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What causes PM2.5 pollution? Cross-economy empirical analysis from socioeconomic perspective

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ABSTRACT

Is it true that, as the mainstream intuition asserts, urbanization and industrialization are the two main socioeconomic drivers of PM2.5? How do the two trends affect PM2.5 emission? This paper quantitatively analyzes the socioeconomic drivers of PM2.5 through assessment on Stochastic Impacts by Regression on Population, Affluence and Technology (STRIPAT), based on the panel data of 79 developing countries over 2001–2010. The average levels of PM2.5 pollution are calculated using remote sensing data, overcoming the difficulties that developing countries are in lack of PM2.5 monitors and that point data cannot reflect the overall level of PM2.5 pollution on a large scale. Squared terms of income and urbanization and their cross term are included in the regression models respectively to analyze the possible heterogeneous impacts on PM2.5 emissions in different development stages. The results show that income, urbanization and service sector have significant impact on PM2.5 pollution. Income has a positive effect on PM2.5 all the time but the effect decreases as the level of urbanization or income goes up. An inverted U relationship exists between urbanization and PM2.5, in which PM2.5 pollution positively correlates with a low level of income or urbanization but negatively at a high level. Policy recommendations from the perspective of macro-level social and economic regulation are provided for developing economies to reduce PM2.5 pollution.

1. Introduction

1.1. Background

According to a global-scale estimate, PM2.5[1] concentrations are high in densely populated areas that are undergoing fast urbanization and industrialization (Van et al., 2010). Throughout history, many severe air pollution events happened in urbanizing and industrializing areas, such as the 1930 Meuse Valley fog (Nemery et al., 2001), the Great Smog of 1952 (Davis, 2002), the Los Angeles photochemical smog (Parrish et al., 2011) and Yokkaichi asthma (Guo et al., 2008). Currently, assessment of data on various countries shows that the PM2.5 accumulation in developed countries with high level of urbanization and industrialization (such as United States and Western Europe) is close to the natural background accumulation,[2] while developing countries that are in the process of rapid urbanization and industrialization are suffering from severe air pollution and people there are exposed to high levels of particulate matter (WHO, 2006). For example, in January 2013, northern China experienced a prolonged smog, the PM2.5 peak shooting over 800 μg/m^3, 32 times higher than the World Health Organization (WHO)'s guideline value (Zhou et al., 2015). In June of the same year, Southeast Asia was hit by a severe haze and PM2.5 accumulations reached 329 μg/m^3 (Betha et al., 2014). Van et al. (2015) estimated that the percentage of global population living in areas where the PM2.5 concentrations were above the WHO guideline level (35 μg/m^3) increased from 22% in 1998–2000 to 30% in 2010–2012.

Given the fact that many developing countries suffer from PM2.5 pollution, it seems plausible that industrialization and urbanization are the main drivers of PM2.5 pollution, which is the mainstream view. However, this view lacks empirical tests and needs to be examined through quantitative analysis. Thus, this study investigates the socioeconomic driving forces of PM2.5 in developing countries, using the Stochastic Impacts by Regression on Population, Affluence and Technology model (STIRPAT), on a panel dataset of 79 developing countries over the period 2001–2010.

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[1] Fine particles with a diameter of 2.5 μm or less.
[2] The accumulation of a given species in a pristine air mass in which anthropogenic impurities of a relatively short lifetime are not present.

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1.2. Literature review

There is large body of literature studying socioeconomic driving forces of air pollution, but most of them focused on carbon dioxide, and others targeted sulfur oxides, oxides of nitrogen or PM10. As for PM2.5, there have been plentiful studies focusing on source apportionment, including both natural processes and human activities, from a micro-level perspective (Kaur et al., 2007; Belis et al., 2013; Pui et al., 2014; Karagulian et al., 2015; Li, Zhou, et al., 2015; Liang et al., 2016), while its socioeconomic driving forces were almost ignored. Only recently, few studies came to realize the importance of the macro drivers of PM2.5 pollution. Xu and Lin (2016) and Xu et al. (2016) analyzed the impact of income, energy intensity, urbanization, private vehicles and coal consumption on PM2.5 pollution with a panel dataset of 29 provinces in China over 2001–2012.

Population, income, technology and industrial structure were the four socioeconomic factors of air pollution that were widely studied in recent literature.

First, in many studies, the population factor is demonstrated by the population size and structure. Population size was related to carbon emissions in Cole and Neumayer (2004), to non-renewable energy consumption in Salim and Shafiei (2014). Population structure mainly refers to the level of urbanization, measured as the percentage of urban population in total population.[3] York (2007) analyzed a panel dataset of 14 European Union countries over 1960–2000 and found that urbanization had a positive, monotonic effect on energy consumption, which indicated increased pollution. A study by Liddle and Lung (2010) on a panel dataset of 17 developed countries covering the period 1960–2005, however, did not find significant impact of urbanization on carbon emission. Martínez-Zarzoso and Maruotti (2011) concluded that there was an inverted-U relationship between urbanization and carbon emission, using a panel dataset of 88 developing countries over the period 1975–2003. Xu and Lin (2015) found the nonlinear effect of urbanization on CO_2 emissions varies across regions in China: inverted U-shaped pattern in the eastern region, positive U-shaped pattern in the central region while insignificant nonlinear effect in the western region. Rafiq et al. (2016) showed that although urbanization is insignificant in impacting CO_2 emissions, it seems to be a major factor behind energy intensity.

Second, income, usually demonstrated as GDP per capita, is mostly regarded to have an inverted-U relationship with environmental pressure, known as Environmental Kuznets Curve (EKC). EKC is expressed as follows: at the early and lower stage of development, environmental pressure increases as income increases; however, when income reaches a threshold value, environmental stress decreases (Grossman and Krueger, 1996). The trade-off between consumption and good environment can explain the phenomena above: people spend most of their income on consumption when income is meagre, causing growing environmental pollution; but as income increases, the marginal utility of clean environment gradually grows and finally surpasses that of consumption (Ji and Chen, 2017). Thus, the willingness to pay for environmental protection rises as well and reduces pollution (Roca, 2003). However, some empirical studies did not support EKC and showed different impact of income on environment. For example, Kaika and Zervas (2013a) summarized 35 studies over 1992–2009 focusing on the impact of income level on carbon emission, and found various results, such as positive, inverted-U or no significant relationship at both national and global level. Baek (2015) examined the EKC hypothesis in the Arctic nations and provided little evidence of the existence of the hypothesis.

Third, energy intensity is widely used as a proxy for technology level. It is a common view that the impact of economic activities on environment is smaller when more energy efficient technologies are applied (Kaika and Zervas, 2013a). Using a panel dataset of 208 countries from year 1975 to 2000, Fan et al. (2006) found that the impact of energy intensity on carbon emission differed across developmental stages: at low income stage, energy intensity had significant effect on carbon emission, while at middle and high income stage, the effect was apparent yet weak. Sadorsky (2014) also found that energy intensity had significant effect on carbon emission, using a panel dataset of 16 emerging countries over year 1971–2009.

Fourth, industrial structure is often measured by the percentage of added value in GDP in different sectors: agriculture, industry and service. The impact of industrial structure on environment pressure is another possible explanation for EKC. At the early stage of development, industrial activities dominate, resulting in higher natural resources consumption and severer environmental degradation; later, as high-tech industry and service sector gradually replace energy intensive industry, the impact of economic activities on environmental pressure becomes smaller (Dinda, 2004). Martínez-Zarzoso and Maruotti (2011) found a weak impact of industrialization on carbon emission, using a panel dataset of 73 countries over 1973–2003. Li and Lin (2015) found that the impacts of industrialization on energy consumption and carbon emission varied with different income levels: in lower middle and high income groups, industrialization accompanied less energy consumption but more carbon emission, while in upper middle income groups no significant effects were found.

1.3. Research objectives

Though many studies have investigated and identified the main socioeconomic driving forces of some air pollutants like carbon dioxide and sulfur oxides, few have explored the socioeconomic drivers of PM2.5. In order to find a reasonable explanation for the severe PM2.5 pollution in developing countries to assist relevant policy design, it is urgent to quantitatively analyze the socioeconomic driving forces and macro mechanism. Since many developing countries lack ground-based monitoring PM2.5 data, this paper uses the global satellite observations of PM2.5 concentrations over 2001–2010, provided by Socioeconomic Data and Applications Center (SEDAC),[4] and socioeconomic data of 79 developing countries to analyze the driving forces and provide a quantitative basis for PM2.5 control.

The rest of this paper is organized as follows: Section 2 presents the data, empirical models and research methodology. Section 3 presents the empirical results. Section 4 discusses the results and Section 5 draws the conclusion.

