and quantile-quantile plot (Q-Q plot) are used to visually check normality. First, we implement the most common Q-Q plot to determine whether the distribution is normal. As shown in Fig. 2, the results of the Q-Q plot are similar to those of the P-P plot, except that the normality is examined by plotting the quantiles of the probability distribution. Moreover, the sample size involved in this study is large, and the Q-Q plot is easier to interpret. If the scatter point corresponding to the sample data basically falls near the 45° line from the origin, i.e., a straight diagonal line, then the data follow a normal distribution. In Fig. 2, the scatter points of $LPM_{2.5}$, LGDP, LSI, LPUC, LFDI, LPD, LBUS and LEL do not exactly match the straight diagonal line. This pattern indicates that none of the variables obey the normal distribution assumption.



(a) (b) (c) (d) (e) (f) (g) (e)

Fig. 2. The normal Q-Q plot

Second, the numerical method is supplementary to the graphical assessment. The main tests are the Anderson-Darling test, Kolmogorov-Smirnov (K-S) test, Shapiro-Wilk test, and Jarque-Bera test [44]. The Jarque-Bera test can assess whether the sample data have goodness of fit of skewness and kurtosis in accordance with the normal distribution. If the result is far greater than zero, the data are not normally distributed. Table 3 shows that the probability values of the Jarque-Bera test for all variables except GDP are less than 5%, which indicates that these variables are not normally distributed. Furthermore, skewness and kurtosis represent the degree of asymmetry and the degree of dispersion in the data distribution, respectively. The skewness coefficient of the normal distribution is 0, and the kurtosis coefficient is 3. These two characteristics can be used to test whether the sample data follow a normal distribution. As shown in Table 3, the skewness coefficients of all variables in this study are nonzero, which indicates that all variables are not normally distributed. Among them, the skewness coefficients of GDP and EL are greater than 0, which indicates that these two variables are right skewed, whereas the other variables are left skewed. Furthermore, the kurtosis coefficients of all variables in this study are not equal to 3, which indicates that these variables are not normally distributed. Among them, the kurtosis coefficient of SI is greater than 3, indicating that the data distribution of SI is more discrete, with fat tails, while the other variables are more dense.

The above tests prove that these variables ($LPM_{2.5}$, LGDP, LSI, LPUC, LFDI, LPD, LBUS and LEL) are not normally distributed. Compared with OLS, quantile regression can obtain more robust results in that it does not require an assumption about the distribution of error terms. Therefore, we employ panel quantile regression to investigate the source of the influence of the $PM_{2.5}$ concentration level.

4.3. Panel quantile regression results

In this section, we investigate the impacts of driving factors of $PM_{2.5}$ concentration across 273 cities in China by applying two-step panel quantile regression. Table 4 shows the estimation results at the different quantile levels and indicate that the impacts of seven determinants on $PM_{2.5}$ are heterogeneous. Fig. 3 intuitively presents the corresponding estimation results, which show the various change patterns of the coefficients of the seven driving factors at different quantile levels.

First, GDP per capita has a negative impact on $PM_{2.5}$ concentration, and this impact is significantly heterogeneous and asymmetric. More specifically, the impact of

