 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at *Sustainability* **2016**, *8*, 812; doi:10.3390/su8080812

Article

Urbanization and Its Effects on Industrial Pollutant emissions: An Empirical Study of a Chinese Case with the Spatial Panel Model

Jin Guo [1,*], Yingzhi Xu [2] and Zhengning Pu [2]

[1] School of Economics and Management, Southeast University, 2 Si Pai Lou, Nanjing 210000, China; guojineconomics@outlook.com
[2] School of Economics and Management, Southeast University, 2 Si Pai Lou, Nanjing 210000, China; xuyingzhi@hotmail.com
[3] School of Economics and Management, Southeast University, 2 Si Pai Lou, Nanjing 210000, China; puzhengning@seu.edu.cn
* Correspondence: guojineconomics@outlook.com; Tel.: +86-187-9589-6287

Abstract: Urbanization is considered as a main indicator of regional economic development due to its positive effect on promoting industrial development; however, many regions, especially developing countries, are troubled by its negative effect — the aggravating environmental pollution. Many researchers have indicated that rapid urbanization stimulated the expansion of industrial production scale and increased industrial pollutant emissions. However, this judgement contains a grave deficiency in that urbanization not only expands industrial production scales but can also increase industrial labour productivity and change the industrial structure. To modify this deficiency, we first decompose the influence which urbanization impacts on industrial pollutant emissions into the scale effect, the intensive effect and the structure effect by using the Kaya Identity and the LMDI Method; second, we perform an empirical study of the three effects' impacts by applying the spatial panel model with data from 282 Chinese cities between 2003 and 2013. Our results indicate that (1) there are significant reverse U-shapes between Chinese urbanization rate and its industrial pollutant emissions; (2) the scale effect and the structure effect have aggravated Chinese industrial waste water discharge, sulphur dioxide emissions and soot (dust) emissions, while the intensive effect has generated a decreasing and ameliorative impact on that aggravated trend. The definite relationship between urbanization and industrial pollutant emissions depends on the combined influence of the scale effect, the intensive effect and the structure effect; (3) there are significant spatial autocorrelations of industrial pollutant emissions between Chinese cities, but the spatial spillover effect from other cities does not aggravate local urban industrial pollutant emissions, we offer an explanation to this contradiction that the vast rural areas surrounding Chinese cities have served as sponge belts and have absorbed the spatial spillover of cities' industrial pollutant emissions. According to the results, we argue that this type of decomposition of the influence into three effects is necessary and meaningful, it establishes a solid foundation for understanding the relationship between urbanization and industrial pollutant emissions, and effectively helps to meet relative policy making.

Keywords: industrial pollutant emissions; urbanization; the spatial panel model; Chinese case

JEL Classification: C33; R11; Q53

---

1. Introduction

The theme of Shanghai World Expo in 2010 — Better City, Better Life — symbolized China's great wish for its urbanization. In fact, current Chinese urbanization has experienced much disappointment, and the aggravating environmental pollution is one of the most serious problems.

The World Bank (1997, 2007) indicated in its reports that since 1978, China's economy had produced economic growth that rated it one of the fastest growing economies in the world; even though tremendous efforts have been made in abating environmental pollution, in the same time period, China has suffered from an increase in environmental pollution and stern criticism.

China's deteriorated environment has lowered its people's quality of life, and it would seem that cities does not bring a better life. Just as Easterlin et al. (2012) documented, self-reported life satisfaction indicators had not increased in China as much as would be expected during a period of 8 percent annual economic growth.

What makes China suffer from so many serious environmental pollution incidents? Haakon Vennemo et al. (2009) noted that China appeared to be following a path similar to the one trodden by more industrialized countries, and the increase in industrial pollutant emissions have deteriorated its environmental state. Furthermore, many researchers stated that China's rapid urbanization stimulated the expansion of its industrial production scale, which then generated enormous volumes of air and water pollutants and consequently causing its air and water quality to deteriorate. Thus, urbanization aggravates environmental pollution.

However, we believe that this judgement contains a grave deficiency. It is true that Chinese urbanization expands its industrial production scale, but the process of urbanization also promotes the industrial labour productivity and upgrades the industrial structures. we can draw a point that even though the expansion of Chinese industrial production scale will aggravate its industrial pollutant emissions, the promotion of its industrial labour productivity and the upgrading of its industrial structures will abate the increasing trend of industrial pollutant emissions. As a result, the definite relationship between urbanization and industrial pollutant emissions is ambiguous, it should be treated cautiously.

In this paper, we will highlight our research in the following aspects: First, we expand the mechanism analysis between urbanization and industrial pollutant emissions and then apply the Kaya Identity and the LMDI Method to decompose out three effects (i.e., the scale effect, the intensive effect and the structure effect) which urbanization impacts on industrial pollutant emissions; Second, we give a description of the relationship between Chinese urbanization rate and its industrial pollutants emissions, and re-examine the reverse U-shapes between them, then we perform an empirical study on the three effects by using data from 282 Chinese cities between 2003 and 2013; Third, as different regions' economic developments are strongly related and the assumption of no spatial autocorrelations has been questioned by many scholars, we amend the traditional panel model by introducing the spatial panel model to take the spatial spillover effect into account.

The rest of our paper is arranged as follows: Section 2 briefly reviews the previous studies; Section 3 analyses the mechanisms between urbanization and industrial pollutant emissions; Section 4 establishes the spatial panel model and introduces the parameters; Section 5 presents the empirical analysis; and Section 6 presents the study's conclusions and offers a discussion.

2. Literature Review

Understanding the trade-off between the positive and negative externalities of urban growth has long been the core issue in urban and environmental economics (Tolley, 1974; Glaeser, 1998). Urbanization is considered as a main indicator of regional economic development due to its positive effect on promoting industrial development, but many regions, especially developing countries, are troubled by its negative effect — the aggravation of environmental pollution (Wan, Guanghu & Wang, Chen, 2014). The relationship between economic development and environmental pollution has been analysed by early representative works such as Grossman and Krueger (1993, 1995) and Panayotou (1993), which together proposed the Environmental Kuznets Curve (i.e., the EKC theory). Based on these influential studies, an entire subfield of environment economics has emerged that focuses on the association between economic and environmental indicators.

One subfield of environment economics studies focuses on the re-examination of the validity of the EKC theory. For example, Lindmark (2002), Nasir & Rehman (2011), Eeteve & Tamarit (2012),

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

Jalil & Mahmud (2009) and Tingting, Li et al. (2016) had applied Swedish, Pakistani, Spanish and Chinese data to perform empirical tests on the reverse U-shapes between national per capita income and environmental pollution status, and their results have strongly supported the EKC theory in various scenarios. However, many other empirical studies, especially those based on time series models, argued that the declining portions of the Environmental Kuznets Curve were illusory, either because they are cross-sectional snapshots that mask a long-run "race to the bottom" in environmental standards or because industrial societies continually produce new pollutants because the old ones are controlled (Stern, 2001, Richard York et al. 2003; Kwon, 2005).