2. Material and methods

2.1. Data

2.1.1. Data of the average PM2.5 concentrations

The average PM2.5 concentrations are calculated based on the global annual average PM2.5 grids over the period 2001–2010, provided by SEDAC (Battelle and Center, 2013; de Sherbinin et al., 2014), according to the boundaries of each country. The original raster grids from SEDAC have a grid cell resolution of $0.5^\circ \times 0.5^\circ$ and cells at different latitudes represent different actual sizes on Earth, which means the arithmetic average of the PM2.5 grids within the boundaries of a country is not the actual average PM2.5 concentrations of that country. To address such problem, the weighted average PM2.5 concentrations of each country are calculated. The formula is as follows,

[3] Some literature explores the relationship between age structure of population and environmental pressure.

[4] SEDAC, the Socioeconomic Data and Applications Center, is one of the Distributed Active Archive Centers (DAACs) in the Earth Observing System Data and Information System (EOSDIS) of the U.S. National Aeronautics and Space Administration.

$$C_{PM2.5} = \frac{\sum \cos(n+0.25) \times d_{n,n+0.5}}{\sum \cos(n+0.25)} \quad (1)$$

in which, $d_{n,n+0.5}$ are the PM2.5 concentrations of the grid cells which have a latitude between $n°$ and $n + 0.5°$, and $C_{PM2.5}$ represents the average PM2.5 concentrations.[5] The countries covering no more than 4 grid cells are excluded for the consideration of data accuracy.[6]

The PM2.5 data provided by SEDAC are estimated from satellite observations, which has two advantages over ground-based monitoring data. One is that many developing countries lack ground-based monitoring networks, while data PM2.5 concentrations in these countries can be estimated from satellite observations (van Donkelaar et al., 2010). Also, ground-based monitoring data can only represent location-specific features and the locations of the monitors depend highly on the objective of monitoring, which can be economic, social or environmental (Chen et al., 2006). Satellite observations, on the contrary, have a global coverage and can measure air pollution on a large scale. Prud'homme et al. (2013) compared air pollution estimates based on satellite remote sensing and ground-based monitoring, and found that both can provide a consistent estimate of air pollution, suggesting that satellite remote sensing can offer estimates for air pollution in areas lacking ground-based monitoring networks.

2.1.2. Indicator for the socioeconomic drivers

The explanatory variables are population size (*POP*), urbanization level (*URB*), GDP per capita (*GDPPC*), percentage of value added of industry in GDP (*IND*), percentage of value added of service in GDP (*SER*) and energy use per GDP (*ERG*).

Their definitions, unit of measurement and data sources are presented in Table 1.

2.1.3. Sample

The developing countries selected in this study are the countries defined as low-income or middle-income countries by World Bank. We use the classification criteria in 2005 because our data sample spans from 2001 to 2010. The dataset in World Bank includes 59 low-income countries and 94 middle-income countries. However, 34 low-income countries and 42 middle-income countries are excluded in our study in order to get a balanced data panel. In addition, the countries covering no more than four grid cells (Lebanon, Trinidad and Tobago) are excluded for the consideration of data accuracy. Therefore, the rest 79 developing countries (25 low-income countries and 54 middle-income countries) are chosen for our study (See Appendix A). In the main results of regression, we pool low-income and middle-income countries together. In the robustness check, we estimate the coefficients for low-income and middle-income countries respectively. The statistical description of variables are shown in Table 2.

2.2. Empirical model and methodology

2.2.1. Empirical model

The regression is based on the STIRPAT model developed on the basis of IPAT identity and ImPACT identity. IPAT identity, I = PAT, is widely used to analyze the effects of economic activity on environment (Stern, 1992; Harrison and Pearce, 2000; York et al., 2003), in which *I* is environmental impact, driven by three key factors: *P* for population, *A* for affluence and *T* for technological level (environmental impact per unit of GDP). ImPACT identity, developed by Waggoner and Ausubel (2002) as I = PACT, is similar to IPAT, except that T is disaggregated into C (consumption per unit of GDP) and T (environmental impact per unit of consumption).

However, unlike IPAT and ImPACT, STIRPAT is not an accounting equation, but a stochastic model used to test hypotheses empirically (York et al., 2003), by adding scaling term *a*, exponential term *b,c,d* and error term *e* to the original IPAT identity. STIRPAT model has been successfully utilized in many empirical studies (Dietz and Rosa, 1997; Cramer, 1998; Shi, 2003; York et al., 2003; Wang et al., 2011; Li et al., 2011; Zhang et al., 2017; Long et al., 2017). The STIRPAT model is as follows:

$$I_i = aP_i^b A_i^c T_i^d e_i \quad (2)$$

Coefficients can be estimated using multivariate regression with the variables in logarithmic form. Coefficient *b*, *c* and *d*, are the elasticities of *P*, *A* and *T*, respectively. Thus,

$$\ln I_i = \ln a + b\ln P_i + c\ln A_i + d\ln T_i + \ln e_i \quad (3)$$

In a standard STIRPAT model as above, we are interested to look into *b*, *c* and *d*, measuring the effects of population, affluence and technology on environmental outcomes.

We further extend the model to include more economic variables for our analysis. *I* denotes annually average PM2.5 concentrations at country level. Population factors (*P*) include population level (*POP*) and population structure (the proportion of urban population in total population, *URB*). Affluence (*A*) is represented by GDP per capita (*GDPPC*). Technology (*T*)[7] has two proxies: industrial structure (*IND*, the percentage of value added of industry in GDP, and *SER*, the percentage of value added of service in GDP) and energy intensity (energy use per GDP, *ERG*). Moreover, there may be country specific effect due to different geographic factors, and time specific effect due to fluctuations of climate, etc. Thus, country dummy variables C_i and time dummy variables Y_t are included in the specified regression models and respective test statistics are calculated to examine whether these dummy variables are appropriate.

2.2.2. Methodology

First, linear effects are considered. Model 1 include the linear terms *POP*, *GDPPC*, *URB*, *IND*, *SER* and *ERG* in the logarithmic form as well as country dummy variable *C* and time dummy variable *Y*. The model is as follows.

Model 1:

$$\ln I_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln URB_{it} + \beta_4 \ln IND_{it} + \beta_5 \ln SER_{it} + \beta_6 \ln ERG_{it} + C_i + Y_t + u_{\text{it}} \quad (4)$$

In order to test multicollinearity among the variables in Model 1, variance inflation factors (VIFs) are calculated (See Appendix B). According to Freund et al. (2006), if 0 < VIF < 10, we can safely conclude that multicollinearity does not exist. Here all VIFs are less than 5, indicating that there is no multicollinearity among the linear variables. In other words, though correlation between the variables exists (See Appendix C), it does not mean multicollinearity.

However, Model 1 fails to express the nonlinear effects of income and urbanization on PM2.5 concentrations. In order to analyze such potential effects, two common approaches can be applied. One is to split the observations into subsamples and examine their effects respectively. For example, Poumanyvong and Kaneko (2010) estimated the impact of urbanization on energy use and emissions They categorized the sample into three groups: low-, middle- and high- income group, to empirically test whether urbanization pressure on energy use and emissions differed across income levels. Similarly, Martínez-Zarzoso and Maruotti (2011) also categorized a sample of 88 countries over 1975–2003 into low-, lower-middle- and upper-middle- groups to

[5] The original grid cells cover the world from 70°N to 60°S latitude and values in some grid cells are removed according to the exclusion criteria (van Donkelaar et al., 2010). Calculation in this research does not include the grid cells with missing data. Since most countries considered in the research locate between 70°N to 60°S latitude, the average PM2.5 concentrations of each country calculated in this research are representative.

[6] Two countries are excluded. They are Lebanon, Trinidad and Tobago.

[7] In the STIRPAT model, T includes all factors other than P and A (York et al., 2003). In this paper, T is decomposed into industrial structure and energy intensity.

Table 1
Description of the variables in the regression analysis.

Variable	Definition	Unit of measurement	Data Source
PM2.5(*PM*)	Annual-average estimated surface PM2.5 concentration at country level	Micro-grams per cubic meter	SEDAC[a] and Natural Earth[b]
Population(*POP*)	Midyear population	Number	World Bank
Urbanization(*URB*)	Urban population (% of total population)	Percent	World Bank
GDP per Capita (*GDPPC*)	Gross domestic product per capita based on purchasing power parity (PPP)	Constant 2011 international dollars	World Bank
Industry(*IND*)	Industry, value added (% of GDP)	Percent	World Bank
Service(*SER*)	Services, etc., value added (% of GDP)	Percent	World Bank
Energy Intensity (*ERG*)	Oil equivalent of energy use per constant PPP GDP	Kilograms of oil equivalent per $1000 GDP (constant 2011 PPP)	World Bank

[a] Battelle, M. I. and F. I. E. S. Center (2013). Global Annual Average PM2.5 Grids from MODIS and MISR Aerosol Optical Depth (AOD). Palisades, NY, NASA Socioeconomic Data and Applications Center (SEDAC).
[b] Made with Natural Earth. Free vector and raster map data are available from http://www.naturalearthdata.com/.

