China Economic Review 59 (2020) 101381

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Has urbanization accelerated $PM_{2.5}$ emissions? An empirical analysis with cross-country data

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ARTICLE INFO

Keywords:
Environmental Kuznets curve
$PM_{2.5}$
Pollution
Urban policy
Urbanization

ABSTRACT

As a prominent indicator of economic development, urbanization can exert a significant impact on the $PM_{2.5}$ level. Using panel data from 126 countries (areas) over the period 1990–2016, this study investigates the relationship between urbanization level and $PM_{2.5}$ density. A modified stochastic impacts by regression on population, affluence, and technology model is applied as the empirical strategy. Results show that the relationship between urbanization and $PM_{2.5}$ density has an inverted U shape. The effects of urban agglomeration and technological progress reduce the density of $PM_{2.5}$ in the late stage of urbanization. This study can help policymakers design appropriate measures relevant to $PM_{2.5}$ attenuation in the context of breakneck urbanization.

1. Introduction

Air pollution exert profound and non-negligible effects on people's physical and mental health, and it adds to the burden of medical expenditures and sabotages the sustainable development of many economic entities (Pangaribuan, Chuang, & Chuang, 2019; Signoretta, Veerle, & Bracke, 2019; Yang & Zhang, 2018). The reasons for the decrement in air quality must be explored from public and private perspectives so that proper actions can be implemented and effective policies can be designed.

China's urbanization rate increased from < 20% in 1980 to 59.58% at the end of 2018. Although the *hukou* system[1] and other factors hinder the free movement of labor internally, many rural workers have found urban employment and now live in cities. This trend is accompanied by the economic reform and upgrading that have been in place since the 1980s. Urbanization and the speed of aggregation in the population and industries in cities play a key role in the national economy and society. On the one hand, rapid urbanization implies that economic or labor resources are more accessible to cities than before, thereby accelerating their development (Dijst et al., 2018). On the other hand, urbanization causes many problems, such as increased auto emissions, water

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[1] The household registration system (hukou system) is a long-standing practice in China. In 1958, China promulgated the "People's Republic of China Household Registration Ordinance" and implemented two household registrations for agricultural and non-agricultural populations. Meanwhile, population mobility was strictly controlled and regulated. After 1978, household registration regulation underwent a semi-deregulation stage. The agricultural population can migrate into urban areas and register as an urban population through household registration exchange, land development, marriage, higher education, buying a house, etc. Meanwhile, a large group of the agricultural population poured into factories in the coastal provinces of China. A large population labeled as "migrant workers" began to appear without urban household registration.

https://doi.org/10.1016/j.chieco.2019.101381
Received 7 February 2019; Received in revised form 8 November 2019; Accepted 11 November 2019
Available online 14 November 2019
1043-951X/

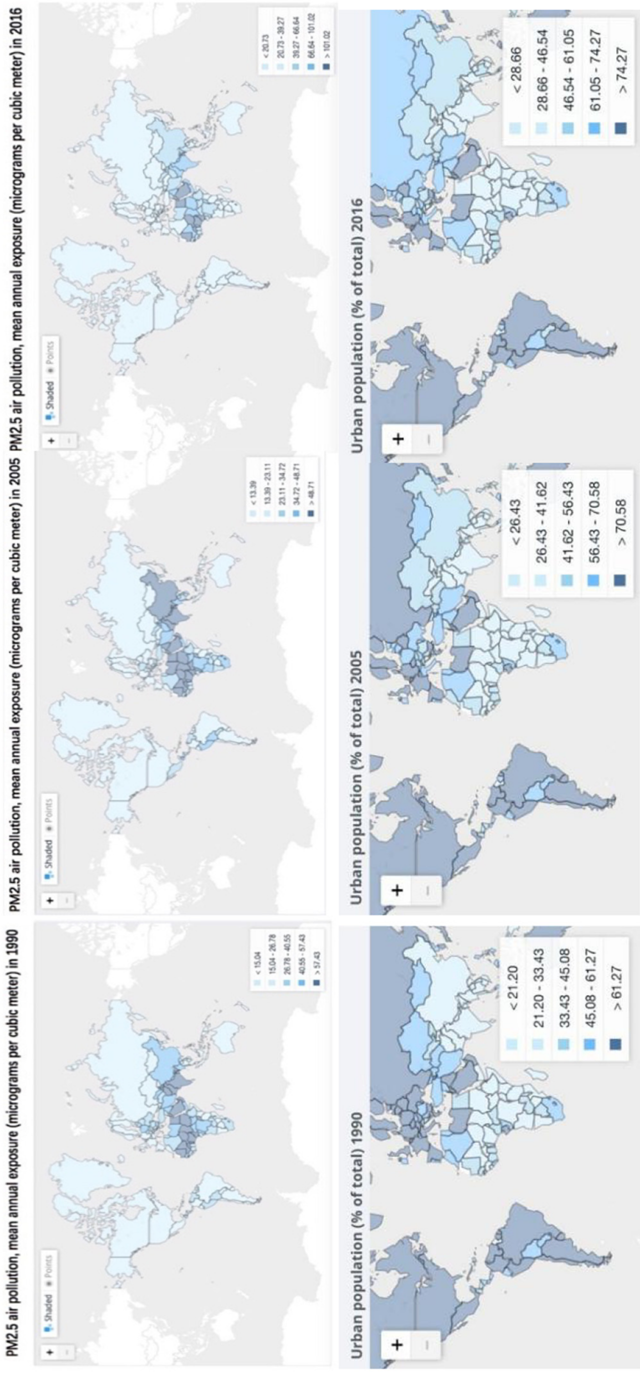

Fig. 1. Urbanization and $PM_{2.5}$ density in different regions and countries, 1990–2016.

contamination, and declining air quality measured in terms of $PM_{2.5}$, as shown in Fig. 1. The relationship between urbanization and the environment has been widely investigated. However, the relationship between urbanization and $PM_{2.5}$ has not been explained in literature partly because tracking of $PM_{2.5}$ began only recently.