Another subfield is the study of the causes of the reverse U-shapes in the Environmental Kuznets Curve. Dasgupta et al. (2002) suggested that the driving forces that made the Environmental Kuznets Curve flatten and shift to the right appeared to be economic liberalization, clean technology diffusion, and new approaches to pollution regulation. Panayotou (2003) offered another visualized explanation based on the decomposition of the influence of economic development on environmental pollution into three effects: the scale effect, the technology effect and the composition effect. He noted that the reverse U-shape of EKC was the comprehensive impact of the three effects.

In term of the relationship between urbanization and industrial pollutant emissions, Kanada and Momoe et al. (2013), Huapeng and Qin et al. (2014), and Huijuan and Dong et al. (2015) studied the way in which urban population growth impacted local pollution levels and indicated that as the urban population became richer, its demand for private transportation and electricity sharply increased; thus, the activities and demands of individuals exacerbated urban pollution externalities. However, Tao and Yu et al. (2016) obtained an opposite result in which the overall quantity of pollutant discharge decreased as cities became more economically developed during the period 2000-2010, and they attributed this positive effect to higher urban production efficiencies. Zhou and Mi et al. (2016) used the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence and Technology) to evaluate whether urbanization would lead to greater environmental pollution. Their study indicated that the estimated contemporaneous coefficients on the urbanization variables were presented as significant reverse U-shapes. In China's case, Siqi Zheng & Matthew E. Kahn (2013) had documented that one-quarter of the rural people who relocated to cities worldwide were in China over the last thirty years, and China was preparing to supply a massive amount of industrial products to meet the demands of growing cities with higher-income urban people. In recent years, China's urbanization has been roundly criticized for its stimulation of the expansion of industrial scale and the aggravation of industrial pollutant emissions (Haakon Vennemo et al., 2009).

In summary, until now, most studies have focused on the empirical testing of the shapes between economic and environmental indicators, and many of their results have strongly supported the EKC theory in various scenarios. Other studies have discussed the underlying driving forces that made the Environmental Kuznets Curve present as a reverse U-shape and have hinted that this reverse U-shape was the comprehensive impacts of different types of effects, but they failed to model the decomposition of these effects or calculate the impact of each effect with empirical data.

Therefore, this paper attempts to address the above shortcomings by decomposing the influence of urbanization on industrial pollutant emissions into the scale effect, the intensive effect and the structure effect by using the Kaya Identity and the LMDI Method and performing an empirical study of the impact of the three effects by applying the spatial panel model with data from 282 Chinese cities between 2003 and 2013.

3. Mechanisms Analysis and Hypotheses

The mechanisms between urbanization and industrial pollutant emissions can be briefly and vividly described as the following process (see Figure 1): Urbanization leads to population redistribution and labour force redistribution between rural areas and cities. Many young, able-bodied rural people migrate to cities to work in industrial production, which aggravates the total industrial pollutant emissions by expanding industrial production scales. On the other side, every unit of industrial production's pollutant emissions will be decreased due to cities' higher

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

industrial labour productivity which benefits from advanced technology, scientific management and the agglomeration economy. Additionally, the industrial structures will also be upgraded due to cities' economic development and division, that will affect industrial pollutant emissions because different industrial sectors have different pollutant emissions intensities. For example, compared with a heavy industry-oriented economy, a service-oriented economy is always regarded as a kind of environment-friendly development mode.

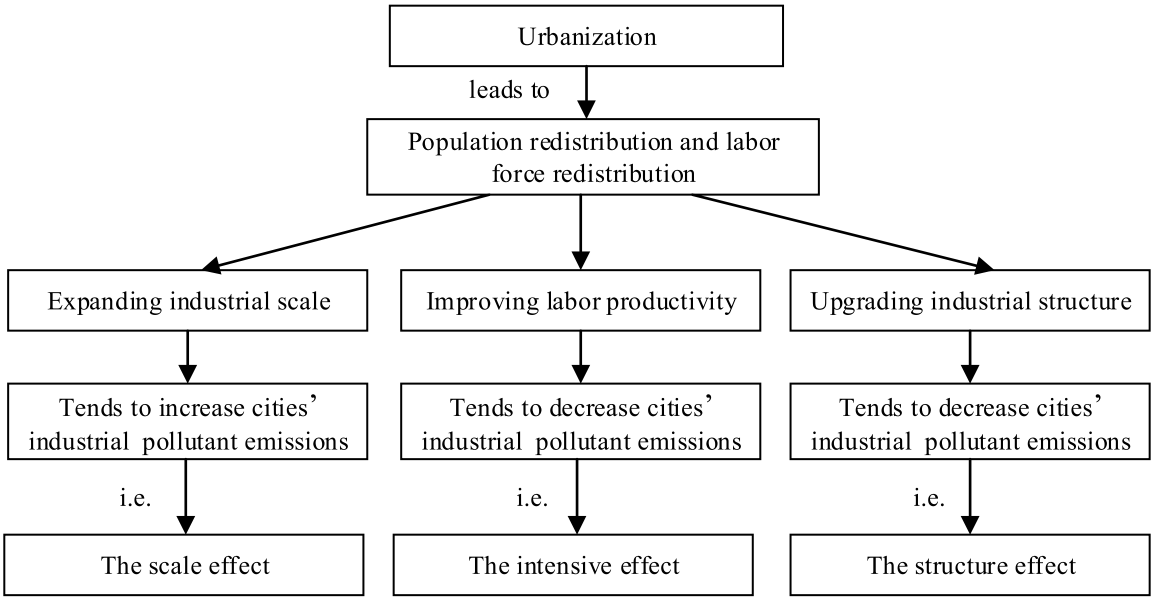


Figure 1. The mechanisms between urbanization and industrial pollutant emissions

In summary, the influence of urbanization on industrial pollutant emissions can be decomposed into three types of effects according to their diverse mechanisms: the scale effect indicates the expansion of industrial production scale and denotes a greater consumption of fossil energy and water, the intensive effect indicates the improvement of industrial technologies and denotes higher production efficiencies, the structure effect indicates the upgrading of industrial structures shifting from high-intensity pollutants emission sectors to low-intensity pollutants emission sectors. Here, we propose three hypotheses and we will test their validities in empirical analysis sections.

Hypothesis 1: The scale effect of urbanization tends to increase industrial pollutant emissions.

Hypothesis 2: The intensive effect of urbanization tends to decrease industrial pollutant emissions.

Hypothesis 3: The structure effect of urbanization tends to decrease industrial pollutant emissions.

We use the Kaya Identity and the LMDI Method to establish a model to present the mechanisms between urbanization and industrial pollutant emissions in Equation (1):

$$\begin{aligned} pollutant &= \frac{pollutant}{output} \times \frac{output}{labor} \times \frac{labor}{population} \times population \\ &= e \times p \times q \times population \end{aligned} \tag{1}$$

Where $pollutant$ denotes total industrial pollutant emissions, $output$ denotes total industrial production scales, $labor$ denotes total industrial labour force, and $population$

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

denotes total population. Thus, $e = \dfrac{pollutant}{output}$ denotes industrial pollutant emission intensity, $p = \dfrac{output}{employee}$ denotes industrial labour productivity, and $q = \dfrac{labor}{population}$ denotes the employment rate.

