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Published in:
Ecological Indicators

Published: 01/11/2021

Document Version:
Final Published version, also known as Publisher's PDF, Publisher's Final version or Version of Record

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Publication record in CityU Scholars:
Go to record

Published version (DOI):
10.1016/j.ecolind.2021.108128

Publication details:

Citing this paper
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Download date: 13/11/2021
Original Articles

Heterogeneity of the Environmental Kuznets Curve across Chinese cities: How to dance with ‘shackles’?

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ARTICLE INFO

Keywords:
Environmental Kuznets Curve (EKC)
Heterogeneity
Haze pollution
Industrial pollution
Chinese cities

ABSTRACT

Although an ‘inverted U-shaped’ economy-environment nexus is proposed in the Environmental Kuznets Curve (EKC) hypothesis, this initial configuration is considered to be too restrictive. Considering the diversified pollution, regional heterogeneity and strong government intervention in China, this article investigates EKC’s heterogeneity in a panel of 290 cities from 2001 to 2018. Through the investigation of the lag effect and spatial spillover effect of pollution emissions, the heterogeneity of EKC is examined among different pollutants and different regions. Moreover, such heterogeneity pattern also exists between pilot cities and non-pilot cities of three environmental policies (‘pollution rights trading (PRT)’, ‘low-carbon city’ and ‘SO2 emission trading’). The results show that different curve shapes and turning points are associated with EKC heterogeneity. Three regulations are considered effective to strike a balance between urban emission reduction and long-term economic growth. Pollution rights’ trading could contribute to the earlier ‘decoupling’ between urban pollution (both industrial pollution and haze pollution) and economic growth in the pilot cities significantly. The implementation of the ‘low-carbon city’ and SO2 emission trading’ are considered conducive to reducing the emissions of industrial SO2, with the former also resulting in fewer industrial smog emissions. The main contributions of this study are to identify both the temporal and spatial effects of pollution, develop the multidimensional analysis framework on the heterogeneity of EKC and investigate the dual effects of institutional power upon EKC as well as EKC heterogeneity. The implications, nevertheless, are considered as 1) the coordinated environment prevention and control between different regions and 2) the strict inspection of existing policy implementation by respecting each of their heterogeneous effects between regions.

1. Introduction

How to dance with ‘shackles’? Due to the rapid economic growth and profound changes in economic and social structure, the challenge of environmental sector is becoming ever huge and complex in China and worldwide (Asian Development Bank, 2012). With China’s rapid development of industrialization and urbanization, pollution and environmental deterioration are becoming increasingly severe. Haze pollution has emerged more often and affect the daily life and human health. According to World Health Organization (WHO) 2016 global pollution data, Chinese cities comprise 30 of the world’s 100 cities with the highest average PM2.5 concentration. Moreover, according to Mian et al. (2016), up to 70% of the total waste generated from East Asia and Pacific region is from China. Recently, the Chinese government has highlighted the prime environment-related concerns faced by the economy to provide prompt and apt solutions (Ahmad et al., 2019), such as the support to the development of green technology, green finance, and clean and efficient energy.

Based on Fig. 1, the discharge of industrial pollutants in urban areas has not significantly decreased over 2003–2015, and PM2.5 emissions have shown a continuing upward trend. At the same time, GDP quadrupled from CNY 13,742 billion to over CNY 68,551 billion, and the proportion of population in urban areas has grown from 40.53% to 56.10% (2016 China Statistical Yearbook, 2016). Furthermore, as one of the critical byproducts of urban lifestyle, the generation of municipal solid waste (MSW) has been increasing rapidly (Zhang et al., 2010; Mian

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https://doi.org/10.1016/j.ecolind.2021.108128
Received 20 October 2020; Received in revised form 18 August 2021; Accepted 18 August 2021
Available online 27 August 2021
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and China has become the largest MSW generator in the world (State Environmental Protection Association, 2006; Chen et al., 2010; Mian et al., 2016). That is, with rapid economic growth and urbanization, environmental problems and the economic-environmental nexus have become of prominent concern. Facing such pressures, China has devoted considerable resources to managing waste and reducing emissions. On the one hand, from an individual perspective, Wu et al. (2017) acknowledge economic viability and governmental supervision to be two significant factors influencing stakeholder behaviors. On the other hand, at the national level, the pursuit of sustainable development and ecological civilization and the specific development goal of ‘in 2025, the economic growth rate will be main