The rapid degradation of air quality has attracted the attention of many scholars (Zhou et al., 2018; Wang, Zhu, Guo, & Peng, 2018; Chen et al., 2017; Chen, Barros, & Gil-Alana, 2016; Xu and Lin, 2016; Ma et al., 2016). Most studies have focused on the impacts of economic and energy indicators on air quality, particularly carbon dioxide (CO_2) emissions (Zhao et al., 2018; Wang et al., 2018; Ma et al., 2016; Xu and Lin, 2016). These studies identified relevant economic and energy indicators. By contrast, research on the relationship between urbanization effects and air quality, particularly the $PM_{2.5}$ level, is rare despite its importance. To fill this gap in literature, the current work explored the casual relationship between urbanization and air quality.

The goal of this study is to examine how urbanization affects air quality, specifically the $PM_{2.5}$ level. To establish a reasonable estimation and mechanism, we used a two-way fixed-effect model to obviate the unobservable variables. We investigated quadratic and nonlinear effects by adding quadratic and cross terms to the empirical model. An instrumental variable and the general method of moments (GMM) were utilized to address the endogeneity problem further. Moreover, a robustness test was conducted using proxy variables, mixed effects, and NASA $PM_{2.5}$ variables to ensure the robustness of the estimation.

This study contributes to literature. First, most current studies focus only on the situation in China. We used cross-country level data to examine the relationship between $PM_{2.5}$ concentration and urbanization. Doing so provides policy implications for countries that are accelerating their urbanization process, especially China whose urbanization level remains to be far below that of developed countries. Second, this study considers the turning point where $PM_{2.5}$ concentration declines with the increase in urbanization rate. The stochastic impacts by regression on population, affluence, and technology (STIRPAT) model was adopted to investigate the major socioeconomic driver of $PM_{2.5}$ concentration. The results are expected to help policymakers implement feasible measures for reducing this type of air pollution. Lastly, we use NASA satellite data to further confirm the robustness of our conclusions. To the best of our knowledge, we are the first to do so.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents the empirical model and the selection of variables and their corresponding definitions. Section 4 shows the empirical results and analysis, and Section 5 concludes the study.

2. Literature review

2.1. Environmental effect of urbanization

Many previous studies have been conducted on the relationship between urbanization and the environment. Chen, Jin, and Lu (2018) examined the nexus between urbanization and CO_2 emissions by using data on 188 Chinese prefecture-level cities and concluded that this nexus has an inverted U shape in western China because the West–East Gas Pipeline Project[2] encourages people in western China to use coal. Lin and Zhu (2018) examined SO_2 and PM_{10} pollutants and confirmed this finding with cross-sectional data on 282 cities in China. Zhang, Yu, and Chen (2017) used data on 141 countries during the period 1961–2011 to verify the inverted U-shaped relationship between urbanization and CO_2 emissions and estimate the turning point. Shahbaz, Loganathan, Muzaffar, Ahmed, and Jabran (2016) analyzed the same relationship by using a special case of Malaysia and the STIRPAT model. Chen (2018) studied the nexus between urbanization and municipal solid waste and found that urbanization has a significant impact on municipal solid waste. Yang et al. (2018) analyzed the effects of urbanization on China's residual energy consumption and discovered that the impact of urbanization varies as it increases energy consumption, thereby narrowing the gap in energy consumption between urban and rural areas. Sheng and Guo (2018) used province-level data and random-effect panel data and found that expanding urbanization increases energy consumption, but also raises energy efficiency to a limited degree. Han, Xie, and Fang (2018) investigated the dynamics of $PM_{2.5}$ density in urban and rural areas of China under the background of rapid urbanization. They reported that $PM_{2.5}$ concentration increased rapidly during 2000–2014. Wu, Zheng, Zhe, Xie, and Song (2018) found that the relationship between $PM_{2.5}$ concentration and urbanization has an inverted N or inverted U shape, and it varies in different regions of China.

2.2. Factors that account for $PM_{2.5}$

Research on the explanatory factors that account for $PM_{2.5}$ emissions had been scarce until recently (Cao, Kostka, & Xu, 2019; Ji, Yao, & Long, 2018; Jiang, Yang, Huang, & Liu, 2018; Wang et al., 2018; Yang, Liu, Lin, & Li, 2018). Several researchers have focused on the dynamics and persistence of $PM_{2.5}$ in massive cities of China (Chen et al., 2016; Kong et al., 2017). Later on, other studies started to track the factors that drive $PM_{2.5}$ levels, with particular emphasis on the relationship between the air pollutant $PM_{2.5}$ and socioeconomic factors. Yu et al. (2017) explored the situation and characteristics of $PM_{2.5}$ emissions of different gas turbine aircraft engines.

According to Ji et al. (2018), the association between increasing income levels and $PM_{2.5}$ demonstrates diminishing marginal effects, and the proportion of the service sector negatively influences $PM_{2.5}$. Yang et al. (2018a) found that natural factors, such as the environment and climate, contribute more to $PM_{2.5}$ level than socioeconomic factors do. However, industrial activities contribute

[2] It involved a set of natural gas pipelines that run from the western part of China to the east. This natural gas transmission project began in 2002 and aimed to achieve mutual and sustainable development for different regions of China.

more to $PM_{2.5}$ concentration than any other factor does; city size and public activities also have significant impacts on $PM_{2.5}$ levels (Jiang et al., 2018). Lin, Liu, and Yang (2012) reported that per capita GDP and energy intensity are the most decisive factors that affect $PM_{2.5}$ levels. Li, Fang, Wang, and Sun (2016) claimed that the $PM_{2.5}$ level of China is driven by economic growth, urbanization, and industrialization simultaneously. They proved this claim by performing a panel Granger causality test with prefecture data of China. Wang et al. (2018) assessed the direct and indirect effects of political globalization and democracy on $PM_{2.5}$ concentration and showed that the effect of political globalization on $PM_{2.5}$ levels is significantly positive in countries with high emissions. Meanwhile, Feng, Dong, Wen, and Chang (2018) and Cao et al. (2019) used the turnover data of a municipal party committee from 2013 to 2016 to analyze the influence of a turnover event on the emission of air pollutant, including SO_2, COD, soot, NHx, and $PM_{2.5}$.