Taking urbanization process into account, Equation (1) can be specified as:

$$\begin{aligned} pollutant &= \frac{pollutant_u + pollutant_r}{output} \cdot \frac{output_u + output_r}{labor} \cdot \frac{labor_u + labor_u}{population} \cdot population \\ &= [\alpha_u e_u + (1 - \alpha_u) e_r][\beta_u p_u + (1 - \beta_u) p_r][\varphi_u q_u + (1 - \varphi_u) q_r] population \end{aligned} \tag{2}$$

Where subscripts u and r denote cities and rural areas, respectively; $\alpha_u = \dfrac{output_u}{output}$ denotes the proportion of urban industrial output in total industrial production; $\beta_u = \dfrac{labor_u}{labor}$ denotes the proportion of urban industrial employees in total industrial labour force; and $\varphi_u = \dfrac{population_u}{population}$ denotes urbanization rate.

Then taking industrial structure into account, Equation (2) can be specified as:

$$\begin{aligned} pollutant &= \frac{pollutant_u + pollutant_r}{output} \cdot \frac{output_u + output_r}{labor} \cdot \frac{labor_u + labor_u}{population} \cdot population \\ &\cdot \frac{\sum_{j=1...n} labor_{u,j} + \sum_{j=1...n} labor_{r,j}}{\sum_{j=1...n} labor_j} \\ &= [\alpha_u e_u + (1 - \alpha_u) e_r][\beta_u p_u + (1 - \beta_u) p_r][\varphi_u q_u + (1 - \varphi_u) q_r] population \\ &[\beta_u \sum_{j=1...n} s_{u,j} + (1 - \beta_u) \sum_{j=1...n} s_{r,j}] \end{aligned} \tag{3}$$

Where subscript j denotes different industrial sectors and $s_{u,j} = \dfrac{labor_{u,j}}{labor_u}$ denotes the proportion of employees who are part of the industrial sector j.

Taking the logarithm for Equation (3), and then we have:

$$\begin{aligned} \ln pollutant &= \underbrace{\ln\{[\phi_u q_u + (1-\phi_u) q_r] \times population\}}_{\text{the scale effect}} + \underbrace{\ln[\beta_u p_u + (1-\beta_u) p_r]}_{\text{the intensive effect}} \\ &+ \underbrace{\ln\left\{[\alpha_u e_u + (1-\alpha_u) e_r] \times [\beta_u \sum_{j=1}^{n} s_{u,j} + (1-\beta_u) \sum_{j=1}^{n} s_{r,j}]\right\}}_{\text{the structure effect}} \end{aligned} \tag{4}$$

 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at *Sustainability* **2016**, *8*, 812; doi:10.3390/su8080812

In Equation (4), β_u, ϕ_u and α_u are variables that reflect population redistribution and labour force redistribution during the process of urbanization. According to the mechanisms analysis, we decompose the scale effect as $\ln\{[\phi_u q_u + (1-\phi_u) q_r] \times population\}$ in the reason that this monomial reflects the scale expansion of industrial production scale; we decompose out the intensive effect as $\ln[\beta_u p_u + (1-\beta_u) p_r]$ in the reason that this monomial reflects the promotion of industrial productivity; we decompose the structure effect as $\ln\left\{[\alpha_u e_u + (1-\alpha_u) e_r] \times [\beta_u \sum_{j=1\ldots n} s_{u,j} + (1-\beta_u) \sum_{j=1\ldots n} s_{r,j}]\right\}$ because this monomial reflects the structure upgrading during urbanization.

In conclusion, by using the Kaya Identity and the LMDI Method, we reasonably decompose the influence of urbanization on industrial pollutant emissions into the scale effect, the intensive effect and the structure effect. Therefore, we can analyse the three effects independently. We argue that this type of decomposition is necessary and meaningful, it establishes a solid foundation for understanding the relationship between urbanization and industrial pollutant emissions, and effectively helps to meet relative policy making.

4. Modelling and Parameters

4.1. Modelling

According to the mechanisms analysis in Section 3, by applying the Kaya Identity and the LMDI Method, we have decomposed out the scale effect as $\ln\{[\phi_u q_u + (1-\phi_u) q_r] \times population\}$, the intensive effect as $\ln[\beta_u p_u + (1-\beta_u) p_r]$, and the structure effect as $\ln\left\{[\alpha_u e_u + (1-\alpha_u) e_r] \times [\beta_u \sum_{j=1\ldots n} s_{u,j} + (1-\beta_u) \sum_{j=1\ldots n} s_{r,j}]\right\}$. In order to analyse the three effects independently, we establish the traditional panel model as follows:

$$
\begin{aligned}
\ln pollutant &= \rho_1 \ln scale\_effect_{i,t} + \rho_2 \ln intensive\_effect_{i,t} + \rho_3 \ln structure\_effect_{i,t} + \pi + \varepsilon_{i,t} \\
&= \rho_1 \ln\{[\phi_{u,i,t} q_{u,i,t} + (1-\phi_{u,i,t}) q_{r,i,t}] \times population_{i,t}\} + \rho_2 \ln[\beta_{u,i,t} p_{u,i,t} + (1-\beta_{u,i,t}) p_{r,i,t}] \\
&\quad + \rho_3 \ln\left\{[\alpha_{u,i,t} e_{u,i,t} + (1-\alpha_{u,i,t}) e_{r,i,t}] \times [\beta_{u,i,t} \sum_{j=1\ldots n} s_{u,j,i,t} + (1-\beta_{u,i,t}) \sum_{j=1\ldots n} s_{r,j,i,t}]\right\} + c + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

Where subscript i denotes the cross-sections; t denotes the time series; c denotes the constant; $\varepsilon_{i,t}$ denotes the random errors; and ρ_1, ρ_2 and ρ_3 are the regression coefficients of the scale effect, the intensive effect and the structure effect, respectively. Specifically, according to

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

the three hypotheses in section 3, ρ_1 is expected to be positive and indicates that the scale effect will aggravate industrial pollutant emissions; ρ_2 and ρ_3 are expected to be negative and indicate that the intensive effect and the structure effect will cause an abatement in industrial pollutant emissions.

One of the assumptions for establishing a traditional panel model, such as Equation (5), is that different cities are completely independent of one another; that is to say, the variables' spatial autocorrelations are non-existent or non-significant. However, this assumption has been questioned by many scholars (Arbia, Giuseppe & Thomas-Agnan, Christine, 2014; LeSage, James P., 2015), who believe that benefiting from the development of transportation networks and communication technologies, different regions' economic developments are strongly related.