Table 2
Statistics on the variables in the regression analysis.

	Whole Sample (Obs.: 790)				Low Income Countries (Obs.: 250)				Middle Income Countries (Obs.:540)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
lnPM	2.239	0.556	0.080	3.710	2.624	0.551	1.363	3.710	2.062	0.461	0.080	3.004
lnPOP	16.552	1.458	14.043	21.014	16.901	1.433	14.699	20.910	16.390	1.442	14.043	21.014
lnGDPPC	8.760	0.850	6.391	10.220	7.750	0.523	6.391	8.776	9.228	0.489	8.075	10.220
lnURB	3.902	0.411	2.637	4.548	3.509	0.371	2.637	4.213	4.084	0.281	2.908	4.548
lnIND	3.417	0.336	2.341	4.349	3.208	0.360	2.341	4.349	3.514	0.275	2.447	4.252
lnSER	3.945	0.241	2.940	4.342	3.827	0.234	2.940	4.305	3.999	0.225	3.169	4.342
lnERG	4.965	0.539	3.973	6.688	5.294	0.540	4.014	6.688	4.812	0.466	3.973	6.518

*All variables are in natural logarithm form.

analyze the impact of urbanization on carbon emissions in each group. The other approach is to add nonlinear terms into regression model to capture the possible nonlinear effects. For instance, Jalil and Mahmud (2009) added the quadratic term of income into their regression function to analyze the nonlinear impact of income on carbon emissions in China from 1975 to 2003. Shafiei and Salim (2014) also added quadratic terms of GDP per capita and urbanization to analyze the possible nonlinear impact of income and urbanization on energy consumption and carbon emissions in the panel dataset of 29 OECD countries from 1980 to 2011.

Since splitting the observations into different groups is not appropriate for this study due to the short time span (2001–2010), the latter approach is applied and Model 1 is augmented with the quadratic term of ln*GDPPC* and ln*URB* respectively as follows:

Model 2:

$$\ln I_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln URB_{it} + \beta_4 \ln IND_{it} + \beta_5 \ln SER_{it} + \beta_6 \ln ERG_{it} + \beta_7 [\ln GDPPC_{it}]^2 + C_i + Y_t + u_{\text{it}} \quad (5)$$

Model 3:

$$\ln I_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln URB_{it} + \beta_4 \ln IND_{it} + \beta_5 \ln SER_{it} + \beta_6 \ln ERG_{it} + \beta_8 [\ln URB_{it}]^2 + C_i + Y_t + u_{\text{it}} \quad (6)$$

Next, the interaction between the two nonlinear variables should be considered in case of strong correlation in between. First, pair-wise correlations are analyzed and the results are shown in Appendix C. According to Gujarati and Porter (2009), correlation is relatively strong when pair-wise correlation coefficients are higher than 0.5. If there is a strong correlation between variables which are in both level term and quadratic term in the regression models, the cross term between the correlated variables should also be taken into consideration in model specification and the theoretical meaning of the result of each model must be carefully interpreted (Southwood, 1978).[8] As shown in the correlation matrix in Appendix C, the correlation coefficient between ln*GDPPC* and ln*URB* is the only one above 0.5 among all independent variables (0.77). Thus, Model 1 is augmented with the cross term of ln*GDPPC* and ln*URB* as follows[9]:

Model 4:

$$\ln I_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln URB_{it} + \beta_4 \ln IND_{it} + \beta_5 \ln SER_{it} + \beta_6 \ln ERG_{it} + \beta_9 [\ln GDPPC_{it} {*} \ln URB_{it}] + C_i + Y_t + u_{\text{it}} \quad (7)$$

If the results of Model 4 are consistent with the ones of Model 2 and Model 3, then the results of Model 4 are to be chosen for further discussion; otherwise the results of Model 2 and Model 3 are discussed further.

There is also a need to test the possible existence of country specific effect, time specific effect and other potential problems such as heteroscedasticity, cross sectional dependence and serial correlation. First, the Hausman test can demonstrate the existence of country specific effect, and F test is able to spot a potential time specific effect. Heteroscedasticity is tested using modified Wald statistics and robust Hausman test (Wooldridge, 2010), and robust F test should be used if heteroscedasticity do exist. As for cross-sectional dependence, the Pesaran test (Pesaran, 2004) is chosen since the panel dataset has a small T (T = 10) and a large N (N = 79). The approach proposed by

[8] For example, if the real relationship of Y to X_1, X_2 is $Y = a_0 + a_1X_1 + a_2X_2 + a_3X_1 \times _2 + u$ (interactive relationship), when X_1 and X_2 is positively correlated, then the regression results of $Y = a_0 + a_1X_1 + a_2X_2 + a_3X_1^2 + u$ (or $Y = a_0 + a_1X_1 + a_2X_2 + a_3X_2^2$) may show that the relationship of Y to X_1 (or X_2) is in a quadratic form.

[9] In models with X_1, X_2 and their cross term $X_1 \times _2$, the correlation between $X_1 \times _2$ and X_1 (or X_2) can be high, but this does not violate the assumption of no multicollinearity and the analysis of interaction effects, unless the correlation is so high that the software cannot calculate the standard error (Jaccard and Turrisi, 2003).

Table 3
Test results of the models.

	Model 1	Model 2	Model 3	Model 4
Hausman Test	$\chi^2(15) = 5.91$	$\chi^2(16) = 122.31$***	$\chi^2(16) = 140.27$***	$\chi^2(16) = 119.53$***
F Statistics (Time Fixed Effect)	F(9696) = 11.71***	F(9695) = 9.60***	F(9695) = 10.70***	F(9695) = 9.71***
Heteroskedasticity	$\chi^2(79) = 3402.79$***	$\chi^2(79) = 5238.02$***	$\chi^2(79) = 3822.50$***	$\chi^2(79) = 4333.10$***
Robust Hausman Test	$\chi^2(6) = 25.96$ ***	$\chi^2(7) = 33.09$***	$\chi^2(7) = 24.39$***	$\chi^2(7) = 30.83$***
Robust F Statistics (Time Fixed Effect)	F(9,78) = 18.52 ***	F(9,78) = 14.63***	F(9,78) = 17.05***	F(9,78) = 15.71***
Cross-sectional dependence[a]	0.363(0.7170)	0.362(0.7175)	0.365(0.7153)	0.326(0.7443)
Serial correlation[a]	F(1709) = 1.23(0.27)	F(1709) = 1.60(0.21)	F(1709) = 1.53(0.22)	F(1709) = 1.83(0.18)

[a] Statistical significance is indicated by: ***p < 0.01, **p < 0.05, *p < 0.1.
[b] p-value in parentheses.

Table 4
Regression results of all four models.

	Model 1	Model 2	Model 3	Model 4
ln*POP*	.325 (1.93)*	0.112 (0.58)	0.287 (1.73)*	0.139 (0.72)
ln*GDPPC*	0.191 (2.23)**	1.323 (3.28)***	0.185 (2.18)**	0.925 (3.64)***
ln*URB*	0.195 (1.10)	0.098 (0.57)	2.555 (2.35)**	1.699 (2.98)***
ln*IND*	0.076 (1.18)	0.085 (1.39)	0.080 (1.27)	0.089 (1.44)
ln*SER*	0.173 (2.14)**	0.141 (1.94)*	0.169 (2.20)**	0.161 (2.15)**
ln*ERG*	0.076 (1.27)	0.094 (1.57)	0.085 (1.43)	0.099 (1.69)*
$[\ln GDPPC]^2$		− 0.064 (−2.80)***		
$[\ln URB]^2$			− 0.328 (−2.26)**	
[ln*GDPPC**ln*URB*]				− 0.189 (−2.91)* **
Constant	− 6.793(−2.06)**	− 7.826(−2.41)**	− 10.311(−2.93)***	− 9.625(−2.98)***
Year Dummies	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes
Observations	790	790	790	790
Groups	79	79	79	79

[a] t statistics in parentheses.
[b] Standard errors are clustered at country level.
[c] Statistical significance is indicated by: ***p < 0.01, **p < 0.05, *p < 0.1.

Wooldridge (2010) [10] is used to test for serial correlation. All test results are listed in Table 3.

As in Table 3, the results of modified Wald test indicate the presence of heteroscedasticity in all four models. Robust Hausman test results and robust F test results prove the existence of country specific effect and time specific effect. Thus, the country dummy variables C_i and time dummy variables Y_t are included in all four models. In cross section dimension, the results of Pesaran test do not reject the null hypothesis of cross sectional independence. In time series dimension, the results of the test proposed by Wooldridge (2010) do not reject the null hypothesis of no serial correlation. Given the presence of heteroscedasticity, cluster-robust standard errors at country level are used (Rogers, 1994).

3. Results

3.1. Results of models 1–4

The regression results of the four models are listed in Table 4.

3.2. Model selection based on the results

In this section, the four models are compared and chosen for further discussion according to their regression results.