GDP per capita on $PM_{2.5}$ concentration in the lower 25th quantile cities is stronger than those in the 25th-50th, 50th-75th and upper 75th quantile cities (Table 5 and Fig. 3). The coefficient increases from -0.128 at the 5th quantile to -0.021 at the 95th quantile. The lower 25th quantile cities are located mostly in economically underdeveloped regions such as Xinjiang, Inner Mongolia, Yunnan and Sichuan provinces. The environmental quality in these provinces is more sensitive to the economic level; that is, increasing the GDP per capita will improve air quality more in these cities than in other cities. Moreover, Table 5 indicates a weak and negligible relationship between GDP per capita and $PM_{2.5}$ concentration in the upper 90th quantile cities, which are mainly located in North China, especially in Henan, Hebei and Shandong provinces. These regions experienced serious air pollution during these years, and decoupling between environmental pollution and the economic level is beginning to emerge. These findings suggest that economic development can significantly decrease the $PM_{2.5}$ concentration in lower quantile cities. China's economic growth in recent decades has mainly depended on fixed asset investment and export trade. From 2013 to 2018, fixed asset investment grew by 10.7% annually, achieving a capital formation rate of 44.9% and contributing 32.4% to economic growth. However, a large amount of investment in fixed assets also has negative impacts on environmental performance. Because large-scale investment in construction and fixed assets is a form of physical investment, which includes roads, bridges, pipelines, large-scale machinery and buildings, these construction activities will inevitably generate a great quantity of energy-intensive processing activities, such as in the steel, cement and other industries, which produce high emissions of atmospheric pollutants. In contrast to our findings, the empirical results obtained by Xu and Lin (2018) showed that the impact of GDP on $PM_{2.5}$ pollution was positive in most quantile provinces [45]. The upper 90th quantile provinces gather the most fixed-asset investment and foreign manufacturing enterprises, resulting in more $PM_{2.5}$ emissions from both direct and indirect perspectives.

Second, the effects of FDI in the upper 75th and lower 25th quantile cities are higher than those in the 25th-50th and 50th-75th quantile cities (Table 5 and Fig. 3). The low quantile cities are mainly distributed in Yunnan, Gansu, Shaanxi, Liaoning, Shanxi, Inner Mongolia, Sichuan and other western provinces. Since 2003, a rising trend was detected in FDI utilized by western regions (including 12 provinces or municipalities directly under the central government). In 2015, the total investment in western regions reached 30.8 billion dollars and represented approximately 24.4% of the national investment. The serious resource depletion, increased labour costs and the deepening of "Great Western Development Strategy" have jointly led to the transfer of FDI from the eastern regions to the western regions. On the one hand, foreign investors will prioritize the transfer of labour-intensive and pollution-intensive industries. On the other hand, western cities will take the initiative to reduce local environmental regulation standards in order to attract more FDI. To a great extent, the level of environmental regulation determines the amount of environmental pollutants directly discharged from production activities. Similar situations of relatively loose environmental standards in developing countries provide opportunities for the transfer of pollution-intensive FDI in the context of globalization, in alignment with the "pollution haven" hypothesis [46]. The relationship between FDI and environmental pollution in developing countries has long been controversial. Pollution-intensive enterprises in advanced countries seek low environmental standards in other countries in order to avoid paying for expensive pollution control domestically. In less-developed countries, domestic enterprises can use foreign advanced technology to improve their environmental efficiency and performance. The empirical findings obtained by Liu et al. (2019) [17] shows that the impact of FDI on PM2.5 are significantly positive in the total cities and lower-middle-income cities, which support the Pollution Haven Hypothesis. Shahbaz et al. (2015) analyzed the nonlinear relationship between FDI and environmental performance in high-, middle- and low-income countries using carbon emissions as environmental cost [47]. The results showed that FDI improves the environmental performance of high-income countries, while low-income countries need to make more efforts to control pollution. In middle-income countries, an inverted U-shaped relationship between FDI and environmental pollution was observed, indicating that both capital infusion and pollution reduction should be achieved.

Third, compared with other variables, PD (population density) exerted the greatest positive effect on $PM_{2.5}$ pollution across all quantile cities. As indicated in Fig. 3, the marginal environmental damage caused by the increasing population density in low-level quantile cities (lower than 25th quantile), middle-level quantile cities (25th-50th and 50th-75th quantiles) and high-level quantile cities (upper 75th quantile) were significant. The impact coefficients remained above 3 in all quantile cities. Therefore, we can effectively control urban pollution in all cities by limiting excessive population inflow. This result is basically consistent with Cheng et al. (2017) [33] and Wang et al. (2017) [18], who estimated a significant positive role of population density in driving haze pollution through the scale effect and aggregation effect, but different with Liu et al. (2019) [17], who found a non-significant influence of population density on PM2.5 based on conditional mean regression. The negative externalities from the scale effect on environmental pollution are greater than the positive externalities from the aggregation effect. China's rapid urbanization has attracted a large influx of people from rural areas. The larger the population, the greater the increase in the material demand for commodities such as housing and automobiles. The resulting emissions of building dust, automobile exhaust and other pollutants will also increase. Beijing is one of the most polluted cities in China in terms of $PM_{2.5}$ concentration. Less than 8% of the central urban area accumulates nearly 80% of the permanent population, with a density of 234,000 people per square kilometre. Beijing and the nearby Jing-Jin-Ji urban agglomeration are also the places with the most serious haze pollution in China.