Therefore, the empirical results of the traditional panel model may generate biased errors due to its omission of variables' spatial autocorrelations. To remedy this drawback, we try to apply the spatial panel model as follows:

$$\begin{aligned} \ln pollutant_{i,t} &= \psi \sum W \ln pollutant_{i,t} + \rho_1 \ln scale\_effect_{i,t} + \rho_2 \ln intensive\_effect_{i,t} \\ &\quad + \rho_3 \ln structure\_effect_{i,t} + \pi + \varepsilon_{i,t} \\ \varepsilon_{i,t} &= \tau \sum W \varepsilon_{i,t} + \upsilon_{i,t} \end{aligned} \quad (6)$$

Where W denotes the spatial weight matrix, ψ is the spatial lag coefficient, and τ is the space error coefficient. Compared to the traditional panel model in Equation (5), the spatial panel model in Equation (6) is more reasonable in two ways: First, it has focused on the spatial autocorrelation of the dependent variable by introducing $\sum W \ln pollutant_{i,t}$; and second, it has focused on the spatial autocorrelations of the omitted variables by extending $\varepsilon_{i,t}$ into $\sum W \varepsilon_{i,t}$.

According to different situations, the spatial panel model can also be subdivided into the Spatial Lag Model (SLM) and the Spatial Error Model (SEM), and which model should be chosen can be assessed by the Lagrange Multipliers (LM) and their robustness tests (Anselin, 1995; Lee & Yu, 2010; Elhorst, 2012). Specifically, if the Lagrange Multiplier of SLM (LM_lag) is more significant than that of SEM (LM_error), and the robustness of SLM (robustness_lag) passes significance testing while the robustness of SEM (robustness_error) does not, then the Spatial Lag Model will be more suitable. Otherwise, the Spatial Error Model will be more suitable.

4.2. Parameters

In this paper, the spatial panel model is established based on data from Chinese 282 prefecture-level cities between 2003 and 2013. The main data are extracted from the China City Statistical Yearbook. Here, we give a brief introduction to the variables.

In terms of the dependent variables, industrial pollutant emissions ($pollutant$) are measured by the volume of industrial waste water discharge ($pollutant\_water$), the volume of industrial sulphur dioxide emissions ($pollutant\_sulphur$) and the volume of industrial soot (dust) emissions ($pollutant\_soot$), respectively.

In terms of the independent variables, employment rates (q_u, q_r) are measured by the ratio of industrial employees to the total population; industrial labour productivities ($p_{u,j}, p_{r,j}$) are measured by industrial output per unit of labour; pollutant emissions intensities ($e_{u,j}, e_{r,j}$) are measured by the ratios of each sector's pollutant emissions to their industrial output; industrial structures ($s_{u,j}, s_{r,j}$) are measured by the proportions of employees in each industrial sector; and the distributions of population (φ_u), industrial employee (β_u) and industrial output (α_u) between cities and rural areas are measured by their proportions in cities.

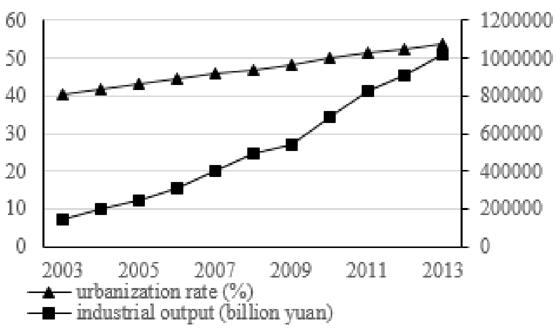
The spatial weight matrix (W) is measured by the reciprocal of the geographic distances between different cities.

5. Empirical Analysis

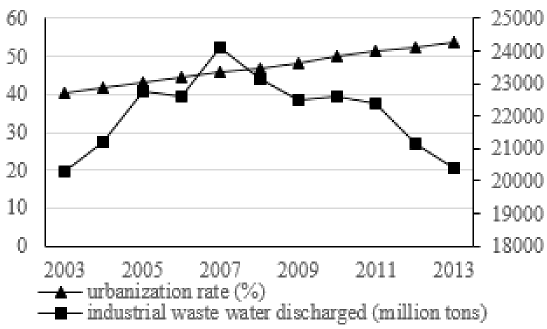
5.1. Description of the relationship between urbanization and industrial pollutants emissions

Figure 2(a) has reported the trend comparison of Chinese urbanization rate and its industrial output between 2003 and 2013. It tells us that Chinese urbanization rate rose steadily from 40.53% in 2003 to 53.73% in 2013. During the same period, Chinese industrial output also showed a gradual upward trend. This phenomenon has supported the view that Chinese urbanization expands its industrial production scale, which many economic scholars refer to as the demographic dividend (Peng, Xizhe, 2013; Song, Shibin et al., 2011).

Figure 2(b), Figure 2(c) and Figure 2(d) have reported the trend comparisons of Chinese urbanization rate and the three types of industrial pollutant emissions between 2003 and 2013. We can see from these figures that with the steady rise of Chinese urbanization rate, the volume of its industrial waste water discharge continued to increase and reached its peak in 2007; after that, the volume of its industrial waste water discharge showed a downward trend. The curves of the volume of Chinese industrial sulphur dioxide emissions and its industrial soot (dust) emissions also fitted reverse U-shapes, especially between the year 2003 and 2010.



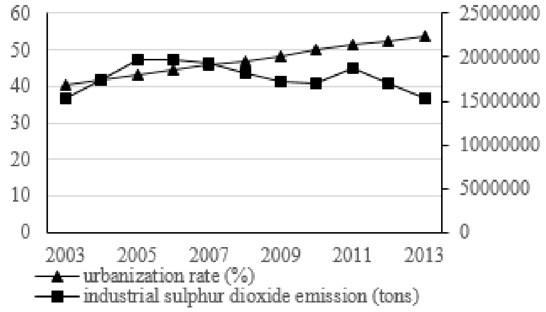
(a)



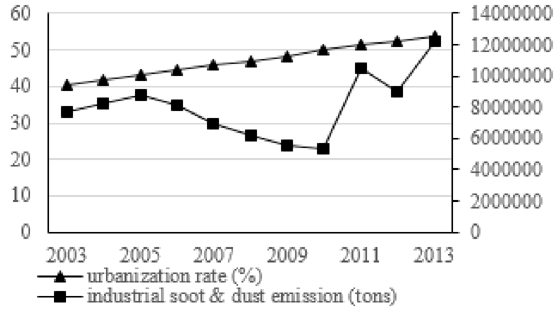
(b)

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812



(c)



(d)

Figure 2. (a) The trend comparison of urbanization and industrial output; (b) The trend comparison of urbanization and industrial waste water discharge; (c) The trend comparison of urbanization and industrial sulphur dioxide emission; (d) The trend comparison of urbanization and industrial soot & dust emission.

As a conclusion, the trend comparisons of Chinese urbanization rate and its three types of industrial pollutant emissions have documented that at the beginning stage of Chinese urbanization, its industrial pollutant emissions shew an aggravating trend accompany with the increase of its urbanization rate. However, with further development in urbanization, some driving forces that made its industrial pollutant emissions flatten and downward. Therefore, we argue that even though urbanization has correlations with industrial pollutant emissions, their definite relationship is ambiguous and should be treated cautiously.