As shown in Table 4, all quadratic terms in Model 2 to Model 4 are significant, indicating the existence of nonlinear impact. Thus Model 2 to Model 4 are chosen for further discussion.

The concept of elasticity and turning point is interpreted here. In Model 2 to Model 4, the coefficients of the level terms ln*GDPPC* and ln*URB* are all positive, while those of quadratic terms all negative. The *GDPPC* elasticity (*URB* elasticity) can be calculated by taking the first partial derivative with respect to ln*GDPPC* (ln*URB*).[11] Here the elasticity decreases as the variable in its expression increases as the coefficients of the level term are positive and the coefficients of the quadratic term are negative. When the elasticity is positive first and decreases as the variable increases, the turning point is where the elasticity is zero. Prior to the turning point, the elasticity is positive and pollution increases as the variable goes up; after the turning point, the elasticity is negative and pollution decreases as the variable goes up.[12] In this paper, *GDPPC* elasticity (*URB* elasticity) is the percentage of the increase in PM2.5 concentrations when there is one percent increase in GDP per capita (urbanization rate). Specifically, when the elasticity is positive, PM2.5 concentrations increase as GDP per capita (urbanization rate) goes up, ceteris paribus.

The comparison of Model 2, Model 3 and Model 4 focuses on the trend of elasticity and whether a turning point exists. The calculation results of elasticity and turning point are listed in Table 5.

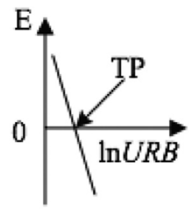
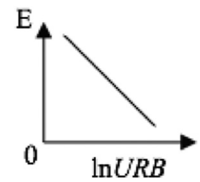
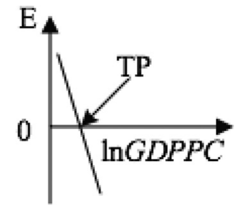
The result of Model 2 shows that *GDPPC* elasticity of PM2.5 concentrations decreases as GDP per capita goes up; however, since the theoretical turning point of *GDPPC* (10.336) is higher than the maximal *GDPPC* in sample countries (10.220) (shown in Table 2), the elasticity does not reach

[10] $\hat{u}_{i,t}$ and $\hat{u}_{i,t-1}$ are the fixed effect residuals. Run the pooled OLS regression $\hat{u}_{i,t}$ on $\hat{u}_{i,t-1}$ ($i = 1,2,\ldots,N$; $t = 2,3,\ldots,T$). δ is the estimated coefficient on $\hat{u}_{i,t-1}$ and test H_0: $\delta = -1/(T-1)$ using the robust standard error. Under the null hypothesis, the errors are serially uncorrelated.

[11] In the model $\ln I = a + b\ln A$, take the derivative relative to $\ln A$, rather than A in original units, and the coefficient is the A elasticity of I. For example, in the model $\ln Q = a + b\ln P$, where Q stands for quantity and P stands for price, the price elasticity of quantity, which is b, is calculated by taking derivative with respect to $\ln P$ rather than P.

[12] When the variable is in a squared term, the elasticity is expressed by the variable itself. When the variable is in an cross term, the elasticity of the variable is expressed by the other variable in the cross term. For example, in the model $\ln I = a + b[\ln A]^2$, the variable in the expression of A elasticity is $\ln A$ (A elasticity is $2b\ln A$, exactly). However, in the model $\ln I = a + b[\ln A*\ln B]$, the variable in the expression of A elasticity is $\ln B$ (A elasticity is $b\ln B$, exactly).

Table 5
Comparison of *GDPPC* elasticity, *URB* elasticity [a] and turning point in Model 2, 3, and 4.

Model	Model 2	Model 3	Model 4[b]	
Variable	*GDPPC*	*URB*	*GDPPC*	*URB*
Elasticity	$\beta_2 + 2\beta_7 \ln GDPPC$	$\beta_3 + 2\beta_8 \ln URB$	$\beta_2 + \beta_9 \ln URB$	$\beta_3 + \beta_9 \ln GDPPC$
Estimates of elasticity	1.323–0.128ln*GDPPC*	2.555–0.656ln*URB*	0.925–0.189ln*URB*	1.699–0.189ln*GDPPC*
Range of elasticity	0.505→0.015	0.825→− 0.428	0.427→0.065	0.491→− 0.233
Turning Point	$-\beta_2/2\beta_7$	$-\beta_3/2\beta_8$	$-\beta_2/\beta_9$	$-\beta_3/\beta_9$
Estimates of turning point	ln*GDPPC** = 10.336	ln*URB** = 3.895	ln*URB** = 4.894	ln*GDPPC** = 8.989
95% confidence interval for turning point	(8.532, 12.033)	(3.374, 4.416)	-[c]	
Diagram of elasticity[d]				
Trend in PM2.5 concentrations	Ceteris paribus, PM2.5 concentration increases as *GDPPC* increases at any income level.	Ceteris paribus, at low level of urbanization, PM2.5 concentration increases as urbanization rate increases; after reaching the turning point, PM2.5 concentration decreases as urbanization rate increases.	Ceteris paribus, PM2.5 concentration increases as *GDPPC* increases at any level of urbanization.	Ceteris paribus, at low income level, PM2.5 concentration increases as urbanization rate increases; at high income level, PM2.5 concentration decreases as urbanization rate increases.

[a] In the model ln I = a + b ln A, the A elasticity of impact (not log A elasticity of impact) can be calculated by taking partial derivative with respect to log A. Similarly, the GDPPC elasticity and URB elasticity are calculated here.
[b] In model 4, the variable in the expression of *GDPPC* elasticity is ln*URB* and thus ln*URB* is depicted on the horizontal axis in the diagram of *GDPPC* elasticity. It is similar for *URB* elasticity.
[c] The 95% confidence intervals of *GDPPC* elasticity and *URB* elasticity are shown in Appendix D.
[d] The variable in the expression of elasticity is depicted on the horizontal axis. TP stands for turning point and E stands for elasticity.

below zero and thus, there are no turning points in reality in the period 2001–2010. The result of Model 3 shows that *URB* elasticity of PM2.5 concentrations decreases as urbanization rate goes up and becomes negative at high level of urbanization, indicating the presence of the urbanization turning point. The results of Model 4 show that the *GDPPC* elasticity goes down without a turning point as urbanization rate goes up as the theoretical turning point of urbanization level (4.894) is higher than the maximal urbanization level (4.548) in sample countries, while *URB* elasticity goes down with a turning point as GDP per capita goes up. The results of Model 4 are consistent with the results of Model 2 and Model 3, since Model 2 and Model 3 display only part of the nonlinear effect. Thus, the following discussion is derived from the results of Model 4.

3.3. Results based on model 4

Three key points in Model 4 are summarized as follows.

Among all factors studied, the impact of total population and industrialization on PM2.5 concentration is not so obvious, the impact of *GDPPC*, *URB* and *SER* is significant, while the impact of energy consumption per unit GDP is statistically insignificant on a 5% significance level.

Second, there is a positive correlation between income and PM2.5 concentration, but the effect of income on PM2.5 decreases as the level of income and urbanization goes up, according to the regression results of the squared term of *GDPPC* and the cross term.

Similarly, an inverted U-shaped relationship between urbanization and PM2.5 concentrations exists, according to the results of the squared term of *URB* and the cross term. At low level of income or urbanization, *URB* has positive correlation with PM2.5 concentrations but negative at a high level of income or urbanization.

3.4. Robustness check

To check robustness and dig deeper into the heterogeneity of countries, we estimate all models for low-income countries and middle-income countries respectively. We keep the quadratic and interaction terms in these estimations because countries within one category are also heterogeneous and nonlinear terms can capture non-constant marginal effects of income and urbanization within each category. As the results shown in columns (2) and (3) in Appendix E Tables E1–E4, the non-linear effects do exist in each category. First, the nonlinear effects of *URB* are significant in low-income countries. Second, the nonlinear effects of *GDPPC* are significant in middle-income countries. Third, the interactive effects of *GDPPC* and *URB* are significant in middle-income countries. These results provide detailed non-linear effects within each category, and basically they are consistent with the main results for our pooled data sample.

Another concern of the fixed effect model used in this paper is that the explanatory variables may not be strictly exogenous. To address this issue, difference generalized moment estimators (Difference GMM) (Arellano and Bond, 1991) are adopted to demonstrate the no significant existence of endogeneity. The instrument variables are the second and third lags of each explanatory variables to deal with the endogeneity due to simultaneity. Results are presented in columns (4) to (6) in Appendix E. By comparing the coefficients estimated in fixed effect models (FE) and Difference GMM, we find that they are not significantly different from each other. To further test whether the explanatory variables are exogenous, difference-in-Hansen tests are conducted and the results are showed in Appendix E. Under the null hypothesis, the explanatory variables are exogenous, and the null is not rejected in all cases. Therefore, the variables can be treated exogenous and the discussion part will focus on fixed effect results.