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tained at 6.5%, and PM

2

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tained at 6.5%, and PM

2

attained at 6.5%, and PM

2

2. Literature review

The relationship between economic growth and environment is most widely studied based on the Environmental Kuznets Curve (EKC). This initially refers to an ‘inverted U-shaped’ relationship first examined by Grossman and Krueger (1993). This argues that, with economic development, environment degradation will first occur in the initial stages, and later replaced by environmental improvement. As a common and conventional setting of EKC, such argument has been followed and supported by a large body of environmental economics research (for instance, Grossman and Krueger, 1995; De Bruyn et al., 1998; List and Gallet, 1999; Stern and Common, 2001; Rupasingha et al., 2004; Peng and Bao, 2006; Gao et al., 2012; Wang and Huang, 2015; Wang et al., 2016a,b; Wang et al., 2019). Furthermore, after Panayotou (1993) first defining the EKC as the correlation between environmental quality and economic growth, measures of environment have gone beyond pollution to verify the ‘inverted U-shaped’ relationship more comprehensively (see, Shafik and Bandyopadhay, 1992; and Shafik, 1994).

On the other hand, the ‘inverted U-shaped’ relationship has also long been challenged. The initial EKC hypothesis has been criticized for its premise of homogeneity between economies (Hsiao et al., 2010; Su and Zhang, 2011; Zhang et al., 2011) and simplification to the isolated impact of economic growth on local environment (Sun et al., 2019). As a result, the heterogeneity assumption has received increasing concern and the spatial analysis has been involved more. Meanwhile, other scenarios and patterns of ‘U shape’, ‘N shape’, ‘inverted N shape’, and ‘rotating J shape’ have been empirically examined. As Rizi et al. (2017) specified, the possible reasons behind the disagreement and controversy are mainly attributed to the settings of empirical models (also supported by Stern and Common (2001) and Dinda (2005)), the proxies for environmental status or pollution (also supported by Peng and Bao (2006)), and heterogeneity of the analysis units (also supported by Nguyen Van and Azomahou (2007) and Zhang et al. (2011)). Regarding the specifications of models, it is highlighted that incorrectly omitting spatially lagged variables may cause the parameters of the EKC to become biased (Maddison, 2006). Thus, the spatial autocorrelation of pollution emissions has been considered when studying EKC in the context of either China (see, Zhu et al., 2010; Xie et al., 2019; and Zhang et al., 2020) or the U.S. (see, Rupasingha et al., 2004). Considering the various pollutants and environmental indicators involved, Stern (1998) argued that the evidence for the inverted-U relationship applied only to a subset of environmental measures. In this regard, current studies usually select a set of environmental measures and specify the EKC for different types of pollution (see, Heerink et al., 2001). In addition, the influence of the heterogeneity of analysis units on EKC is partly ameliorated by introducing control variables in empirical models. However, heterogeneity between regions and cities in China is widely acknowledged, not only in terms of location and population scale, but also concerning industrial structure, innovation capacity, infrastructure investment, environmental policies, marketization, globalization, etc. Therefore, it is urgent for more multi-dimensional analyses of the EKC heterogeneity. Based on this, more effective and targeted policies could be conducted to address the economy-environment issues and strike a balance between pollution emissions and economic growth. This is exactly what we define as “to dance with ’shackles’”. Taking both spatial autocorrelations of pollution emissions and spatial heterogeneity of EKC into consideration, this research provides a relatively robust understanding and synthetical insight of EKC, particularly in the Chinese context.

To some degree, the heterogeneity of EKC hypothesis has been observed and discussed across different income levels in either Sub-Saharan African countries (Bah et al., 2019), the newly industrialized countries (Destek and Sarkodie, 2019) or some developing countries (Ahmad et al., 2021a), and at province levels of China (Ahmad et al., 2019; Ahmad et al., 2021b). However, this research provides some different findings and extensions. Firstly, micro-level data for Chinese cities is used. This will extend the practical evidence to more tailor-made policy discussions for cities in global south countries such as China. Secondly, this study takes the spatial–temporal autocorrelations of pollution emissions into consideration. Rather than the co-integration methods and panel estimations applied in the research mentioned above, this study employs the dynamic spatial models with panel data. In this regard, the methodological try in this paper could help investigate the ‘growth-environment’ relationship in a dynamic way.