5.2. Test of industrial pollutant emissions' spatial autocorrelations

In this paper, we apply the Moran's Index to test the spatial autocorrelations of cities' industrial pollutant emissions. The Moran's Index can be calculated as seen in Equation (7).

$$Moran's\ I = \frac{\sum_{c2}\sum_{c1} W(pollutant_{c1} - \bar{pollutant})(pollutant_{c2} - \bar{pollutant})}{S^2 \sum_{c2}\sum_{c1} W} \tag{7}$$

Where $c1$ and $c2$ denote different cities, $\bar{pollutant}$ denotes the average industrial pollutant emissions of the entire city, W denotes the spatial weight matrix, $S^2 = \frac{1}{n}\sum_{c1}(pollutant_{c1} - \bar{pollutant})$ and n denotes the number of cities.

Table 1 has reported the Moran's Indexes for the three types of Chinese cities' industrial pollutant emissions between 2003 and 2013. We can conclude from Table 1 that all the Moran's Indexes are significant and positive, which indicates that there are significant spatial autocorrelations of industrial pollutant emissions between different cities.

Table 1. The Moran's Indexes of Chinese cities' industrial pollutant emissions

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
pollutant_water	0.050***	0.057***	0.064***	0.076***	0.078***	0.075***	0.080***	0.082***	0.087***	0.085***	0.084***
	(8.054)	(9.136)	(10.183)	(12.019)	(12.349)	(11.866)	(12.663)	(12.967)	(13.646)	(13.293)	(13.152)
pollutant_sulphur	0.048***	0.045***	0.052***	0.053***	0.036***	0.040***	0.035***	0.031***	0.052***	0.058***	0.083***

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

	(7.851)	(7.328)	(8.416)	(8.473)	(6.049)	(6.639)	(5.877)	(5.390)	(8.507)	(9.469)	(13.229)
pollutant_soot	0.085***	0.080***	0.083***	0.086***	0.071***	0.066***	0.063***	0.053***	0.094***	0.087***	0.086***
	(13.390)	(12.593)	(13.068)	(13.563)	(11.303)	(10.500)	(10.121)	(8.637)	(14.795)	(13.737)	(13.488)

Notes: The figures in () are Z statistics; ***, ** and * denote the level of significance at 1%, 5% and 10%, respectively.

Figure 3 to Figure 5 have reported the cluster maps of Chinese cities' three types of industrial pollutant emissions in 2013, respectively. We can see from these figures that the High-High clusters of cities' industrial waste water discharge are concentrated in Chinese Beijing-Tianjin-Hebei Urban Agglomeration and Yangtze River Delta Urban Agglomeration. The High-High clusters of cities' industrial sulphur dioxide emissions and soot (dust) emissions are concentrated in the northeast of China. Most cities in Chinese west region are presented the Low-Low clustering phenomena or are not significant.

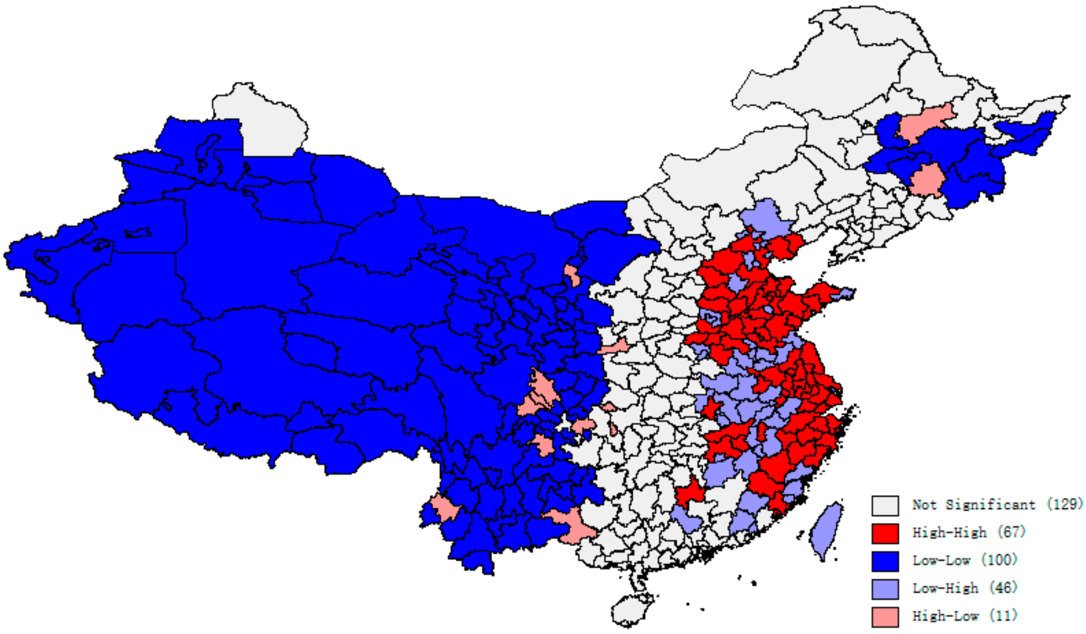


Figure 3. The cluster map of cities' industrial waste water discharge in 2013

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

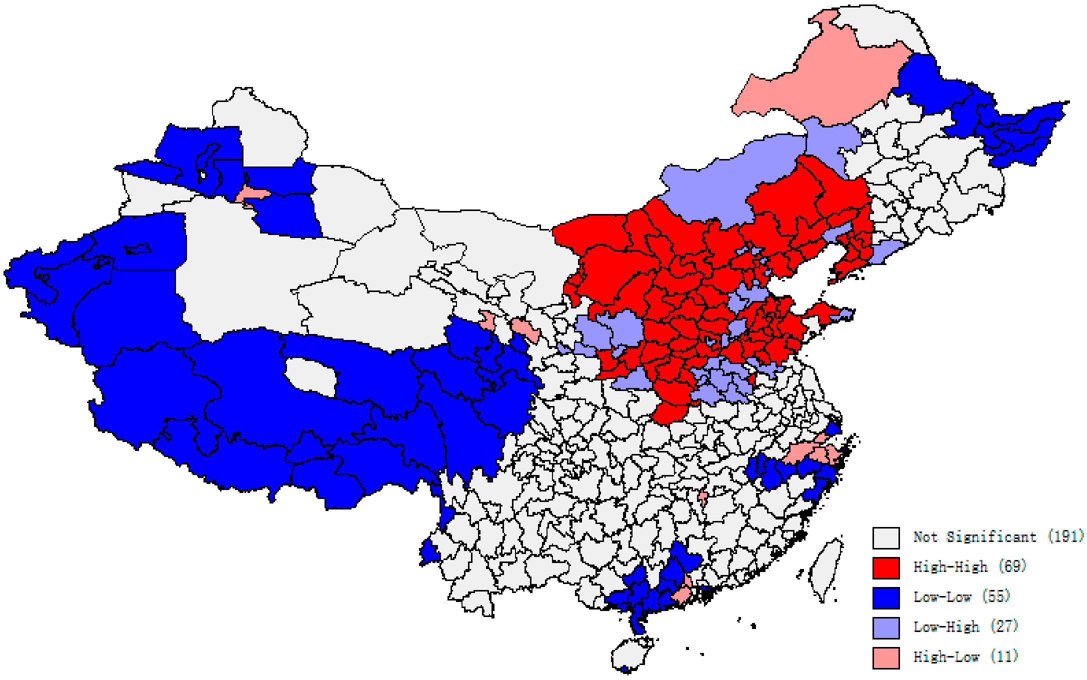


Figure 4. The cluster map of cities' industrial sulphur dioxide emissions in 2013