3. Methodology, variables, and data specification

The influence, population, affluence, and technology (IPAT) model, which was proposed by Ehrlich and Holdren (1971), is widely used to describe the effects of human activities on the environment. In the model, environmental impact (I) is decomposed into three main driving factors: population size (P), affluence (A), and environmentally unfriendly technology level or the impact per unit of economic activity (T). The model's mathematical equation has a simple framework but has been criticized for not allowing hypothesis testing and assuming a strict proportionality between factors.

$$I = P * A * T \tag{1}$$

On the basis of the IPAT model, Dietz and Rosa (1997) formulated the STIRPAT model, as follows:

$$I_{it} = \alpha_i P_{it}^b A_{it}^c T_{it}^d e_{it} \tag{2}$$

In the STIRPAT model, the parameter α_i is a constant, and b, c, and d are parameters corresponding to P, A, and T, respectively. The variable e_{it} is a random error term. The countries are denoted by i (i = 1, 2, …, n), and the period is t (t = 1, 2, …, T). Other studies used different variables (Liu & Xiao, 2018; Zhang et al., 2017). For example, Waggoner and Ausubel (2002) used I for impact (all/emission), P for population (parents/capita), A for affluence (workers/GDP per capita), C for intensity of use (consumers/energy per GDP), and T for efficiency (producers/emission per energy).

By taking the logarithmic form of both sides of Eq. (2), Eq. (3) uses panel data in a linear specification and reduces the correlation between variables.

$$\ln I_{it} = \ln \alpha_i + \mathrm{b} \ln P_{it} + c \ln A_{it} + d \ln T_{it} + e_{it} \tag{3}$$

Several studies have added explanatory variables to the STIRPAT model on the basis of the research subject (Martínez-Zarzoso et al., 2007; Poumanyvong & Kaneko, 2010; Rafiq, Nielsen, & Smyth, 2017). Similarly, we added a variable for urbanization level, which affects $PM_{2.5}$ concentration in the STIRPAT model. Therefore, the revised model can estimate the impact of urban development on $PM_{2.5}$ concentration. The model is expressed as follows:

$$\ln I_{it} = \ln \alpha_i + \mathrm{b} \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \beta \ln urban + e_{it}. \tag{4}$$

I is the total environmental impact in the STIRPAT model. Accordingly, in our empirical models, we used total $PM_{2.5}$ (*pm2.5*) as a dependent variable in line with the studies of Sadorsky (2014) and Salim and Shafiei (2014). The explanatory variables were selected based on data availability and their frequency of use in previous literature. Following Dietz and Rosa (1997), we utilized population density (*density*) and GDP per capita (*gdpp*) to measure the impact of demographic and economic factors. Similar to Al-Mulali, Saboori, and Ozturk (2015) and Liddle and Lung (2010), we considered them in our models. Trade openness (*open*) is the share of imports and exports over the total GDP. In this study, we applied the share of the urban population (*urban*) in the total population in the basic model. Aside from the share of the total urban population, the percentage of the population in an urban agglomeration of > 1 million people (*agg*) is also important for describing the urbanization level. Therefore, urban agglomeration was used as an alternate variable in our robustness tests. Other control variables, such as the proportion of the secondary industry, energy efficiency, and proportion of fossil fuel, were considered. We logged all of these variables in the regression to investigate the effect of percentage change in each explanatory variable on the percentage change in $PM_{2.5}$ density.

With regard to empirical methods, this study initially applied a two-way fixed-effect model for panel data to control for unobservable factors. To explore the nonlinear effect of urbanization, this study also added quadratic and cross terms. Instrumental variables and two-stage least-squares (2SLS) methods were used to address the endogeneity problem caused by reverse causality. A robustness test was also conducted to ensure the robustness of the results.

In addition to linearizing $PM_{2.5}$ density with urbanization, we added quadratic and cross terms of urbanization to our regression. We assumed that urbanization has a high-order impact on $PM_{2.5}$ density, and this assumption was tested in our empirical analysis. We also added cross terms to our empirical analysis to examine the interaction of variables and nonlinear effects. The statistical descriptions of the variables are provided in Appendix Table 1. The standard deviation of *lndensity* is > 1 because the populations of countries vary considerably. Furthermore, the member countries of the Organization for Economic Cooperation and Development (OECD), which are developed countries, are likely to produce less $PM_{2.5}$ than poor countries and have higher levels of urbanization.

We obtained data from World Bank Open Data, which include 126 countries and economic entities from 1990 to 2016. Before 2010, $PM_{2.5}$ data were recorded every five years and annually afterward.

Small island developing states and members of the Organization of Petroleum Exporting Countries (OPEC) have particular characteristics; hence, they were omitted from the sample. Countries with missing data on the variables were also omitted. We adopted an unbalanced panel dataset of 126 countries over the period 1990–2016. In consideration of the differences in economic development, we divided these countries into three groups, namely, OECD, non-OECD, and less developed countries, in accordance with the standards used by the World Bank.

4. Empirical results and analysis

We initially applied a basic two-way fixed-effect model. We added quadratic and cross terms to consider the nonlinear effects. 2SLS regression and an alternate-variable mixed-effect model were used to address endogeneity problems and check the robustness of the empirical results.

4.1. Basic model

The null hypothesis of random effects was rejected on the basis of the results of Hausman tests. Hence, we applied a two-way fixed model to evaluate the impact of urbanization on $PM_{2.5}$ density. Our basic STIRPAT model can be written as follows:

$$\begin{aligned} \ln pm2.5_{it} = \alpha + \beta_1 \ln industry_{it} + \beta_2 \ln intensity_{it} + \beta_3 \ln open_{it} + \beta_4 \ln energy_{it} \\ + \beta_5 \ln density_{it} + \beta_6 \ln urban_{it} + \gamma_i + \lambda_t + e_{it}, \end{aligned} \tag{5}$$

where γ_i and λ_t are the individual and time effects, respectively.