Finally, compared with the previous research, this study extends the
heterogeneity analysis of EKC. Except for EKC heterogeneity resulting from different pollutants and locations, the effects of environmental regulations are also included. Most previous research confirms the primary role of regulations and policies in emission abatement (Dasgupta et al., 2002) and in the emergence of a downward sloping EKC segment through introducing regulatory variables (for example, Li and Shen, 2008; Zhang et al., 2009; and Shao et al., 2019). This study compares the heterogeneous shape and turning points of EKC between pilot and non-pilot cities of environmental regulations in China. This helps specify EKC heterogeneity and is another contribution of this study in expanding knowledge and understanding, not only on the effects of institutional power on EKC, but on EKC heterogeneity as well.

In terms of contribution to the literature – firstly, at the city level, this study examines the EKC for urban industrial pollution and haze pollution in China through dynamic spatial analysis. Secondly, it probes into EKC heterogeneity, not only for different types of pollution, but also between regions and cities with different environmental regulations, which further discusses the possible mechanisms involved. In other words, the spatial analysis and multidimensional discussions of the EKC heterogeneity are the key theoretical contribution of this study in extending the analytic framework of EKC research. Furthermore, the investigation of the dual effects of institutional power on EKC as well as EKC heterogeneity in the Chinese context helps provide innovative policy implications.

3. Theoretical discussion

In the Chinese context, the existence of heterogeneity between regions, provinces, and even cities has been the subject of many empirical studies (see Auffhammer and Carson, 2008; Co et al., 2008; Cheng et al., 2016b; Wang et al., 2020; Yan et al., 2021; etc.). Heterogeneity among regions and cities will directly decrease the accuracy of the test results based on the national full sample, when exploring the relationships between urban pollution and economic growth. This may further lead to misleading and ineffective policy implications. Therefore, this study examines the necessity for distinguishing EKC heterogeneity between different regions and cities in terms of the inconsistency of curve position and curve shape, based on a brief inspection of the full sample and independent tests of subsamples. These could be viewed as two major manifestations of the EKC heterogeneity.

Fig. 2 illustrates the situation involving three economic growth-pollution emissions curves, where curve 2 represents the estimated ‘inverted U-shaped’ curve based on the full data, while curves 1 and 3 show the curves of two different subsamples. There are four cities (A, B, C, and D), shown as points on different curves in the following figure. With respect to curve 2 of the full data, the pollution level of city B reaches the peak and will decline with any increase or decrease in its economic growth. However, to curve 1, it can predict its pollution level to display the negative correlation with economic growth of city B.

Similarly, regarding curve 2, the pollution level of city C can be expected to grow with the level of local economic growth, while, with respect to curve 1, the opposite trend occurs. Thus, even though the growth-emission curves are both ‘inverted U-shaped’, cohort or subgroup analysis will draw different conclusions. In other words, the analysis at the aggregate level tends to balance out the disparities and heterogeneity between cities and regions. As a result, neglecting particularities makes it quite likely to misguide any policy changes relating to local economic growth aimed at reducing local pollution emissions.

Furthermore, if the relationship between pollution emissions and economic growth is not ‘inverted U shaped’, contradictions between the findings of the full data and subsamples also exist and are, to some degree, more complex. As Fig. 2 shows, regarding economic development, city D’s pollution is believed to decrease according to the estimated curves of both the full sample (i.e., curve 2) and subsample 1 (i.e., curve 1). Thus, more emphases are laid on the issues of efficiency than environment. However, under the assumption of an ‘N-shaped’ curve (i.e., curve 3), after reaching the second turning point, a positive correlation between pollution emissions and economic growth will occur, which cannot be captured in curve 2 and will further reduce local social welfare.

In summary, the inconsistency of turning points and trends between the estimated full sample and subsample curves will result in contrary conclusions and ineffective implications. Therefore, specifying EKC heterogeneity is fundamental and crucial for this study and other relevant research as well.