Fourth, the impact of SI on the $PM_{2.5}$ concentration is always positive across different quantiles, which is consistent with Wang et al. (2017) [18] and Hao and Liu (2016) [20] by conditional mean regression. But beyond that, our study also finds that the impact of SI on the $PM_{2.5}$ concentration in the upper 75th quantile cities is larger than those in the 0-25th, 25th-50th, and 50th-75th quantile cities (Table 5 and Fig. 3). The impact coefficients are stable in the low- and middle-level quantiles and show a significant increasing trend in the high-level quantiles, increasing from 0.085 in the 70th quantile to 0.353 in the 90th quantile. The high proportion of enterprises with high pollution and high energy consumption in the economic structure contributes to large emissions of polluting gas that exceed the self-purification ability of the local environment. In the same way, the empirical results from Xu and Lin (2018) confirmed that the sensitivity of haze pollution to industrialization is greater in highly polluted provinces than in less-polluted provinces [45]. The strategy prioritizing the development of heavy industry implemented by the central government stabilized the national economic system, but large-scale industrial production also consumes a large amount of fossil fuels, which will inevitably increase $PM_{2.5}$ emissions. Although transformation of industrial structure is unlikely to occur in the short term, it is an indispensable step to reduce $PM_{2.5}$ pollution. For highly polluted cities, more social investment in green industry should be encouraged to reduce the sensitivity of air pollution to industrial activities.

Finally, the impact of the variable BUS (number of public buses) on the $PM_{2.5}$ concentration is higher in the upper 90th quantile cities than in the other quantile cities

(Table 5 and Fig. 3). In most quantiles, an increase in the number of buses can improve urban air quality, but in highly polluted cities, such improvement effects are not obvious. Overall, the number of public buses has a statistically significant and negative impact on $PM_{2.5}$ concentrations at lower quantile levels. In addition, the PUC (proportion of urban construction land) has a weak stimulating effect on $PM_{2.5}$ concentrations in most quantile and shows a decreasing trend (Fig. 3). The impact of EL (total electricity consumption) on $PM_{2.5}$ concentration first increases and then decreases from the lower to upper quantiles (Fig. 3). Compared with other variables, these two variables were less important in highly polluted cities. This suggests that the environmental regulation policies of cities with different pollution levels should deal with different influencing variables. To the best of our knowledge, this study is the first to investigate the heterogeneous effects of socioeconomic variables on $PM_{2.5}$ pollution at the city scale using the quantile panel method. Compared to the studies with province-level data (e.g., Xu and Lin, 2018 [45]) or the literature using conditional mean regression to investigate the city-level data (e.g., Cheng et al., 2017 [33] and Liu et al. ,2019 [17]), this study considers the city-level data and two-step panel quantile regression, which could not only provide more in-depth and specific analysis about the impacts of driving forces of $PM_{2.5}$ concentration in these 273 cities in China but also more robust and accurate estimation results.