Table 2 shows that the coefficients of *lnurban* are significantly positive in three of the four columns, indicating that $PM_{2.5}$ density is significantly increased by urbanization, particularly in developing countries. This scenario is intuitive because cities are prone to pollution in the urbanization process. In most cases, non-OECD and poor countries cannot deal with the high cost of environmental improvements. The magnitude of the coefficient of *lnurban* suggests that a 1% increase in urbanization level is associated with an increase in $PM_{2.5}$ density of about 0.329%–0.39% in most countries. Additionally, the coefficients of *lnurban* in the full sample resemble those of non-OECD countries, which are much lower than those of poor countries. Presumably, this is due to the lack of institutions and regulations of environmental protection in poor countries.

The coefficient of *lnurban* is negative in the OECD countries. According to Chauvin (2017), the factors that prompt urbanization in many countries are similar; however, equilibrium can vary among economies. In OECD countries, advanced urbanization leads to environmental improvement because of the relatively comprehensive regulation and advanced technology, but developing and poor countries do not obtain this benefit.

Other factors, such as *lndensity* and *lnenergy*, can have a significantly negative impact on $PM_{2.5}$ density. A large population increases the denominator of the equation for calculating $PM_{2.5}$ density. Consequently, $PM_{2.5}$ density decreases. The $PM_{2.5}$ level rises as the proportion of the secondary industry increases because the secondary industry causes considerable pollution. With regard to energy intensity, negative coefficients indicate that the rise in energy consumption per GDP increases $PM_{2.5}$ density. For urbanization level, positive GDP growth is associated with an increase in $PM_{2.5}$ density, indicating that in most countries, a high level of economic development leads to a high $PM_{2.5}$ level. However, trade openness does not play a beneficial role in decreasing pollution in cities. In other words, trade can lead to increased pollution in several countries, as verified in many previous studies (Grether & Mathys, 2013; Lin, 2017).

4.2. Basic model with the quadratic term added

Fig. 2a shows the linear fit between *lnpm2.5* and *lnurban,* and Fig. 2b shows the quadratic fit between *lnpm2.5* and *lnurban*. The scatterplot of $PM_{2.5}$ and urbanization in Fig. 2b has an inverted U shape that looks like a Kuznets curve. We assumed that urbanization has a quadratic relationship with $PM_{2.5}$ emissions. Therefore, we added the quadratic term of a logarithmic form of urbanization (Brajer, Mead, & Xiao, 2011; Shen, 2006).

Table 3 presents the regression results after the quadratic term of a logarithm of urbanization was further added to the empirical equation. According to Table 3, the coefficient of urbanization in poor countries became insignificant when the quadratic term of urbanization was added. Developing countries are not growing rapidly, especially those struggling with war and political turbulence. In this case, urbanization tends to stabilize at a certain level. In the three other groups, the first term of urbanization is positive, whereas the second term of urbanization negatively affects $PM_{2.5}$ emissions. Both terms are significant.

Table 1 shows that with the development of urbanization, the $PM_{2.5}$ density increases initially then declines. Almost all developed countries and emerging market entities have undergone this experience. That is, when an economic entity begins to accelerate its development, as urbanization proceeds, the entity is supposed to utilize cost merits to attract investments. When it enters a relatively adroit level, it tends to improve the environmental situation. This scenario is in accordance with the graph shown above, also verifying the Kuznets curve. The other variables do not range drastically compared with those in the previous analysis.

4.3. Basic model with the interaction term added

Next, we explored the nonlinear effect of urbanization on air quality. We integrated urbanization and GDP per capita as cross terms because the impact of urbanization on the $PM_{2.5}$ level may vary with the value of GDP per capita. In Table 4, *ug* is the cross term of urbanization and GDP per capita. After this cross term was included in the model, *ug* became significant with respect to the level of

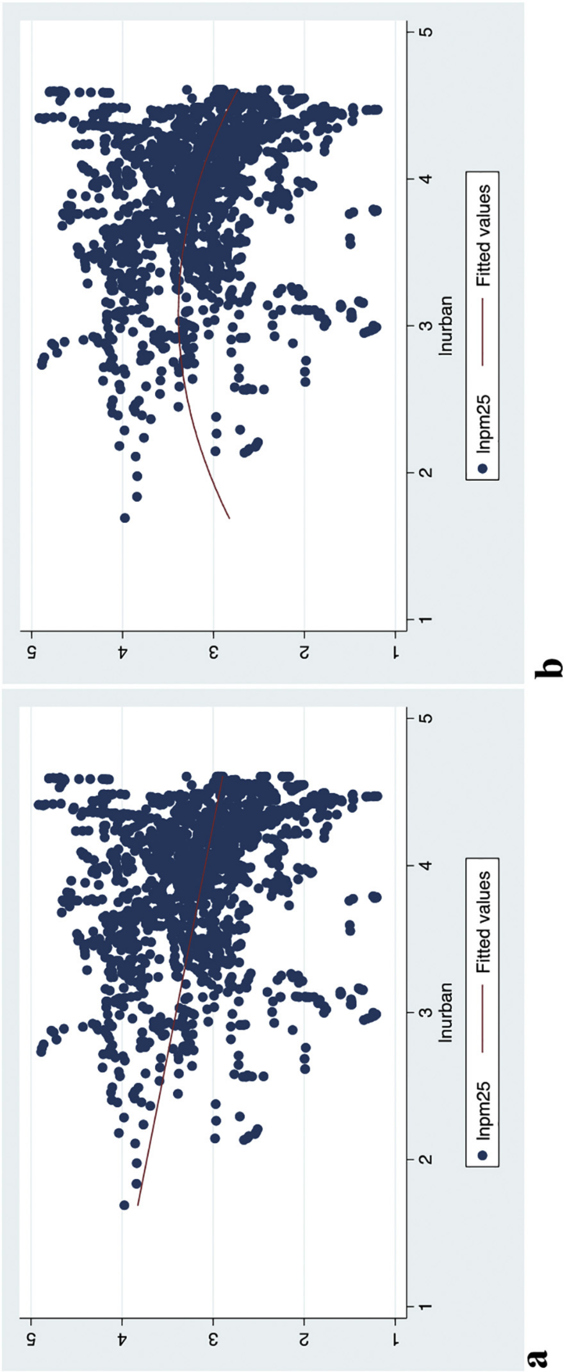

Fig. 2. (a) Linear fit between *lnpm2.5* (b) Quadratic fit between *lnurban* and *lnpm2.5* and *lnurban.*

Table 1
Definition of variables.