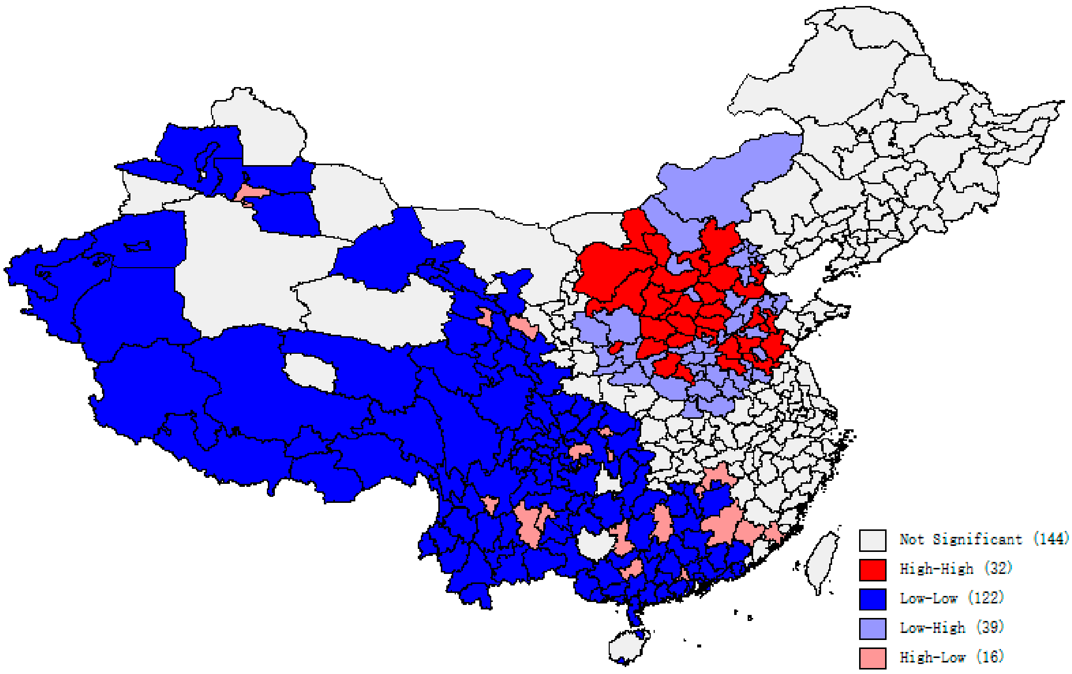


Figure 5. The cluster map of cities' industrial soot (dust) emissions in 2013

The most important conclusion we can draw from the above testing is that there are significant spatial autocorrelations of industrial pollutant emissions between different cities, so applying the spatial panel model will be more reasonable than applying the traditional panel model in this paper.

5.3. Regression result analyses

5.3.1. Analysis of the scale effect, the intensive effect and the structure effect

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

Table 2 has reported the regression results of the scale effect, the intensive effect and the structure effect of Chinese urbanization on its industrial waste water discharge, sulphur dioxide emissions, and soot (dust) emissions.

We list three models: the OLS denotes regression results when applying the traditional panel model and the SLM and SEM denote regression results when applying the Spatial Lag Model and the Spatial Error Model, respectively. The non-FE denotes regression without fixed effects, while FE denotes regression with fixed effects. Following the judgment rules in Section 4.1, we finally choose the Spatial Lag Model with fixed effect as the optimal model, and regard other models as control groups.

We can see from Table 2 that the regression coefficients $\rho 1$, $\rho 2$ and $\rho 3$ have all passed the significance testing, and $\rho 1$ and $\rho 3$ are positive in each model, while $\rho 2$ are always negative. As $\rho 1$, $\rho 2$ and $\rho 3$ reflect the impacts of the scale effect, the intensive effect and the structure effect of Chinese urbanization on its industrial pollutant emissions, we can draw the conclusion that the scale effect and the structure effect of Chinese urbanization have aggravated its industrial waste water discharge, sulphur dioxide emissions and soot (dust) emissions; however, the intensive effect has generated a decreasing and ameliorative impact on its industrial pollutant emissions.

The orientation of the scale effect and the intensive effect are in line with our expectations, but the orientation of the structure effect is beyond our expectation. That is to say, Hypothesis 1 and Hypothesis 2 have been tested and proved correct, while Hypothesis 3 cannot pass the test. Specifically, the population redistribution and labour force redistribution during Chinese urbanization expanded its industrial production scale and have generated increasing pollutant emissions. The improvement of Chinese industrial labour productivity has decreased every unit of industrial production's pollutant emissions and has generated an ameliorative impact on its industrial pollutant emissions. However, the changes of Chinese cities' industrial structures have not decreased its industrial pollutant emissions but rather aggravated them. We can speculate from these conclusions that Chinese industrial structures did not upgrade significantly but tended to aggravate its heavily polluting industries. In fact, our speculation is consistent with many other studies (Haakon Vennemo et al., 2009; Yu, Lihong; He, Yuan, 2012; Zhang, Miao & Rasiah, Rajah, 2015), they documented that China appeared to be following a path similar to that trodden by more industrialized countries, the development of its high-tech and service industries shows slow growth tendencies.

Table 2. The regression results of the scale effect, the intensive effect and the structure effect

model	OLS		SLM		SEM	
	Non-FE	FE	Non-FE	FE	Non-FE	FE
dependent variables	pollutant_water					
scale effect (ρ1)	0.579^{***}	0.608^{***}	0.554^{***}	0.536^{***}	0.535^{***}	0.534^{***}
	(25.182)	(25.567)	(24.525)	(23.952)	(24.808)	(24.775)
intensive effect (ρ2)	-0.135^{***}	-0.196^{***}	-0.100^{***}	-0.060^{***}	-0.060^{***}	-0.052^{***}
	(-6.213)	(-7.603)	(-4.716)	(-3.153)	(-3.816)	(-3.544)
structure effect (ρ3)	0.608^{***}	0.658^{***}	0.559^{***}	0.532^{***}	0.533^{***}	0.528^{***}
	(12.329)	(13.052)	(11.559)	(-3.366)	(11.374)	(11.262)
LM spatial lag	328.639^{***}	401.383^{***}				