4. Models and data

For empirical analysis, Shaﬁk and Bandyopadhyay (1992) and Shaﬁk (1994) have articulated that the shape of the relationship between income and environmental indicators should be cubic, quadratic or log linear. The speciﬁcation is determined by the ﬁtness of models and the explanatory power of terms. That is, if the coefﬁcient of the cubic term is not signiﬁcant, the quadratic and linear model are tested successively. Thus, it is believed that the EKC is not necessarily limited to an inverted U shape or even a U shape – an N shape or inverted N shape is also possible. Considering these forms and employing them to the EKC analysis of haze and industrial pollution, the models adopted are

\[
\begin{align*}
\lnpm &= f(\lnpcgdp, (\lnpcgdp)^2, (\lnpcgdp)^3, \text{control}) \\
\lnpollution & = f(\lnpcgdp, (\lnpcgdp)^2, (\lnpcgdp)^3, \text{control}) \\
\lnwater & = f(\lnpcgdp, (\lnpcgdp)^2, (\lnpcgdp)^3, \text{control}) \\
\lnso2 & = f(\lnpcgdp, (\lnpcgdp)^2, (\lnpcgdp)^3, \text{control}) \\
\lnsmog & = f(\lnpcgdp, (\lnpcgdp)^2, (\lnpcgdp)^3, \text{control})
\end{align*}
\]

where the dependent variables \(\lnpm, \lnwater, \lnso2, \lnsmog,\) and \(\lnpollution\) represent five types of pollutant emissions of city \(i\) in year \(t\); the core independent variable \(\lnpcgdp\) reflects urban economic growth; and the datasets for control variables contain 9 variables affecting environmental pollution. The calculations and descriptions of variables in the empirical models are elaborated as follows.

The basic PM2.5 concentration \((\mu g/m^3)\) data are from the Socioeconomic Data and Application Center (SEDAC) of Columbia University. Based on aerosol optical depth measured by the Moderate-Resolution Imaging Spectroradiometer and Multi-angle Imaging Spectroradiometer, the haze emissions data are further transferred into raster data (Van Donkelaar et al., 2015). Then, the annual mean PM2.5 concentration of 290 Chinese cities in 2001–2016 is calculated for analysis. Urban industrial wastewater emissions (water), industrial SO2 emissions (so2), and industrial smog emissions (smog) are used for measuring specific industrial pollution. To analyze aggregate industrial emissions, referring to the
research of Liu and Lin (2019), this study applies the entropy weight method to calculate the composite index (pollution) based on the emission data of the above three industrial pollutants. As EKC concentrates on the nexus between environmental pollution and economic development, the crucial variable of urban economic growth is measured by real urban per capital GDP (pcgdp).

The models contain nine control variables:

(1) Industrial structure reflects not only industrialization but also the pollution intensity of production activities (Xu and Deng, 2012). Due to the heavy reliance on energy consumption, the secondary industry proportion is positively correlated with the elasticity of energy and further has an important impact on the emissions of pollutants (Deng et al., 2019). Therefore, the secondary industry output share (s) is used to depict the effects of industrial structure on haze pollution and industrial pollution.

(2) The environmental impact of technology has been directly captured and specified via IPAT model (Ehrlich et al., 1971) and STIRPAT model (Diets and Rosa, 1994). Technical change is considered as the long-run determinant of pollution control and abatement, especially in terms of the green technology adoptions (Cheng, 2016) and cost reductions (see, Pasurka, 2001; and Baker et al., 2008). Moreover, a higher innovation capacity could result in a higher efficiency of production with fewer inputs (particularly in terms of such production factors as capital or labor) and less pollution (see, Zhang et al., 2011; and Xu and Deng, 2012).

From the perspective of input, the expenditure on science (tech) is used for analysis.

(3) Through fiscal transfer, taxation, price adjustment, and policies, the government can realize the governance and control of haze and industrial pollution (Li and Shen, 2008). Here, local financial expenditure gov (excluding expenditure on science) is used to reflect government intervention and support.

(4) Since Copeland and Taylor (1994) proposed ‘Pollution Haven Hypothesis’, which explored the effect of trade on pollution abatement, globalization, international trade, and foreign investment have been acknowledged to play a significant role in energy consumption and pollution control (see, Shen and Tang, 2008; Zhang et al., 2011; Xu and Deng, 2012; and Ahmad et al., 2021b). In this regard, foreign direct investment (FDI) (fdi) is used here, which has covered the funding gap during the rapid development and promoted innovation and marketization (Zhong, 2010), as one of fundamental and crucial engines of the economic growth in China as well.