Variable label	Variable	Definition	Measurement
pm25	$PM_{2.5}$ density	mean annual exposure*	Micrograms per cubic meter
industry	industrial structure	value of secondary industry divided by GDP	%
intensity	efficiency of fossil fuel-based energy	actual fuel used divided by total fuel	%
open	trade openness	trade value divided by GDP	%
energy	proportion of fossil fuel-based energy	fossil fuel-based energy divided by total energy	%
density	density of population	population divided by area of a country	per sq. km. of land area
urban	urbanization rate	ratio of the population living in cities	%
gdpp	GDP value of a country per capita	production value of a country	2010 US dollars
agg	urban agglomeration	percentage of the population living in urban agglomerations of > 1 million people	%

Note: The descriptive statistics of these variables are provided in Appendix Table 1.
* Population-weighted exposure to ambient $PM_{2.5}$ pollution is defined as the average level of exposure of a country's population to concentrations of suspended particles.

Table 2
Results of the basic model.

	Full sample	OECD	Non-OECD	Poor countries
lnurban	0.390*	−3.587*	0.329***	1.401**
	(0.172)	(1.707)	(0.090)	(0.439)
lnindustry	0.0332	0.0448	0.0400	−0.238
	(0.0224)	(0.0585)	(0.0242)	(0.302)
lnintensity	0.0230	0.00932	0.0425	0.362
	(0.0251)	(0.0532)	(0.0276)	(0.217)
lnopen	0.0288*	0.124**	0.0230	0.773**
	(0.0133)	(0.0424)	(0.0142)	(0.266)
lnenergy	−0.136***	−0.00484	−0.147***	−0.701***
	(0.0253)	(0.0529)	(0.0279)	(0.165)
lndensity	−0.645***	−0.569***	−0.597***	−0.929***
	(0.0377)	(0.0935)	(0.0422)	(0.143)
lngdpp	0.284**	1.083	0.337***	6.038**
	(0.0868)	(0.704)	(0.0983)	(2.316)
_cons	0.795	−10.170	0.423	−44.86**
	(0.650)	(7.508)	(0.736)	(14.43)
N	1061	210	851	77
R^2	0.981	0.988	0.970	0.982

Note: Each column shows results from an ordinary least-squares regression in which the dependent variable is *lnpm2.5*, and the key explanatory variable is *lnurban*. Standard errors are in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

$PM_{2.5}$ in OECD countries.

In OECD countries, the inverted U-shaped curve still holds. In particular, in addition to the significantly positive coefficient of *lnurban*, which remains the same as in the empirical estimation, the interaction term is statistically significant. This finding demonstrates that when the increase in GDP per capita in this group of countries exceeds 1.02% (0.61/0.598), urbanization has a negative impact on $PM_{2.5}$. Hence, the inverted U-shaped curve is verified.

The inverted U-shaped curve still holds in poor countries. However, the threshold for the adverse effect of urbanization is much higher than that before. In this group of countries, only when the GDP per capita increment rate is raised to higher than 2.92% (13.1/4.493) can urbanization decrease the $PM_{2.5}$ density. However, this observation does not indicate that these countries quickly move to the right-hand side of the Kuznets curve. With regard to the marginal effect of GDP per capita, when the increase rate in urbanization is higher than 3.24% (14.54/4.493), GDP per capita growth helps decrease the $PM_{2.5}$ level. Therefore, a decline in the $PM_{2.5}$ level requires relatively rapid increases in urbanization and GDP per capita.

On the contrary, in non-OECD countries, an increase in urbanization drives the $PM_{2.5}$ level despite the inclusion of an interaction term for urbanization and GDP per capita, which makes sense in emerging markets.

4.4. Endogeneity test

In our analysis, we set the logarithm of $PM_{2.5}$ as the explanatory variable, and urbanization was the primary explanatory variable. Endogeneity problems were considered in the causal estimation. Here, the primary source of endogeneity problems is reverse

Table 3
Basic model with the quadratic term added.

	Full sample	OECD	Non-OECD	Poor countries
lnurban	1.841***	3.090***	2.053***	1.537
	(0.331)	(0.5908)	(0.360)	(3.724)
lnurban2	−0.237***	−0.344	−0.272***	−0.0903
	(0.0465)	(0.339)	(0.0512)	(0.581)
lnindustry	0.0313	0.0364	0.0390	−0.0998
	(0.0219)	(0.0593)	(0.0236)	(0.371)
lnintensity	0.0454	0.0107	0.0720**	0.342
	(0.0252)	(0.0540)	(0.0276)	(0.243)
lnopen	−0.0281*	−0.138**	−0.0217	−0.967***
	(0.0131)	(0.0441)	(0.0140)	(0.277)
lnenergy	−0.143***	−0.00558	−0.161***	−0.484**
	(0.0244)	(0.0545)	(0.0267)	(0.159)
lndensity	−0.649***	−0.590***	−0.596***	−0.921***
	(0.0370)	(0.0927)	(0.0415)	(0.174)
lngdpp	0.190***	−0.329***	0.278***	−0.803*
	(0.0251)	(0.0871)	(0.0291)	(0.399)
_cons	−1.426*	−1.672	−2.419**	−3.768
	(0.668)	(6.512)	(0.744)	(6.453)
N	1061	210	851	77
R^2	0.982	0.971	0.988	0.982

Note: Each column shows results from an OLS regression where the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnurban*. *lnurban2* is the quadratic term of *lnurban*. Standard errors are in parentheses.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Baseline model with interaction terms added.