4. Discussion

The following discussion focuses on the impact of income (*GDPPC*), urbanization (*URB*), service sector (*SER*) and energy intensity (*ERG*) on PM2.5 concentration.

4.1. The impact mechanism of income on PM2.5

A positive correlation between income and PM2.5 exists all the time, but it is marginally decreasing with the rising level of income and urbanization.

First, why does the positive correlation exist all the time? If holding population, urbanization, technological level and industrial structure unchanged, higher income usually involves more industry activities, thus implying more energy consumption and transportation activities, all resulting in pollutants emissions, which is the proportional effect of economic growth on the environment (Grossman and Krueger, 1992).

Second, why is the positive correlation marginally decreasing along with the rising level of income? This is due to the technological effect of economic growth (Grossman and Krueger, 1992; Dinda, 2004). The technological effect brought by economic growth enables the replacement for heavily-polluting production technologies with cleaner ones. Since we did not find the turning point of income on PM2.5, the performance of proportional effect outweighs technological effect in the sample countries during the observation period.

Third, why is the positive correlation marginally decreasing along with the rising level of urbanization? This is because urbanization makes economic growth "greener" gradually. At the early stage of urbanization, economic growth is basically realized by "more production", while at the middle to late stage of urbanization, "efficient production" contributes to economic growth mainly. Such transformation can be observed in many of our studies. Generally speaking, urbanization not only brings about innovative management idea and raises production efficiency, but also shortens distance across production chains, thus cutting down transport cost and environmental cost.

As Fig. 1 illustrates, average industrial output and energy use per capita have been constantly increasing, demonstrating that higher income is correlated to greater industrial output and energy consumption, so there is positive correlation between income and PM2.5 emission. However, energy use per output shows a downward trend, probably due to technological effect and promotion of green production associated with the increase of income, and as a result, the positive correlation between income and PM2.5 emission marginally decreases.

4.2. The impact mechanism of urbanization on PM2.5

Inverted U-shaped relationships between PM2.5 and urbanization exist across both urbanization level and income level, that is, urbanization's impact on PM2.5 concentration at different urbanization levels and different income levels presents heterogeneity. The inverted U-shaped relationship between PM2.5 and urbanization means that some factors (like various types of production activities) in urbanization will lead to increase in PM2.5 pollution and other factors (like agglomeration effect, energy structure transformation and environment protection and improvement) can help reduce pollution. Generally, the former factors play the leading role in the early stage of urbanization while the latter ones come up later.

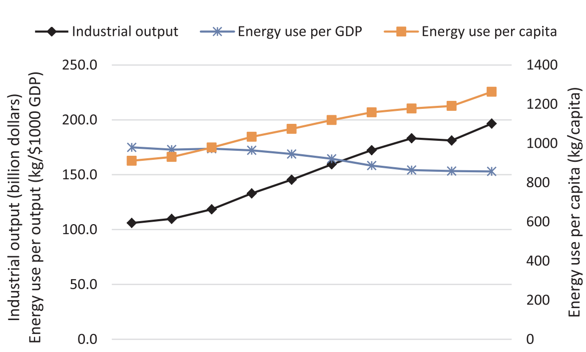


Fig. 1. Industrial output (billion constant 2011 international dollars), Energy use per GDP (kg of oil equivalent per $1000 GDP in constant 2011 PPP), and Energy use per capita (kg of oil equivalent per capita). Average over all countries in our data sample.
Data source: World Bank.

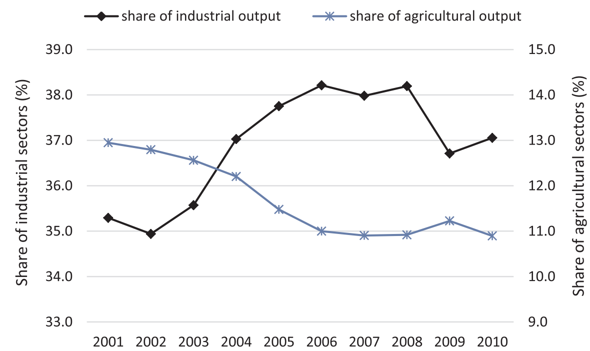


Fig. 2. Share of industrial sectors and agricultural sectors. Average over all countries in our data sample.
Data source: World Bank

Specially, prior to the turning points, in the process of urbanization at low level of urbanization or income, urban construction replaces agricultural production and rural construction. During this period, urbanization is accompanied by the increase of urban production and construction activities. The industries that keep the urban society and economy functioning gradually develop, such as mining, construction, transportation and industry. All of these are major emission sources of PM2.5. In this period, the country transforms from an agricultural society to an industrial one and starts to control environmental pollution. Production activity is the main factor of PM2.5 pollution in this period. As Fig. 2 shows, prior year 2008, the average output share of industrial sectors over all 79 countries is generally increasing with minor fluctuation, and the average output share of agricultural sectors is constantly decreasing.

When urbanization or income level is higher than their turning points, urbanization means not only that new kinds of urban socioeconomic activities will replace agricultural socioeconomic activities, but also the update and optimization of the original ones. In this period, the mitigation effect of urbanization on PM2.5 pollution gradually appears. The mitigation effect might be rooted in three aspects.

First is the progressive decrease of marginal industrial emission cost (emission per unit GDP) as the returns to scale of industrial pollution control increase progressively. In the process of urbanization, industrial activities agglomerate in urban areas results in the agglomeration of energy consumption and pollution emission in cities. However, for the country as a whole, marginal industrial emission cost decreases in the latter stage, benefitting from the economy of agglomeration and scale. Meanwhile, due to the increasing return to scale of industrial pollution control, unit cost of pollution control will decrease with the expansion of production scale, and thus industrialization will promote pollution control (Stern, 2004).

Second is the cleaner energy consumed by households. Urbanization implies the transformation of rural household lifestyle to urban one, during which household energy structure transforms from unclean energy (such as fuel wood and coal) to clean energy (such as gas). A study on urban household energy structure in developing countries (Barnes et al., 2010) showed that the transformation took place by three stages: the first stage focused on fuel wood, the second charcoal, coal and kerosene, and the third modern energy such as LPG (liquefied petroleum gas), gas and electricity. Since burning unclean energy is the key source of PM2.5 (David et al., 2014), the transformation from unclean energy structure to a clean one will reduce PM2.5 pollution. Aunan and Wang (2014) found that during 2001–2010, in most families migrating from rural to urban areas, energy consumption transformed from biomass fuel and coal to clean energy, and their household PM2.5