Robust LM spatial lag	48.911***	19.204***				
LM spatial error	281.658***	428.553***				
Robust LM spatial error	1.930	46.374***				
Adj-R^2	0.316	0.319	0.348	0.334	0.349	0.341
Log-likelihood	-4.048×10^3	-4.035×10^3	-3.977×10^3	-4.005×10^3	-3.975×10^3	-3.993×10^3
dependent variables	pollutant_sulphur					
scale effect (ρ1)	0.410***	0.419***	0.408***	0.409***	0.409***	0.403***
	(15.770)	(15.670)	(15.705)	(15.923)	(15.778)	(15.705)
intensive effect (ρ2)	-0.068***	-0.083***	-0.067***	-0.064***	-0.068***	-0.059***
	(-2.773)	(-2.871)	(-2.734)	(-2.930)	(-2.772)	(-2.696)
structure effect (ρ3)	0.786***	0.800***	0.784***	0.783***	0.785***	0.776***
	(14.115)	(14.126)	(14.069)	(14.159)	(14.124)	(14.022)
LM spatial lag	3.171*	156.666***				
Robust LM spatial lag	19.391***	3.864**				
LM spatial error	0.009	166.477***				
Robust LM spatial error	16.229***	13.674***				
Adj-R^2	0.227	0.232	0.227	0.214	0.227	0.211
Log-likelihood	-4.424×10^3	-4.395×10^3	-4.424×10^3	-4.460×10^3	-4.424×10^3	-4.456×10^3
dependent variables	pollutant_soot					
scale effect (ρ1)	0.389***	0.419***	0.383***	0.378***	0.372***	0.359***
	(14.647)	(15.425)	(14.464)	(14.367)	(14.196)	(13.756)
intensive effect (ρ2)	-0.147***	-0.217***	-0.140***	-0.113***	-0.119***	-0.085***
	(-5.848)	(-7.398)	(-5.536)	(-5.015)	(-5.092)	(-4.039)
structure effect (ρ3)	0.553***	0.601***	0.545***	0.536***	0.530***	0.512***
	(9.728)	(10.450)	(9.613)	(9.442)	(9.410)	(9.078)
LM spatial lag	60.582***	613.836***				
Robust LM spatial lag	102.032***	66.642**				
LM spatial error	25.610***	547.420***				
Robust LM spatial error	67.060***	0.226				
Adj-R^2	0.139	0.143	0.142	0.116	0.141	0.116
Log-likelihood	-4.424×10^3	-4.443×10^3	-4.486×10^3	-4.543×10^3	-4.488×10^3	-4.532×10^3

Notes: The figures in () are Z statistics; ***, ** and * denote the level of significance at 1%, 5% and 10%, respectively.

5.3.2. Analysis of the spatial spillover effect

Table 3 has reported the spatial lag coefficient (ψ) and the spatial error coefficient (τ). By analysing these coefficients, we can gain an insight into the spatial spillover effect of Chinese urbanization on its industrial pollutant emissions.

In terms of Chinese industrial waste water discharge, both the spatial lag coefficient (ψ) and the spatial error coefficient (τ) are significant and negative; however, in terms of its industrial sulphur dioxide emissions and industrial soot (dust) emissions, neither of these two spatial coefficients passes the significant testing. That is to say, the spatial spillover from other cities' industrial pollutant emissions does not aggravate the local city's industrial pollutant emissions, and the spatial

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 14 July 2016 doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at Sustainability 2016, 8, 812; doi:10.3390/su8080812

spillover effect is non-existent. This result is beyond our expectation, moreover, it has established a contradiction with the conclusion which we draw in section 5.2.1: there are significant spatial autocorrelations of industrial pollutant emissions between different cities, but the spatial spillover effect from other cities does not aggravate local industrial pollutant emissions.

We offer an explanation that there are vast rural areas surrounding Chinese cities, these vast rural areas serve as sponge belts and absorb the spatial spillover effect of industrial pollutant emissions from Chinese cities, so the spatial spillover effect from other cities does not aggravate local city's industrial pollutant emissions. But, from another point of view, cross-regional economic relationships are shown in many forms, such as population flows, industrial associations, and material exchanges, these cross-regional activities have made Chinese industrial pollutant emissions present significant spatial autocorrelations, but cities' industrial pollutant emissions themselves have failed to affect each other.

Table 3. The regression results of the spatial spillover effect

model	SLM		SEM	
	Non-FE	FE	Non-FE	FE
dependent variables	pollutant_water			
spatial lag coefficient (ψ)	-0.812*** (-4.047)	-0.666*** (-3.366)		
spatial error coefficient (τ)			-0.990*** (-3.561)	-0.990*** (-3.561)
dependent variables	pollutant_sulphur			
spatial lag coefficient (ψ)	-0.045 (-0.250)	-0.167 (-1.109)		
spatial error coefficient (τ)			-0.005 (-0.026)	-0.009 (-0.047)
dependent variables	pollutant_soot			
spatial lag coefficient (ψ)	-0.158 (-0.805)	-0.121 (-0.751)		
spatial error coefficient (τ)			-0.236 (-1.055)	-0.284 (-1.237)

Notes: The figures in () are Z statistics; ***, ** and * denote the level of significance at 1%, 5% and 10%, respectively.

6. Discussion and Conclusions

In this paper, we first decompose the influence which urbanization impacts on industrial pollutant emissions into the scale effect, the intensive effect and the structure effect by using the Kaya Identity and the LMDI Method; second, we perform an empirical study of the three effects' impacts by applying the spatial panel model with data from 282 Chinese cities between 2003 and 2013. Our results indicate that (1) there are significant reverse U-shapes between Chinese urbanization rate and the volume of its industrial waste water discharge, sulphur dioxide emissions and soot (dust) emissions; (2) the scale effect and the structure effect of Chinese urbanization have aggravated its industrial waste water discharge, sulphur dioxide emissions and soot (dust) emissions, while the intensive effect has generated a decreasing and ameliorative impact on that aggravated trend. The orientation of the scale effect and the intensive effect are in line with our expectations, but the impact of the structure effect is beyond our expectation, we speculate that Chinese industrial structures did not upgrade significantly but tended to aggravate its heavily polluting industries; (3) there are significant spatial autocorrelations of industrial pollutant emissions between Chinese cities, but the spatial spillover effect from other cities does not aggravate local urban industrial pollutant emissions, we offer an explanation to the contradiction that the vast rural areas surrounding Chinese cities have served as sponge belts and have absorbed the spatial spillover of cities' industrial pollutant emissions.

Based on the above conclusions, we argue that even though urbanization has correlations with industrial pollutant emissions, their effects should be treated cautiously, it depends on the combined influence of the scale effect, the intensive effect and the structure effect. China is in a phase of rapid urbanization, and tremendous efforts have been made in abating industrial pollutant emissions, but our research suggests that the lock-in of its heavily polluting industries has introduced a more difficult problem in the attempt to reduce its environmental pollution. During the past 38 years after the reform and opening up, China appeared to be following a path similar to that travelled by more industrialized countries, and the development of its high-tech and service industries shew slow growth tendencies. Fortunately, the vast rural areas surrounding Chinese cities have absorbed and cushioned the spatial spillover of cities' industrial pollutant emissions, but as Chinese industrialization has been spreading to the countryside, its rural areas are facing a growing threat from industrial pollution.