Table 5 Panel quantile regression results

Variables	OLS	Quantile regressions										
		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
Intercept	5.367	2.285**	2.338**	2.081**	1.540	1.812*	1.869*	2.122**	2.642***	1.920*	1.887**	1.826**
	(0.304)	(0.019)	(0.011)	(0.022)	(0.123)	(0.077)	(0.077)	(0.033)	(0.005)	(0.070)	(0.049)	(0.023)
GDP	-0.136***	-0.128**	-0.158**	-0.095	-0.051	-0.092	-0.076	-0.087	-0.112	-0.078	-0.088	-0.021
	(0.000)	(0.049)	(0.021)	(0.175)	(0.312)	(0.212)	(0.272)	(0.243)	(0.177)	(0.274)	(0.186)	(0.378)
SI	-0.189***	0.090	0.212	0.141	0.188	0.242	0.185	0.097	0.085	0.187	0.353***	0.262***
	(0.000)	(0.350)	(0.193)	(0.282)	(0.259)	(0.199)	(0.262)	(0.342)	(0.337)	(0.149)	(0.001)	(0.001)
PUC	0.006	0.041	0.054	0.063	0.030	0.033	0.034	0.017	0.040	0.029	-0.007	0.002
	(0.559)	(0.192)	(0.121)	(0.105)	(0.314)	(0.304)	(0.309)	(0.375)	(0.281)	(0.324)	(0.390)	(0.397)
FDI	-0.001	0.096***	0.116***	0.103***	0.074**	0.070**	0.068**	0.067**	0.088***	0.072***	0.098***	0.118***
	(0.836)	(0.001)	(0.001)	(0.003)	(0.031)	(0.018)	(0.021)	(0.020)	(0.001)	(0.002)	(0.000)	(0.000)
PD	0.005	0.310***	0.317***	0.336***	0.354***	0.352***	0.337***	0.348***	0.315***	0.354***	0.326***	0.361***
	(0.900)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
BUS	-0.003	-0.083*	-0.032	-0.107*	-0.081	-0.067	-0.074	-0.075	-0.079	-0.057	0.048	0.028
	(0.781)	(0.065)	(0.323)	(0.073)	(0.152)	(0.213)	(0.204)	(0.214)	(0.213)	(0.278)	(0.248)	(0.331)
EL	0.020*	-0.036	-0.050	-0.039	-0.039	-0.032	-0.013	0.011	0.020	0.013	-0.001	-0.0227
	(0.080)	(0.255)	(0.179)	(0.261)	(0.254)	(0.292)	(0.378)	(0.383)	(0.346)	(0.376)	(0.399)	(0.311)

Note: Numbers in the parentheses represent P-value. * indicates the parameter at the 10% significant level, ** indicates the parameter at the 5% significant level, *** indicates the parameter at the 1% significant level.