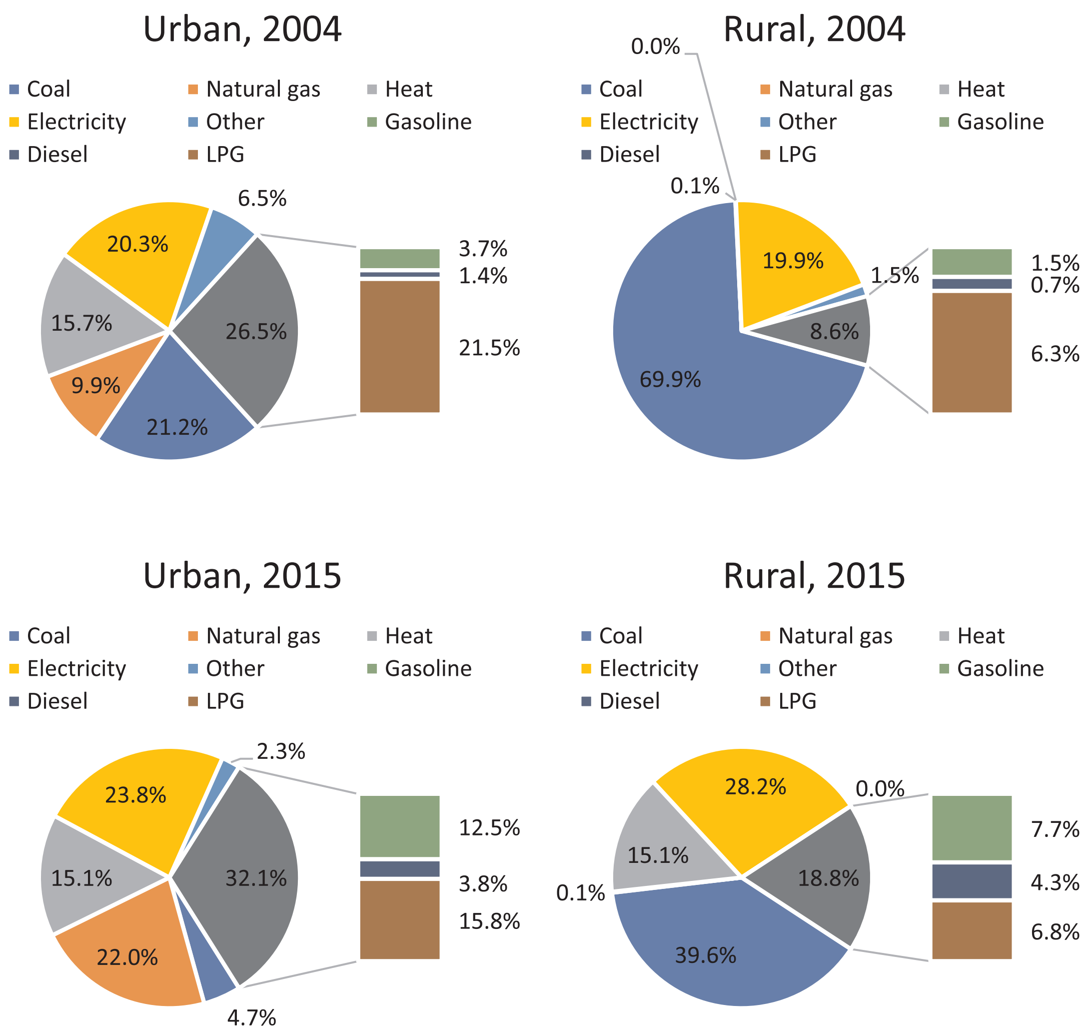


Fig. 3. Urban and rural residential energy consumptions by sources in 2004 and 2015.
Data sources: China Energy Statistical Yearbook

pollution concentrations reduced by nearly 50 μg/m,[3] 60% of which related with the migration from rural areas to urban areas. Herrerias et al. (2016) suggest that urbanization has led to coal being replaced by electricity in urban residential energy consumption. Besides residential consumption, a general transition from high-pollution coal to clean electricity driven by urbanization is found in Ma (2015). Taking China as an example, as Fig. 3 shows, urban residents rely significantly less on coal and more on natural gas than rural residents. Also, urban population consumes more LPG than rural population. Share of clean energy (LPG, gas, electricity) increases from 51.6% to 61.6% in urban area in China from 2004 to 2015.

Third is the effectiveness of environmental protection and control. Cities are the main PM2.5 polluted zones, and people living there are the main victims, as well as the most motivated people to promote the establishment of environmental protection system and the implementation of environmental control policies. In the early stage of urbanization, urban population is smaller than rural population, and it is difficult for them to improve environment through political appeal. When urbanization reaches a certain level, urban population becomes the majority, and large citizen class' focus on environmental pollution will urge government to establish environmental protection systems and issue relative policies. Meanwhile, it is more effective for citizens to supervise the environment control process through media (Neverla, 2007). Furthermore, environmental problems' effect on the benefits of urban elite class will also prompt them to support pollution prevention and control (Gonzalez, 2002). Fig. 4 plots the trend of the average Policy and Institutions for Environmental Sustainability Ratings over countries in our sample, which indicates the extent to which environmental protection policies promote the sustainable use of resources and the management of pollution. The rating shows an upward trend with some fluctuations along with the increase of urbanization rate.

Some scholars think that urbanization is not good for environmental protection because economic activities become highly centralized in urban areas during this progress (Deshpande and Mishra, 2007; Sarzynski, 2012; Tuo et al., 2013). However, this paper's empirical study shows that, on the one hand, this conclusion is too one-sided and the environment protection effect of urbanization differs across development stages. In the stage of higher urbanization and income, urbanization is good for environment protection. On the other hand, such conclusion confounds the two concepts—environment protection of urban and environment protection of urbanization. If population, income and technology are held the same, urbanization also brings about the opportunity to make use of resource and environment service efficiently and intensively. Urbanization is not leading to an increase in energy consumption and pollutant emission for the whole country, instead, it only triggers an intensive gathering in urban zones (Ji, 2011). Glaeser (2011) indicated the similar opinion that it is of un-ignored significance for urbanization to protect natural environment in his book, *Triumph of the City*.

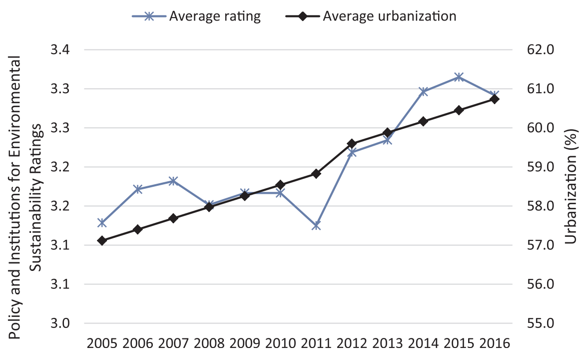


Fig. 4. Policy and Institutions for Environmental Sustainability Ratings and urbanization. Rating: 1 = lowest, 6 = highest. Time interval does not exactly match our data sample because ratings data on World Bank are only available as of year 2005.
Data source: World Bank.

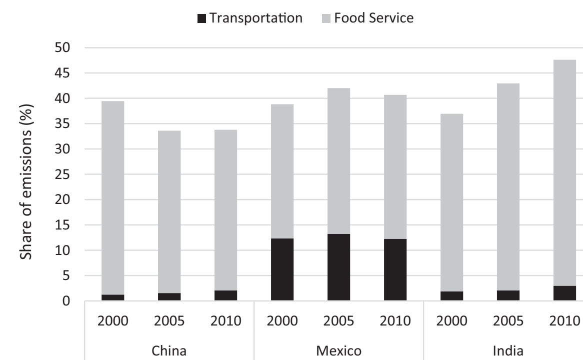


Fig. 5. Share of emissions contributed by transportation sector and food service sector in China, Mexico and India, in 2000, 2005 and 2010.
Data sources: IIASA.

4.3. The impact mechanism of services sector on PM2.5

Services sector can cause an increase of PM2.5 concentrations. This is different from the generally accepted point of view that "service sector is friendlier to environment than industry" because of the specificity of PM2.5 pollution sources. First, different from pollutants of industrial activities such as sulfur dioxide, the main sources of PM2.5 in service sectors[13] are the burning of fossil energy in transportation (Wang et al., 2006; Kinney et al., 2011; Cui et al., 2015) and lampblack in food service sector (Chow and Watson, 2002; Li, Shu, et al., 2015). Therefore, the pollutant sources of service sector cannot be ignored in the survey of PM2.5 pollution problem. Fig. 5 illustrates the share of total emissions contributed by transportation sector and food service sector in three representative countries in our data sample in 2000, 2005 and 2010. The total of the two sectors accounts for around 40% of total PM2.5 emissions in each country, and food service sector emits more.

Second, different from industrialization production, energy consumption and pollutant emission is scattered instead of concentrated, such as exhaust gas and road dust in transporting and heating, and raising dust in building repair and maintenance (office buildings, stores and warehouses) [14] (Kaika and Zervas, 2013b). Due to the disperse of energy consumption and pollution control, it is difficult to produce economies of scale in service industries to reduce marginal cost. Similar to this research, Alcántara and Padilla (2009) and Piaggio et al. (2015) in Spain and Uruguay found that the service sector had a positive effect on carbon emission, which to some extent is constant with the research results of this paper.

4.4. The impact mechanism of energy intensity on PM2.5

We do not find significant impact of energy intensity on PM2.5 pollution, which might not meet the intuition. The specificity of PM2.5 sources can be one reason. Besides industrial production, as the preceding analysis, PM2.5 sources include automobiles, cooking activities and construction, which are irrelevant with energy intensity. Secondly, energy intensity only describes the economic efficiency level of energy utilization, but not the energy quality, which has important impact on PM2.5 pollution. On the one hand, quality of different energy sources differs significantly. Empirical results showed that the burning of biomass and coal were the main human activities generating PM2.5, while natural gas contributed less to PM2.5 pollution (Tessum et al., 2014; Zhang and Cao, 2015; Li et al., 2016; Liu et al., 2016). On the other hand, the quality of a certain type of energy also varies when the emission standard changes. The consumption of energy with lower emission standard cause more PM2.5 pollution. For example, empirical results showed that the concentrations of pollutants in automobile waste air decreased significantly as emission standard becomes stricter (Shen et al., 2014; Cao et al., 2016). Thus, the result that energy intensity does not have significant impact on PM2.5 pollution sounds reasonable.

5. Conclusion

This paper analyzes socioeconomic driving factors of PM2.5 pollution in 79 developing countries from 2001 to 2010 using environmental driving model STIRPAT. The PM2.5 pollution level in the paper comes from satellite remote sensing data, which makes up for the lack of surface observation, and addresses the problem that point data cannot describe the overall situation of large-scale space.