	Full sample	OECD	Non-OECD	Poor countries
lnurban	1.946***	0.610	2.149***	13.10**
	(0.333)	(3.063)	(0.360)	(4.069)
lnurban2	−0.315***	−0.674	−0.365***	−2.514***
	(0.0581)	(0.584)	(0.0623)	(0.753)
ug	0.0591*	−0.598*	0.076**	−4.493***
	(0.0268)	(0.284)	(0.0291)	(0.969)
lnindustry	0.0364	0.0560	0.0451	−1.174**
	(0.0219)	(0.0586)	(0.0236)	(0.396)
lnintensity	0.0494*	0.0146	0.0766**	0.0897
	(0.0251)	(0.0528)	(0.0275)	(0.217)
lnopen	0.0282*	0.0993*	0.0219	0.523*
	(0.0130)	(0.0460)	(0.0139)	(0.257)
lnenergy	−0.131***	−0.0181	−0.145***	0.916***
	(0.0248)	(0.0535)	(0.0272)	(0.166)
lndensity	−0.639***	−0.564***	−0.586***	−0.590***
	(0.0373)	(0.0954)	(0.0416)	(0.167)
lngdpp	−0.0302	2.225	−0.00526	14.54***
	(0.103)	(1.214)	(0.112)	(3.328)
_cons	−0.881	−9.600	−1.624*	−69.81***
	(0.710)	(7.437)	(0.800)	(15.30)
N	1061	210	851	77
R^2	0.982	0.988	0.972	0.982

Note: Each column shows results from an OLS regression in which the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnurban*. *ug* is the interaction term of *lnurban* and *lngdpp*. Standard errors are in parentheses.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

causation resulting from the possibility that $PM_{2.5}$ density can affect urbanization; that is, as $PM_{2.5}$ density increases, people are likely to emigrate to other areas or cities where air pollution is less severe (Aunan & Wang, 2014; Bayer, Keohane, & Timmins, 2009).

This study used the lag of variables as instrumental variables (IV). In the overall sample, a one-phase lag of the urbanization level was used as the IV because we assumed that $PM_{2.5}$ density does not affect urbanization in the lag phase. The results of 2SLS are shown in Table 5, and the regression outcome in this section is consistent with that in the previous analysis wherein the endogeneity

Table 5
Regression using 2SLS.

	Full sample	OECD	Non-OECD	Poor countries
lnurban	0.160*	0.0437***	0.158*	0.762***
	(0.0680)	(0.015)	(0.0772)	(0.161)
lnindustry	0.0554*	0.109*	0.0498*	0.148*
	(0.0216)	(0.0520)	(0.0245)	(0.0580)
lnintensity	0.0478	0.138**	0.0577	0.0729
	(0.0282)	(0.0437)	(0.0332)	(0.103)
lnopen	0.00151	0.0157	0.000858	0.0134
	(0.0121)	(0.0378)	(0.0136)	(0.0447)
lnenergy	−0.0563*	−0.117**	−0.0659*	−0.0912**
	(0.0258)	(0.0446)	(0.0302)	(0.0310)
lndensity	−1.097***	−1.106***	−1.090***	−1.734***
	(0.0363)	(0.112)	(0.0408)	(0.105)
lngdpp	−0.00706	−0.372***	0.00525	0.253*
	(0.0255)	(0.0620)	(0.0293)	(0.119)
N	976	197	779	69
R^2	0.981	0.995	0.982	0.995

Note: Each column shows results from the GMM method in which the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnurban*. The instrumental variable is the lag term of *lnurban*, which is the endogenous variable. Standard errors are in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 6
Regression with urban agglomeration.

	Full sample	OECD	Non-OECD	Poor countries
lnagg	0.488	5.001***	0.350	3.481**
	(0.344)	(1.183)	(0.382)	(1.114)
lnagg2	−0.148*	−0.748***	−0.314***	−0.0338
	(0.0587)	(0.181)	(0.0759)	(0.160)
ag	−0.120***	0.0166	−0.118***	−0.454**
	(0.00989)	(0.0513)	(0.0194)	(0.135)
lnindustry	−0.136	0.114	−0.259*	0.315
	(0.114)	(0.307)	(0.131)	(0.222)
lnintensity	0.453***	0.594**	0.286***	0.292
	(0.0764)	(0.199)	(0.0842)	(0.164)
lnopen	0.885***	1.668***	0.687***	0.389*
	(0.0548)	(0.121)	(0.0619)	(0.185)
lnenergy	−0.0826	−0.252	−0.0307	−0.879***
	(0.0655)	(0.198)	(0.0759)	(0.161)
lndensity	−0.149***	−0.212***	−0.133***	1.099***
	(0.0278)	(0.0428)	(0.0330)	(0.147)
_cons	0.825	−11.01***	1.592	−10.46***
	(0.800)	(3.190)	(0.847)	(1.801)
N	827	194	633	65
R^2	0.973	0.982	0.972	0.981

Note: Each column shows results from an OLS regression in which the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnagg*. *lnagg2* and *ag* are the quadratic terms for *lnagg* and the interaction terms *lnurban* and *lngdpp*, respectively. Standard errors are in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

problem was controlled for.

With regard to the impacts of each variable, the coefficient and significance level of *lnurban* and other variables remained similar to those in the baseline estimation.

4.5. Further investigation and robustness test

4.5.1. Alternative variables

A notable feature of urbanization in most countries is urban agglomeration, which is defined as urban concentrations of populations of > 1 million; urban agglomeration used to describe population sizes in large cities (Zhang et al., 2017). High agglomeration usually indicates overconcentration and inefficient urbanization. A strand of literature has explored the effects of urbanization on the

Table 7
Mixed-effect model.*

	(1)	(2)	(3)
	Random intercept 1: grouped by countries	Random intercept 2: grouped by time	Random intercept and slope model
lnurban	1.980***	1.297***	1.808***
	(0.305)	(0.390)	(0.319)
lnurban2	−0.287***	−0.254***	−0.265***
	(0.0423)	(0.096)	(0.0444)
lnindustry	0.125***	0.494***	0.122***
	(0.0198)	(0.0417)	(0.0197)
lnintensity	0.597***	0.694***	0.649***
	(0.0489)	(0.0379)	(0.0577)
lnopen	0.0146	0.0793***	0.0162
	(0.0119)	(0.0227)	(0.0117)
lnenergy	−0.0607**	−0.0303	−0.0685**
	(0.0220)	(0.0260)	(0.0218)
lndensity	−0.00672	−0.110***	−0.0102
	(0.0229)	(0.0109)	(0.0228)
lngdpp	0.0477**	0.312***	0.0515***
	(0.0153)	(0.0167)	(0.0152)
_cons	0.200	3.134***	0.643
	(0.565)	(0.763)	(0.590)
N	1070	1070	1070
Log likelihood	219.664	−1546.104	221.218
chi2	342.630	731.490	326.440

Note: Each column shows results from a mixed-effect model, in which the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnurban*. Standard errors are in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 8
Robustness test that includes NASA data.