(5) The production process is the main source of industrial pollution, while the haze pollution mainly originated from secondary chemical reactions, vehicle emissions, and combustion emissions (including coal combustion and biomass burning) (Han et al., 2019). Green areas can absorb SO2 and dust in the air and further decrease atmospheric pollution. The green coverage rate (g), measured as the proportion of green area in the urban built-up area, is used to represent a city’s ecological resilience ability and the pollution absorption capacity of urban public facilities.

(6) In terms of policies, regulations, or rules, environmental regulation is another crucial factor with a relatively direct impact on production and pollution emissions (Li and Shen, 2008). It is usually estimated by relevant expenditure or cost (see, Edelberg et al., 2005; Levinson and Taylor, 2008; Zhang et al., 2011b; and Li, 2017), or the pollutant removal level (see, Cole and Elliott, 2003; Pu and Zhou, 2010). Considering the availability of city-level data, the entropy weight method is used to combine two indicators – the removal rates of urban industrial SO2 and urban industrial smog (reg) – to measure the level of environmental regulation.

(7)-(9) Referring to other research (e.g., Yang, 2011; Song, 2017; Wang et al., 2019), the urban total electricity consumption (ec), urban population density (den), and urban hospital beds (mc) are used to examine their corresponding influence on pollution.

Except for the PM2.5 concentration data, the data are mainly collected from the 2002–2019 China City Statistical Yearbook and China Statistical Yearbook. Table 1 provides the descriptive statistics for all the data. To eliminate extreme values problems, all variables are first Winsorized and any missing values are estimated by linear interpolation. The variables relating to technical change, government intervention, and globalization are converted to 2001 constant prices. All the variables involved in the empirical models are in the logarithmic form.

Since the omission of spatial autocorrelations and lag terms could lead to biased, inconsistent, or even wrong estimates and tests of parameters (see, Anselin, 1988; Zhu et al., 2010; and Xie et al., 2019), the dynamic Spatial Lag Model (SLM) and dynamic Spatial Durbin Model (SDM) are used.

5. Empirical findings

5.1. Spatial autocorrelation analysis

5.1.1. Global spatial autocorrelation

Before constructing the spatial models, it is necessary to examine the spatial autocorrelations of the dependent variables. First introduced by Moran (1950) and Geary (1954), respectively, Moran’s I index and Geary’s C index are used in the analysis as measures of spatial autocorrelation for single variables (Legendre, 1993) with

\[
\text{Moran IS} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]
$\text{Gear y}'s C = \left(\frac{1}{n}\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (Y_i - \bar{Y}) (Y_j - \bar{Y})\right)^2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}$

where $S^2 = \sum_{i=1}^{n} \left(Y_i - \bar{Y}\right)^2 / n; \bar{Y} = \sum_{i=1}^{n} Y_i / n (n = 290); Y_i$ represents the values of $\text{Inpm}, \text{Inpollution}, \text{Inwater}, \text{Inso2},$ or $\text{Insmog}$ of city $i$ and $w_{ij}$ denotes the spatial matrix that reflects the spatial relationships between cities.

Two types of spatial matrices are applied. On the one hand, according to the distance attenuation method, the geographical distance Table 2