The study finds that income, urbanization and service sector are the key driving factors of PM2.5 pollution level. The details are as follows:

(1) Income Level: The positive effect of income on PM2.5 concentration is ever-present. Theoretically, the inverted U-shaped curve relation might exist between income and PM2.5 concentration, but all the developing countries in this study are on the left side of the turning point. This implies that the technical effect of economic growth on environment cannot make up for the proportion effect in these countries during the observation period of the study.
(2) Urbanization: Two inverted U-shaped curve relationship exists between urbanization and PM2.5 concentration. The result shows that the increasing urbanization will reduce PM2.5 pollutant emission after urbanization level or income level reaches their turning points. The study finds that urbanization's positive effect on environment can be attributed to scale economy of industrial pollution control, optimization of household energy structure and effectiveness of environment protection and control.
(3) Service sector: Service sector is causing PM2.5 pollutant emission. First, transportation and catering are parts of service sectors which are both notable factors of PM2.5 pollution. Second, service sector is scattered in terms of energy consumption and pollutant emission, so it is difficult to obtain economies of scale in energy consumption reduction and pollution control for service sector.

However, the conclusion of this paper does not imply that the pollution of PM2.5 will reduce spontaneously with the advancement of economic level and urbanization. The PM2.5 pollution problems in developing countries should be addressed rationally and positively.

[13] The World Bank divides industries using International Standard Industrial Classification of All Economic Activities (ISIC), according to http://data.worldbank.org/indicator/NV.SRV.TETC.ZS.

[14] According to International Standard Industrial Classification of All Economic Activities, the value added of these activities is partially counted into industrial sectors, but the increase of value added of service sector means increase of the proportion of these dispersed pollution activities.

First, the basic law of economic development and urbanization process should be respected. A mechanism directly regulating urbanization and industrialization is infeasible and unreasonable, so the role of market and government in allocating resources and environmental governance needs to be balanced. To achieve this, we must first emphasize market efficiency in the allocation of resources and environmental governance. Scale of economies and technological effects derived along with the processes of wealth accumulation and urbanization can lead to conservation and positive environmental outcomes.

Second, what government should do is to make economic growth and urbanization “greener” through promotion of cleaner technologies. In pursuit of economic growth, many developing countries focus on urbanization and industrial growth without paying attention to the severe environmental outcomes before the turning point of income and urbanization. Promotion of green technology results in better environmental outcome, without harming economic growth in the long run, and overall, achieve higher social welfare. However, absent rational and positive government intervention, promotion of cleaner technologies lacks or lags in the early stage of development because it needs necessary short-term investments. Due to the present of such market failure, government plays a crucial role before the natural evolution of green trend. They are supposed to take actions, such as enhancing economic efficiency and promoting cleaner technologies, to reduce damages before the green trend takes field and eventually bring forward the green trend.

Third, how to enhance economic efficiency and promote cleaner technologies in the transition period in developing countries should be discussed concerning both the political and economic feasibility. On one hand, incentive-based instruments, such as pollution tax or emission trading scheme, can motivate firms to actively eliminate out-of-date production capacity and adopt high-quality clean technologies. In addition to thoroughly assess the economic outcome and distributional effects of policy instrument, government needs to guarantee the development of market-based transactions, provide effective regulatory platform to build third-party emissions verification mechanisms and certification system, and establish relevant laws and regulations. On the other hand, provision of good-quality public service, such as optimizing the city's function zoning and improving public transportation, provides a more convenient and cleaner option for private consumption. Public-Private Partnership (PPP) model can be used to guide private capital into public goods supply, integrate government's matching fund provision with advantages of private capital in operation and innovation, so as to enhance economic and environmental efficiency of public service provision.

Acknowledgements

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Appendix A

List of 79 countries in the sample

Angola, Albania, Armenia, Azerbaijan, Benin, Bangladesh, Bulgaria, Bosnia and Herzegovina, Belarus, Bolivia, Brazil, Botswana, Chile, China, Cote d'Ivoire, Congo Rep, Colombia, Costa Rica, Cuba, Czech Republic, Dominican Republic, Algeria, Ecuador, Egypt Arab Rep, Estonia, Ethiopia, Gabon, Georgia, Ghana, Guatemala, Honduras, Croatia, Hungary, Indonesia, India, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Cambodia, Sri Lanka, Lithuania, Latvia, Morocco, Moldova, Mexico, Macedonia, Mongolia, Mozambique, Malaysia, Namibia, Nigeria, Nicaragua, Nepal, Pakistan, Panama, Peru, Philippines, Poland, Paraguay, Russian Federation, Sudan, Senegal, El Salvador, Slovak Republic, Togo, Thailand, Tajikistan, Turkmenistan, Tunisia, Turkey, Tanzania, Ukraine, Uruguay, Uzbekistan, Venezuela, Vietnam, South Africa, Zambia

Low-income countries:

	Low-income countries				
1	Benin	9	Kyrgyz Republic	17	Pakistan
2	Bangladesh	10	Cambodia	18	Sudan
3	Cote d’Ivoire	11	Moldova	19	Senegal
4	Congo, Rep.	12	Mongolia	20	Togo
5	Ethiopia	13	Mozambique	21	Tajikistan
6	Ghana	14	Nigeria	22	Tanzania
7	India	15	Nicaragua	23	Uzbekistan
8	Kenya	16	Nepal	24	Vietnam
				25	Zambia

Middle-income countries:

	Middle Income Country				
1	Angola	19	Ecuador	37	Malaysia
2	Albania	20	Egypt, Arab Rep.	38	Namibia
3	Armenia	21	Estonia	39	Panama
4	Azerbaijan	22	Gabon	40	Peru
5	Bulgaria	23	Georgia	41	Philippines
6	Bosnia and Herzegovina	24	Guatemala	42	Poland
7	Belarus	25	Honduras	43	Paraguay
8	Bolivia	26	Croatia	44	Russian Federation
9	Brazil	27	Hungary	45	El Salvador

10	Botswana	28	Indonesia	46	Slovak Republic
11	Chile	29	Jordan	47	Thailand
12	China	30	Kazakhstan	48	Turkmenistan
13	Colombia	31	Sri Lanka	49	Tunisia
14	Costa Rica	32	Lithuania	50	Turkey
15	Cuba	33	Latvia	51	Ukraine
16	Czech Republic	34	Morocco	52	Uruguay
17	Dominican Republic	35	Mexico	53	Venezuela, RB
18	Algeria	36	Macedonia, FYR	54	South Africa

Appendix B

VIF test for collinearity

Variable	Model 1
ln*POP*	1.13
ln*GDPPC*	4.18
ln*URB*	2.67
ln*IND*	3.80
ln*SER*	3.33
ln*ERG*	1.27
Mean VIF	2.73

Appendix C

Summary Correlations

	ln*POP*	ln*GDPPC*	ln*URB*	ln*IND*	ln*SER*	ln*ERG*
ln*POP*	1					
ln*GDPPC*	− 0.176	1				
ln*URB*	− 0.268	0.771	1			
ln*IND*	0.068	0.464	0.382	1		
ln*SER*	− 0.167	0.354	0.308	− 0.500	1	
ln*ERG*	0.100	− 0.456	− 0.372	− 0.227	− 0.194	1

Appendix D

See Figs. D1 and D2.

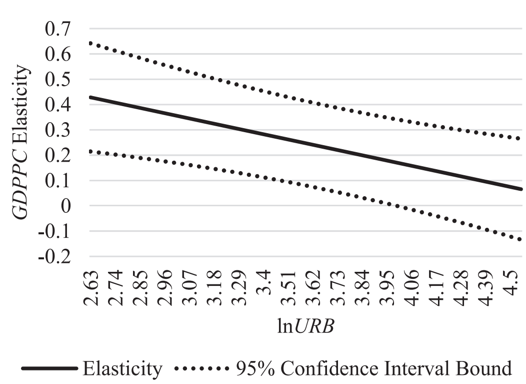

Fig. D1. 95% Confidence Interval of *GDPPC* Elasticity.

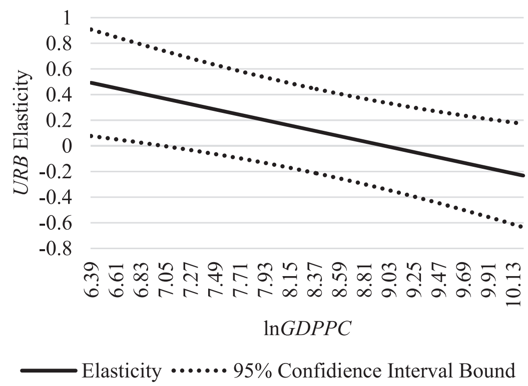

Fig. D2. 95% Confidence Interval of *URB* Elasticity.

Appendix E

See Tables E1–E4.

Table E1
Regression results of Model 1 (no nonlinear variable).