	(1)	(2)	(3)	(4)
	Full sample	OECD	Non-OECD	Poor countries
lnurban	−0.355**	1.254*	−0.523***	0.889***
	(0.125)	(0.575)	(0.134)	(0.198)
lnindustry	−0.315*	−0.838**	−0.711***	0.270
	(0.127)	(0.295)	(0.152)	(0.450)
lnintensity	−0.374***	−0.672*	−0.253*	−0.941***
	(0.0866)	(0.260)	(0.0984)	(0.205)
lnopen	2.050***	2.133***	1.745***	0.231
	(0.0831)	(0.0994)	(0.112)	(0.281)
lnenergy	−0.306***	−1.224***	−0.344***	1.231***
	(0.0786)	(0.176)	(0.0895)	(0.186)
lndensity	−0.264***	−0.137**	−0.289***	0.550***
	(0.0314)	(0.0475)	(0.0378)	(0.0845)
lngdppn	−0.0284	−2.156***	0.306***	−4.645***
	(0.0389)	(0.447)	(0.0606)	(0.365)
_cons	6.104***	27.27***	6.468***	33.17***
	(0.860)	(4.144)	(0.931)	(2.292)
N	1005	224	781	66
R^2	0.987	0.975	0.972	0.963

Source: https://nasasearch.nasa.gov/search?query=PM2.5&affiliate=nasa&utf8=%E2%9C%93/.
Note: Each column shows results from an OLS regression, in which the dependent variable is *lnpm2.5,* and the key explanatory variable is *lnurban*. Standard errors are in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

environment (Han et al., 2018; Liang, Wang, & Li, 2019; Liu, Tian, Li, Song, & Ma, 2018), particularly the effect of urban agglomeration. Replacing the urbanization level with urban agglomeration as the key explanatory variable helps explain the effect of urbanization on the environment in cities. Thus, the natural logarithm of urban agglomeration was used as a proxy variable in our empirical analysis in this section.

Table 6 shows that we substituted the logarithm of urbanization level with the natural logarithm of urban agglomeration (*lnagg*). The regression results are similar, and the level of significance remains the same because of the close relationship between urban agglomeration and urbanization, thereby verifying our previous empirical results. In particular, the inverted U-shaped curve and interactions still hold. As demonstrated in Table 7, energy efficiency and industrial structure significantly boost $PM_{2.5}$ levels in non-OECD countries. Table 7 shows that urban agglomeration significantly increases $PM_{2.5}$ levels, except in poor countries. $PM_{2.5}$ density is curbed by energy consumption and the demographic structure but increased by trade openness.

4.5.2. Mixed effects

Considering the heterogeneity of the samples and the omitted values, we applied a mixed-effect model to address this problem and serve as a robustness test. In light of the grouping variable (i.e., country and time), we used country and time in the random intercept model, respectively. We also included a random intercept and slope model, assuming that the grouping variable may also influence the coefficient of *lnurban*. The results in Table 7 are highly consistent with those of the earlier analysis and thus confirm that our results are robust.

4.5.3. Robustness test with NASA indicators

Given the variety of ways to measure the degree of $PM_{2.5}$, we applied other indicators to test the robustness of our empirical results. Data in many developing countries may lead to inaccurate estimations because monitoring in these countries is sparse. Data collected by satellites may be more comprehensive. Consequently, we used $PM_{2.5}$ data from 2001 to 2016 from NASA.[3] Fig. 3 illustrates the worldwide distribution of $PM_{2.5}$ based on NASA data.

The overall impression provided by Fig. 3 is consistent with that of the World Bank Database. Thus, NASA data were combined with our original dataset to calculate $PM_{2.5}$ density and conduct an empirical analysis. The results are presented in Table 8.

The results in Table 8 confirm the robustness of our empirical results because the sign of most variables remains the same as those in our previous analysis. Owing to the limited time range, several differences were found in the values and significance levels compared with those in the previous analysis. Nevertheless, most variables, particularly *lnurban*, have the same sign and significance level as before.

5. Conclusion and policy caveats

China has undergone extensive economic development and urbanization and thus experiences severe air pollution. To address pollution while continuing with national development, the Chinese government has proposed that all cities in China attain air quality rated as "good" or better on at least 80% of the days monitored. Hence, exploring the impact of urbanization and other economic indicators on air quality is useful.

By applying economic and demographic data on different countries from 1990 to 2016, this study provides robust evidence on the impact of urbanization on $PM_{2.5}$ density. By using several empirical methods to address the endogeneity problem and check robustness, we found that the emissions due to urbanization and $PM_{2.5}$ density have an inverted U-shaped relationship. In other words, as a crucial indicator of modernization, urbanization initially increases the $PM_{2.5}$ density level. As urbanization proceeds, urban agglomeration and technological progress help reduce $PM_{2.5}$ density.

The empirical results suggest specific policy implications. For countries with low levels of urbanization, urban development is likely to be the priority of policymakers, and infrastructure construction is of great importance. Both can drive urbanization. With the advantage of a scale economy and agglomeration effects, urbanization significantly boosts industrial development and thus accelerates the structural transformation of the economy.

When the GDP per capita approaches that of high-income countries and the economic growth rate converges to a low level, $PM_{2.5}$ density is eventually reduced. At this stage, governments should not pursue economic growth at the cost of environmental protection. Policymakers should recognize the importance of the pattern of urbanization, which is a prerequisite for ensuring that the relevant policy is efficient and appropriate.

This study explored the impacts of urbanization on the $PM_{2.5}$ density level, which has been rarely covered in extant literature. To do so, we conducted an extensive country-level analysis with numerous robustness tests. The results were confirmed with data from NASA. The environmental Kuznets curve on the nexus of urbanization and $PM_{2.5}$ density was confirmed, and policy caveats were provided for the reference of policy makers to address this environmental issue in the context of breakneck urbanization.