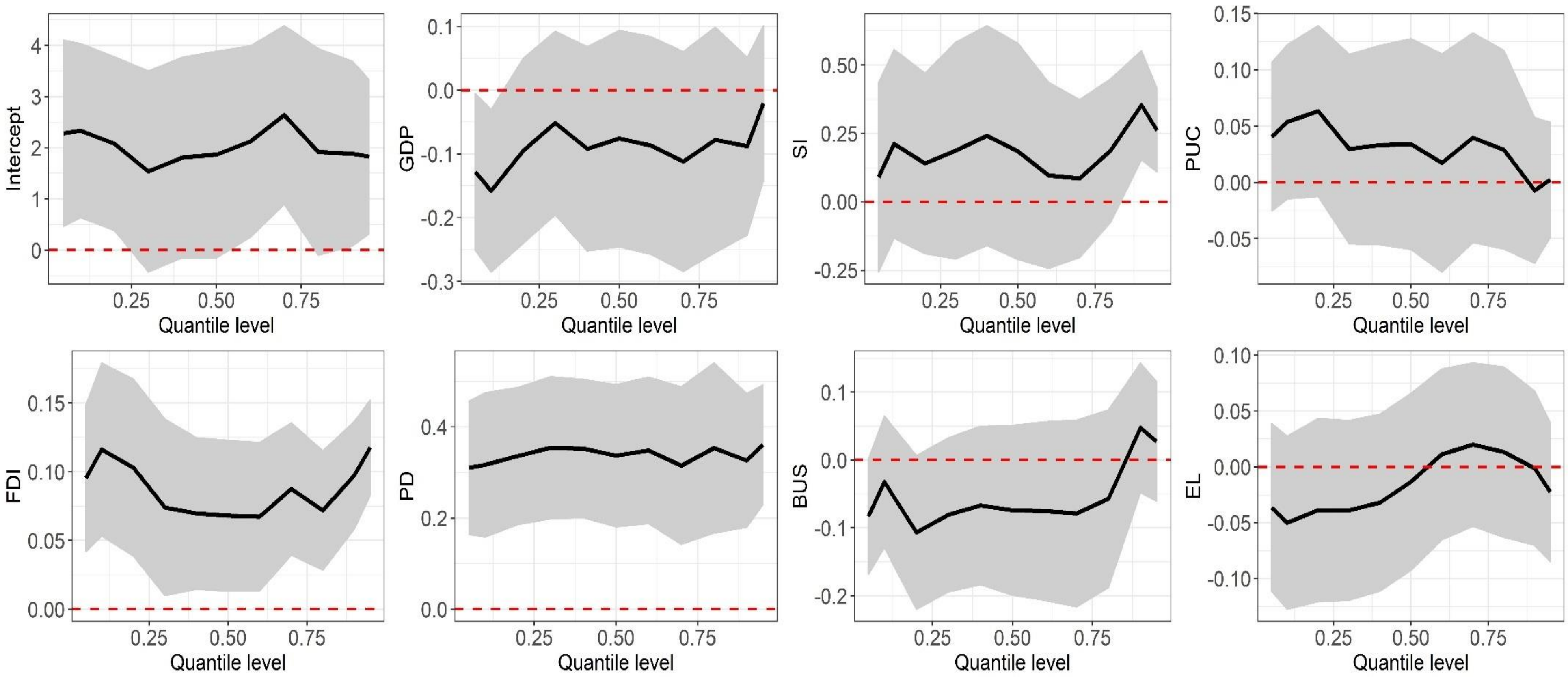


Fig. 3. Changes in panel quantile regressions coefficients. Notes: The x-axis denotes the conditional quantiles of $PM_{2.5}$, and the y-axis presents the coefficient values of the different variables. The shaded areas correspond to the 95% confidence intervals of the quantile estimation.

5. Conclusions and implications

5.1 Conclusions

Urban $PM_{2.5}$ pollution is influenced by natural and socioeconomic conditions. Natural factors are uncontrollable, and socioeconomic development is a complex, multifactor coupled dynamic system. To simplify the analysis, we assumed that GDP per capita, industrial structure, urbanization, FDI, population density, number of buses and electricity consumption in part represent the overall trend and situation of Chinese cities from various perspectives. Based on panel data of 273 prefecture-level cities in China, this study examined the heterogeneous effects of these seven determinants on $PM_{2.5}$ concentration using a two-step panel quantile regression. The empirical results indicated the following: (1) The relationships of $PM_{2.5}$ concentration with economic growth, urbanization, industrialization and FDI are heterogeneous. Compared with other variables, population density has the greatest positive effect on $PM_{2.5}$ pollution across all quantile cities, as population aggregation stimulates high energy-consuming industries, such as automobiles. Therefore, we can effectively control urban pollution by limiting excessive population inflow for all cities. (2) The impact of GDP per capita on $PM_{2.5}$ concentration is stronger in the lower 25th quantile cities than in the 25th-50th, 50th-75th and upper 75th quantile cities. This is mainly because the lower quantile cities are economically underdeveloped, and haze pollution is more sensitive to economic development. (3) The effects of FDI are higher in the upper 75th and lower 25th quantile cities than in the 25th-50th and 50th-75th quantile cities, which supports the "pollution haven" hypothesis. The lower quantile cities are mainly distributed in the western region, and the relatively loose environmental standards in western cities lead to numerous environmental pollutant emissions. (4) The impact of SI on the $PM_{2.5}$ concentration is larger in the upper 75th quantile cities than in the 0-25th, 25th-50th, and 50th-75th quantile cities. This finding suggests that $PM_{2.5}$ concentrations in highly polluted cities are more susceptible to changes in industrial structure. In brief, the heterogeneous effects of socioeconomic determinants should be taken into consideration when discussing emissions reductions in cities in the developing world.