	(1) Fixed Effect Whole Sample	(2) Fixed Effect Low Income	(3) Fixed Effect Middle Income	(4) Difference GMM Whole Sample	(5) Difference GMM Low Income	(6) Difference GMM Middle Income
ln*POP*	0.325 (1.93) *	0.294 (0.72)	0.191 (0.89)	0.119 (0.45)	0.137 (0.33)	− 0.015 (−0.05)
ln*GDPPC*	0.191 (2.23) **	0.288 (1.26)	0.216 (2.28) **	− 0.031 (−0.15)	0.393 (1.44)	0.010 (0.04)
ln*URB*	0.195 (1.10)	− 0.002 (0.00)	0.154 (0.77)	0.754 (1.41)	0.097 (0.22)	0.430 (1.10)
ln*IND*	0.076 (1.18)	0.080 (1.02)	0.040 (0.34)	0.064 (0.30)	− 0.038 (−0.4)	− 0.129 (−0.41)
ln*SER*	0.173 (2.14) **	0.163 (1.58)	0.112 (0.70)	0.102 (0.60)	0.048 (0.32)	− 0.075 (−0.31)
ln*ERG*	0.076 (1.27)	0.187 (1.33)	0.079 (1.24)	− 0.111 (−0.76)	0.070 (0.39)	− 0.144 (−0.71)
[ln*GDPPC*]^2						
[ln*URB*]^2						
[ln*GDPPC**ln*URB*]						
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes			
Diff-Hansen Test[d]	1.000	1.000	1.000			
Observations	790	250	540	711	225	486
Groups	79	25	54	79	25	54

[a] t statistics in parentheses. [b] Standard errors are clustered at country level. [c] Statistical significance is indicated by: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ [d] Difference in Hansen tests of exogeneity of instrument subsets. The p values are listed. Here, we compare the case using no instruments with the case using the lags of explanatory variables as instruments. Under the null, the explanatory variables in Fixed Effect models are exogenous. If the tests do not reject the hypothesis, then the explanatory variables can be treat as exogenous. In column (4) and (6), the second and third lags are used, and only the second lags are used in column (5) due to limitation of observations.

Table E2
Regression results of Model 2 (including quadratic term of *GDPPC*).

	(1) Fixed Effect Whole Sample	(2) Fixed Effect Low Income	(3) Fixed Effect Middle Income	(4) Difference GMM Whole Sample	(5) Difference GMM Low Income	(6) Difference GMM Middle Income
ln*POP*	0.112 (0.58)	0.205 (0.54)	0.025 (0.11)	− 0.425 (−1.61)	0.006 (0.01)	− 0.331 (−1.02)
ln*GDPPC*	1.323 (3.28) ***	0.288 (0.93)	2.099 (3.45) ***	2.610 (3.71) ***	1.694 (1.27)	2.046 (2.03) **
ln*URB*	0.098 (0.57)	− 0.010 (−0.03)	0.005 (0.02)	0.251 (0.94)	− 0.017 (−0.04)	0.422 (1.19)
ln*IND*	0.085 (1.39)	0.112 (1.37)	0.000 (0.00)	0.246 (1.45)	0.075 (0.61)	0.137 (0.44)
ln*SER*	0.141 (1.94) *	0.193 (1.71) *	0.024 (0.17)	0.101 (0.82)	0.185 (1.26)	0.022 (0.08)
ln*ERG*	0.094 (1.57)	0.207 (1.42)	0.068 (1.08)	0.051 (0.36)	0.169 (0.90)	− 0.187 (−1.01)
[ln*GDPPC*]^2	− 0.064 (−2.80) ***	− 0.047 (−0.7)	− 0.106 (−3.09) ***	− 0.142 (−3.69) ***	− 0.082 (−1.03)	− 0.119 (−2.06) **
[ln*URB*]^2						
[ln*GDPPC**ln*URB*]						
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes			
Diff-Hansen Test[d]	1.000	1.000	1.000			
Observations	790	250	540	711	225	486
Groups	79	25	54	79	25	54

[a] t statistics in parentheses. [b] Standard errors are clustered at country level. [c] Statistical significance is indicated by: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ [d] Difference in Hansen tests of exogeneity of instrument subsets. The p values are listed. Here, we compare the case using no instruments with the case using the lags of explanatory variables as instruments. Under the null, the explanatory variables in Fixed Effect models are exogenous. If the tests do not reject the hypothesis, then the explanatory variables can be treat as exogenous. In column (4) and (6), the second and third lags are used, and only the second lags are used in column (5) due to limitation of observations.

Table E3
Regression results of Model 3 (including quadratic term of *URB*).

	(1) Fixed Effect Whole Sample	(2) Fixed Effect Low Income	(3) Fixed Effect Middle Income	(4) Difference GMM Whole Sample	(5) Difference GMM Low Income	(6) Difference GMM Middle Income
ln*POP*	0.287 (1.73) *	0.388 (1.03)	0.192 (0.90)	0.091 (0.43)	0.426 (1.03)	0.008 (0.02)
ln*GDPPC*	0.185 (2.23) **	0.321 (1.45)	0.215 (2.17) **	0.049 (0.30)	0.473 (1.54)	−0.002 (−0.01)
ln*URB*	2.555 (2.35) **	3.269 (2.64) **	0.288 (0.12)	4.664 (2.93) ***	5.628 (3.12) ***	3.958 (0.78)
ln*IND*	0.080 (1.27)	0.117 (1.65)	0.040 (0.34)	0.071 (0.42)	0.161 (2.16) **	−0.160 (−0.54)
ln*SER*	0.169 (2.20) **	0.199 (2.13)	0.112 (0.70)	0.070 (0.50)	0.298 (2.54) **	−0.128 (−0.61)
ln*ERG*	0.085 (1.43)	0.243 (1.66)	0.079 (1.22)	−0.064 (−0.46)	0.327 (1.58)	−0.146 (−0.80)
$[\ln GDPPC]^2$						
$[\ln URB]^2$	−0.328 (−2.26) **	−0.505 (−2.93) ***	−0.018 (−0.05)	−0.586 (−2.59) **	−0.886 (−3.11) ***	−0.473 (0.70)
[ln*GDPPC**ln*URB*]						
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes			
Diff-Hansen Test[d]	1.000	1.000	1.000			
Observations	790	250	540	711	225	486
Groups	79	25	54	79	25	54

[a] t statistics in parentheses. [b] Standard errors are clustered at country level. [c] Statistical significance is indicated by: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ [d] Difference in Hansen tests of exogeneity of instrument subsets. The p values are listed. Here, we compare the case using no instruments with the case using the lags of explanatory variables as instruments. Under the null, the explanatory variables in Fixed Effect models are exogenous. If the tests do not reject the hypothesis, then the explanatory variables can be treat as exogenous. In column (4) and (6), the second and third lags are used, and only the second lags are used in column (5) due to limitation of observations.

Table E4
Regression results of Model 4 (including interaction term of *GDPPC* and *URB*).

	(1) Fixed Effect Whole Sample	(2) Fixed Effect Low Income	(3) Fixed Effect Middle Income	(4) Difference GMM Whole Sample	(5) Difference GMM Low Income	(6) Difference GMM Middle Income
ln*POP*	0.139 (0.72)	0.156 (0.47)	0.134 (0.56)	−0.239 (−0.97)	0.003 (0.01)	−0.105 (−0.33)
ln*GDPPC*	0.925 (3.64) ***	1.377 (2.92) ***	0.737 (1.50)	1.283 (2.84) ***	1.754 (2.39) **	0.595 (0.89)
ln*URB*	1.699 (2.98) ***	2.272 (2.50) **	1.290 (1.14)	3.054 (3.93) ***	2.593 (2.21) **	1.942 (1.35)
ln*IND*	0.089 (1.44)	0.151 (2.00) *	0.040 (0.34)	0.178 (1.06)	0.115 (1.08)	−0.043 (−0.14)
ln*SER*	0.161 (2.15) **	0.235 (2.37) **	0.112 (0.70)	0.112 (0.93)	0.304 (2.4) **	0.074 (0.34)
ln*ERG*	0.099 (1.69) *	0.240 (1.71) *	0.079 (1.24)	−0.009 (−0.06)	0.277 (1.36)	−0.153 (−0.77)
$[\ln GDPPC]^2$						
$[\ln URB]^2$						
[ln*GDPPC**ln*URB*]	−0.189 (−2.91) ***	−0.311 (−3.17) ***	−0.134 (−1.04)	−0.325 (−3.27) ***	−0.380 (−2.30) **	−0.172 (−1.05)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes			
Diff-Hansen Test[d]	1.000	1.000	1.000			
Observations	790	250	540	711	225	486
Groups	79	25	54	79	25	54

[a] t statistics in parentheses. [b] Standard errors are clustered at country level. [c] Statistical significance is indicated by: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ [d] Difference in Hansen tests of exogeneity of instrument subsets. The p values are listed. Here, we compare the case using no instruments with the case using the lags of explanatory variables as instruments. Under the null, the explanatory variables in Fixed Effect models are exogenous. If the tests do not reject the hypothesis, then the explanatory variables can be treat as exogenous. In column (4) and (6), the second and third lags are used, and only the second lags are used in column (5) due to limitation of observations.

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