Acknowledgements

This paper has been presented in the conference "The Economic Challenges and Opportunities of Urbanization and Migration in China" at Jinan University. We are grateful to the helpful comments of the participants, the editor and the anonymous reviewers. Meanwhile, we thank the support provided by the National Natural Science Foundation of China (NSFC) [Grant No. 71704065], the Key Project of Philosophy and Social Sciences Research of Ministry of Education of China [Grant No. 17JZD013], the Fundamental

[3] According to the user guide, this data set combines AOD retrievals from multiple satellite instruments, including the NASA Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging Spectroradiometer (MISR), and the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS). The GEOS-Chem chemical transport model is used to relate this total column measure of aerosol to near-surface PM2.5 concentration.

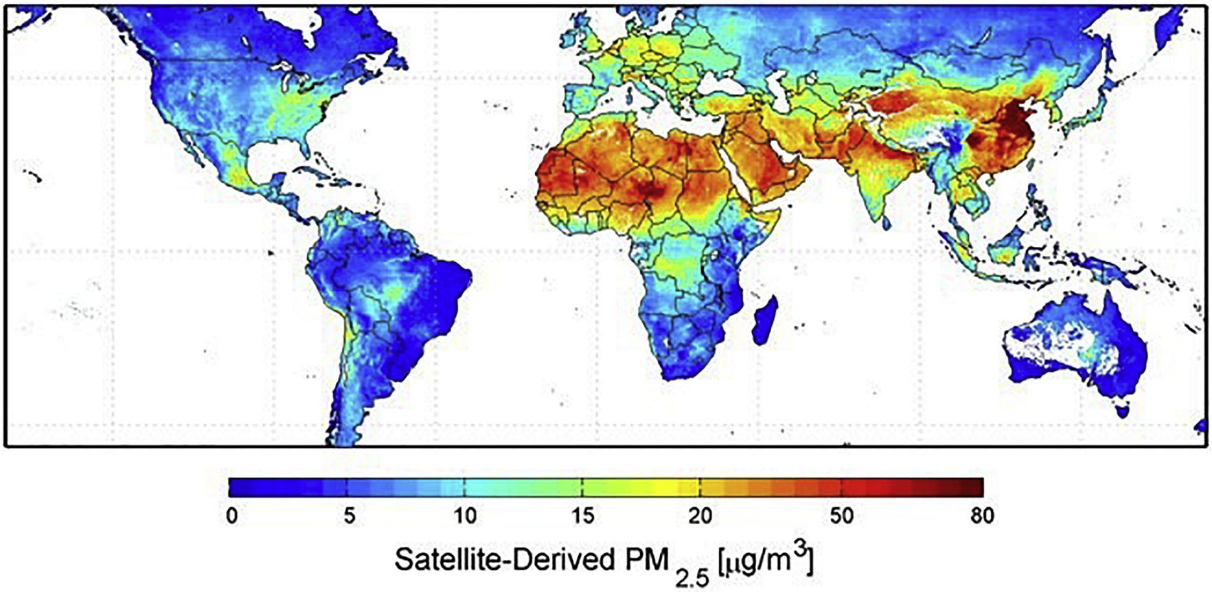

Fig. 3. Depiction of $PM_{2.5}$ derived by NASA.
Source: https://nasasearch.nasa.gov/search?query=PM2.5&affiliate=nasa&utf8=%E2%9C%93/.

Research Funds for the Central Universities-Ningjingzhiyuan Project of Jinan University [19JNQM21] and the China Postdoctoral Science Foundation [Grant No. 2017M620022].

Appendix Table 1
Descriptive statistics of the variables.

	Obs.	Mean	Std. dev.	Min	Max
Full sample					
lnpm2.5	1940	3.123	0.698	1.195	4.909
lnindustry	6539	3.263	0.473	0.632	5.365
lnintensity	3447	4.912	0.574	1.515	7.088
lnopen	8193	4.173	0.672	−3.863	6.758
lnenergy	5743	4.052	0.718	0.495	4.605
lndensity	11,548	4.020	1.678	−2.316	9.971
lnurban	11,976	3.733	0.673	0.731	4.605
lnurban2	11,976	14.391	4.591	0.534	21.208
lngdp	10,808	24.550	2.970	16.881	31.955
OECD countries					
lnpm2.5	230.000	2.357	0.342	1.642	3.013
lnindustry	697.000	3.330	0.212	2.481	3.802
lnintensity	598.000	4.777	0.381	3.840	6.131
lnopen	1257	4.046	0.590	2.189	6.039
lnenergy	1272	4.323	0.315	2.328	4.605
lndensity	1187	3.917	1.586	0.311	6.220
lnurban	1288	4.298	0.171	3.554	4.584
lnurban2	1288	18.503	1.431	12.631	21.009
lngdp	1231	26.635	1.647	21.442	30.440
Poor countries					
lnpm2.5	270.000	3.611	0.497	2.061	4.882
lnindustry	981.000	2.890	0.429	0.632	3.853
lnintensity	267.000	5.607	0.672	3.418	7.088
lnopen	1160	3.889	0.473	2.412	5.741
lnenergy	480.000	2.660	1.047	0.495	4.549
lndensity	1394	3.533	1.144	0.887	6.156
lnurban	1508	2.902	0.699	0.731	4.109
lnurban2	1508	8.912	3.810	0.534	16.882
Non-OECD					
lnpm2.5	1220	3.313	0.599	1.195	4.882
lnindustry	4276	3.287	0.456	0.632	4.572

(*continued on next page*)

Appendix Table 1 (*continued*)

	Obs.	Mean	Std. dev.	Min	Max
lnintensity	2224	5.012	0.610	1.515	7.088
lnopen	4877	4.087	0.674	−1.787	6.276
lnenergy	3512	3.910	0.807	0.495	4.605
lndensity	7056	3.860	1.582	−2.316	9.860
lnurban	7160	3.621	0.701	0.731	4.605
lnurban2	7160	13.604	4.615	0.534	21.208

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