5.2 Policy implications

Quantifying the heterogeneous effects of the socioeconomic determinants of urban $PM_{2.5}$ concentrations could assist policymakers in implementing differentiated policies for cities with different levels of air pollution. These results not only contribute academically to illustrating the interactive relationship between $PM_{2.5}$ concentration and economic growth at the city level but also provide guidance for urban development in developing countries at similar stages. On this basis, broader policies and countermeasures are put forward to alleviate $PM_{2.5}$ pollution. There are 334 prefecture-level cities in China, but these cities have different economic development levels, and different factors play different roles. The results of this study show that different socioeconomic factors exert heterogeneous effects on $PM_{2.5}$ pollution. It is necessary for cities in different quantiles to formulate targeted strategies that suit the local conditions from a sustainable perspective. First, for less-polluted cities, $PM_{2.5}$ prevention is more important than $PM_{2.5}$ mitigation. The government should properly stimulate the economic development of less-polluted cities because the environmental technological progress brought by economic development exceeds the negative environmental externality. For a long time, the general view has been that extensive economic growth reduces environmental carrying capacity, resulting in serious haze pollution. However, based on the findings of this study, it can be inferred that high-quality economic growth can improve air quality in less-polluted areas.

Second, spatial expansion in all quantiles should be controlled to prevent excessive population inflow. The contribution of population density to haze pollution is greater than those of other socioeconomic factors, and higher air quality can be achieved through urban form planning and population management policies. According to the Notice on the Adjustment of Urban Scale Classification Standards issued by the State Council of China, an urban resident population of more than 10 million corresponds to a super large-sized city. At present, there are six super large-sized cities in China: Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin and Chongqing. Therefore, the governments of these cities can take various measures to reduce the sensitivity of $PM_{2.5}$ pollution to population change, such as controlling the blind expansion of urban land, encouraging polycentric urban forms, and planning population-intensive institutions such as schools and medical institutions in the suburbs.

Third, the governments of cities in western China should pay attention to improving local environmental regulation standards. According to the results of this study, environmental regulation plays an intermediary role in the impact of foreign investment on $PM_{2.5}$ emission-related pollution. Western cities are located mostly in economically underdeveloped regions, and the impetus to promote economic development is greater than that to prevent pollution, leading to loose environmental regulations to attract investment. Western cities must actively stimulate enterprises to carry out technological innovation through environmental regulation. In addition, we should control existing FDI stock and optimize investment structure. For example, foreign investors should be encouraged to invest in primary or tertiary industries with relatively low emissions, along with preferential policies for technology-intensive foreign investment.

Finally, the central and local governments should realize that the mode of economic development that relies on heavy industry is not sustainable and needs to be changed, especially in highly polluted areas. Social demand, technological innovation and FDI have played strong roles in changes in industrial structure. The adjustment of industrial structure is conducive to pollution reduction. Specific recommendations include supporting the expansion of tertiary industries, restricting the establishment of heavy polluting enterprises, and encouraging enterprises to change from being resource consumption-driven to technological innovation-driven, thereby improving their energy efficiency and standards of air pollution emissions. The adjustment of industrial structure cannot be accomplished without the participation of the government, industry and the public, but the primary needs of different stakeholders vary, which may lead to conflict among different stakeholders.

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Appendix A

Table A1 Abbreviation summary

Category	Variable name	Abbreviation

Independent variable	Fine particulate matter	$PM_{2.5}$
Explanatory variables	GDP per capita	GDP
	Foreign direct investment	FDI
	Population density	PD
	Secondary industry	SI
	Number of public buses	BUS
	Electricity consumption	EL
	Proportion of urban construction land	PUC
Methods	Ordinary least squares	OLS
	Geographically weighted regression	GWR
	Autoregressive distributed lag approach	ARDL

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