Acknowledgments: This work was supported by the Key Project of National Philosophy and Social Science Foundation of China under Grant No. 15AJY009; the Major Project of the Philosophy and Social Science Foundation of Jiangsu Province, China under Grant No. 14ZD011; and the Key Project of the Philosophy and Social Science Foundation of Jiangsu Province, China under Grant No. 14EYA003. We appreciate the constructive suggestions from peer reviewers and the help of editors. Special thanks go to the Sustainable Asia Conference 2016 in Jeju Island, Korea for the discussion and suggestions from other participants. All remaining errors are ours.

Author Contributions: Jin Guo and Yingzhi Xu came up with the original idea for this article; Yingzhi Xu carried out the mechanism analysis; Zhengning Pu designed the theoretical model; Jin Guo collected the data and carried out the empirical analysis. Jin Guo and Zhengning Pu wrote the paper. All authors read and approved this version.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. World Bank. Clear water, blue skies: China's environment in the new century. World Bank: Washington D.C., 1997.
2. World Bank. Cost of pollution in China: economic estimates of physical damages. World Bank: Washington D.C., 2007.
3. Easterlin Richard A.; Robson Morgan; Malgorzata Switek; Fei Wang. China's life satisfaction, 1990–2010. Proceedings of the National Academy of Sciences, 2012: 109(25): 9775–80.
4. Haakon, Vennemo; Kristin, Aunan; Henrik, Lindhjem; Hans, Martin, Seip. Environmental pollution in China: Status and trends. Review of Environmental Economics and Policy, 2009, 3(2): 209-350.
5. Tolley, George S. The welfare economics of city bigness. Journal of Urban Economics, 1974, 1(3): 324–45.
6. Glaeser, Edward L. Are cities dying? Journal of Economic Perspectives, 1998, 12(2): 139–60.
7. Wan, Guanghu; Wang, Chen. Unprecedented Urbanisation in Asia and Its Impacts on the Environment. Australian Economic Review, 2014, 47(3): 378-385.
8. Grossman, Gene M.; Alan B. Krueger. Environmental impacts of a North-American free-trade agreement. Conference on the Mexico-US Free Trade Agreement Location, Brown University, Providence, 1993.
9. Grossman, Gene M.; Alan B. Krueger. Economic growth and the environment. Quarterly Journal of Economics, 1995, 110(2): 353–77.

doi:10.20944/preprints201607.0033.v1

Peer-reviewed version available at *Sustainability* **2016**, *8*, 812; doi:10.3390/su8080812

10. Panayotou, T. Empirical tests and policy analysis of environmental degradation at different stages of economic development. ILO, Technology and Employment Programme, Geneva, 1993.
11. Lindmark M. An EKC-pattern in historical perspective: carbon dioxide emissions, technology, fuel prices and growth in Sweden 1870 -1997. Ecological Economics, 2002, 42(1/2): 333-347.
12. Nasir M.; Ur Rehman F. Environmental Kuznets Curve for carbon emissions in Pakistan: an empirical investigation. Energy Policy, 2011, 39(3): 1857-1864.
13. Esteve V.; Tamarit C. Threshold cointegration and nonlinear adjustment between CO2 and income: the Environmental Kuznets Curve in Spain, 1857 -2007. Energy Economics, 2012, 34(6): 2148-2156.
14. Jalil A.; Mahmud S.F. Environment Kuznets Curve for CO2 emissions: A cointegration analysis for China. Energy Policy, 2009, 37(12): 5167-5172.
15. Tingting, Li; Yong, Wang; Dingtao Zhao. Environmental Kuznets Curve in China: New evidence from dynamic panel analysis. Energy Policy, 2016, 91: 138-147.
16. David I. Stern. Is there an Environmental Kuznets Curve for Sulfur? Journal of Environmental Economics and Management, 2001, 41(1): 162-178.
17. Richard York; Eugene A. Rosa; Thomas Dietz. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics, 2003, 46(3): 351-365.
18. Tae Hyeong Kwon. Decomposition of factors determining the trend of CO2 emissions from car travel in Great Britain (1970 -2000). Ecological Economics, 2005,53(2): 261-275.
19. Dasgupta, S.; B. Laplante; H. Wang; Wang; D. Wang. Confronting the Environmental Kuznets Curve. Journal of Economic Prespectives, 2002, 16: 147-168.
20. Panayotou, T. Economic growth and the environment. United Nations Economic Commission, Geneva, 2003.
21. Siqi Zheng; Matthew E. Kahn. Understanding China's urban pollution dynamics. Journal of Econom ic Literature, 2013, 51(3), 731–772.
22. Kanada, Momoe; Dong, Liang; Fujita, Tsuyoshi; Fujii, Minoru; Inoue, Tsuyoshi; Hirano, Yujiro; Togawa, Takuya; Geng, Yong. Regional disparity and cost-effective SO2 pollution control in China: A case study in 5 mega-cities. Energy Policy, 2013, 61: 1322-1331.
23. Huapeng, Qin; Qiong, Su; Soon Thiam, Khu; Nv, Tang. Water Quality Changes during Rapid Urbanization in the Shenzhen River Catchment: An Integrated View of Socio-Economic and Infrastructure Development. Sustainability, 2014, 6(10): 7433-7451.
24. Huijuan, Dong; Hancheng, Dai; Liang, Dong; Tsuyoshi, Fujita; Yong Geng; Zbigniew, Klimont; Tsuyoshi, Inoue; Shintaro, Bunya; Minoru, Fujii; Toshihiko, Masui. Pursuing air pollutant co-benefits of CO2 mitigation in China: A provincial leveled analysis. Applied Energy, 2015, 144: 165-174.
25. Tao, Yu; Li, Feng; Crittenden, John C.; Lu, Zhongming; Sun, Xiao. Environmental Impacts of China's Urbanization from 2000 to 2010 and Management Implications. Environment Management, 2016, 57(2): 498-507.
26. Zhou, Mi; Zhao Xiao Lin; Huang Li. The effects of urbanization on the environment pollution in China (2002-2012). International Conference on Electronic, Information and Computer Engineering, Hong Kong, China, 2016.
27. LeSage, James P. Software for Bayesian cross section and panel spatial model comparison. Journal of Geographical Systems, 2015, 17(4): 297-310.
28. Arbia, Giuseppe; Thomas-Agnan, Christine, 2014. Introduction: advances in cross-sectional and panel data spatial econometric modeling. Geographical Analysis, 2014, 46(2): 101-103.
29. Yu, Lihong; He, Yuan. Energy consumption, industrial structure, and economic growth patterns in China: A study based on provincial data. Journal of Renewable and Sustainable Energy, 2012, 4(3).
30. Zhang, Miao; Rasiah, Rajah. Globalization, industrialization and labour markets in China. Journal of the Asia Pacific Economy, 2015, 20(1): 14-41.
31. Peng, Xizhe. Understanding China's demographic dividends and labor issue. Journal of Policy Analysis and Management, 2013, 32(2): 408-410.
32. Song, Shibin; Song, Qi; Zhong, Tao. Demographic dividend and economic growth in China mainland. 2011 International Conference on Applied Social Science, Changsha, China, 2011.