<table>
<thead>
<tr>
<th>Year Range</th>
<th>Moran’s I Distance matrix</th>
<th>lnwater</th>
<th>Inso2</th>
<th>Insmog</th>
<th>Inpollution</th>
<th>lnpm</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001–2003</td>
<td>W1</td>
<td>0.037**</td>
<td>0.092***</td>
<td>0.045**</td>
<td>0.084***</td>
<td>0.372***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.078**</td>
<td>0.150***</td>
<td>0.039</td>
<td>0.109***</td>
<td>0.325***</td>
</tr>
<tr>
<td>2004–2006</td>
<td>W1</td>
<td>0.144***</td>
<td>0.092***</td>
<td>0.127**</td>
<td>0.142***</td>
<td>0.376***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.195***</td>
<td>0.139***</td>
<td>0.158**</td>
<td>0.220***</td>
<td>0.318***</td>
</tr>
<tr>
<td>2007–2009</td>
<td>W1</td>
<td>0.181***</td>
<td>0.094***</td>
<td>0.128**</td>
<td>0.162***</td>
<td>0.399***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.212***</td>
<td>0.139***</td>
<td>0.148**</td>
<td>0.231***</td>
<td>0.347***</td>
</tr>
<tr>
<td>2010–2012</td>
<td>W1</td>
<td>0.186***</td>
<td>0.091***</td>
<td>0.145**</td>
<td>0.187***</td>
<td>0.376***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.226***</td>
<td>0.121***</td>
<td>0.154**</td>
<td>0.277***</td>
<td>0.321***</td>
</tr>
<tr>
<td>2013–2015</td>
<td>W1</td>
<td>0.195***</td>
<td>0.242***</td>
<td>0.203**</td>
<td>0.211***</td>
<td>0.376***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.235***</td>
<td>0.257***</td>
<td>0.219**</td>
<td>0.292***</td>
<td>0.325***</td>
</tr>
<tr>
<td>2016–2018 (2016 for lnpm)</td>
<td>W1</td>
<td>0.203***</td>
<td>0.107***</td>
<td>0.151**</td>
<td>0.217***</td>
<td>0.435***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.252***</td>
<td>0.111***</td>
<td>0.200**</td>
<td>0.316***</td>
<td>0.373***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year Range</th>
<th>Geary’s C Distance matrix</th>
<th>lnwater</th>
<th>Inso2</th>
<th>Insmog</th>
<th>Inpollution</th>
<th>lnpm</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001–2003</td>
<td>W1</td>
<td>0.924**</td>
<td>0.885***</td>
<td>0.936**</td>
<td>0.880***</td>
<td>0.503***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.875***</td>
<td>0.810***</td>
<td>0.915**</td>
<td>0.813***</td>
<td>0.513***</td>
</tr>
<tr>
<td>2004–2006</td>
<td>W1</td>
<td>0.780***</td>
<td>0.776***</td>
<td>0.806**</td>
<td>0.811***</td>
<td>0.503***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.685***</td>
<td>0.735***</td>
<td>0.753**</td>
<td>0.659***</td>
<td>0.517***</td>
</tr>
<tr>
<td>2007–2009</td>
<td>W1</td>
<td>0.738***</td>
<td>0.755***</td>
<td>0.813**</td>
<td>0.789***</td>
<td>0.485***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.660***</td>
<td>0.655***</td>
<td>0.735**</td>
<td>0.632***</td>
<td>0.500***</td>
</tr>
<tr>
<td>2010–2012</td>
<td>W1</td>
<td>0.676***</td>
<td>0.753***</td>
<td>0.801**</td>
<td>0.730***</td>
<td>0.510***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.626***</td>
<td>0.657***</td>
<td>0.784**</td>
<td>0.628***</td>
<td>0.525***</td>
</tr>
<tr>
<td>2013–2015</td>
<td>W1</td>
<td>0.669***</td>
<td>0.605***</td>
<td>0.766**</td>
<td>0.686***</td>
<td>0.520***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.647***</td>
<td>0.600***</td>
<td>0.742**</td>
<td>0.625***</td>
<td>0.533***</td>
</tr>
<tr>
<td>2016–2018 (2016 for lnpm)</td>
<td>W1</td>
<td>0.699***</td>
<td>0.772***</td>
<td>0.827**</td>
<td>0.705***</td>
<td>0.482***</td>
</tr>
<tr>
<td></td>
<td>W2</td>
<td>0.614***</td>
<td>0.775***</td>
<td>0.773**</td>
<td>0.609***</td>
<td>0.524***</td>
</tr>
</tbody>
</table>

Note: The asterisks ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Fig. 3. Moran’s I index and Geary’s C index of industrial pollution (2001–2018) and PM$_{2.5}$ (2001–2016) pollution in China.
weight matrix is usually calculated by: \( W_1 = W_d = 1/(d_{ij}^2) \) (if \( i \neq j \); else, 0). On the other, based on several studies (for example, Shao and Li, 2016; Han and Li, 2019; etc.), the economic distance weight matrix is calculated by: \( W_e = 1/(\|Q_i - Q_j\| + 1) \), where \( Q_i \) and \( Q_j \) represent the means of per capital GDP in 2001–2018 (or 2001–2016 for haze emissions) of cities \( i \) and \( j \), respectively. Moreover, it is important to note that both geographical proximity and economic connection are crucial for the spatial layout of economic activities (Han and Li, 2019). Thus, a spatial matrix is also constructed containing both the economic distance and geographical distance between cities. The economic-geographical distance matrix is in the form of the product, i.e., \( W_2 = W_{de} = W_d \times W_e \).

The value of Moran’s I index lies between 1 and 1. When Moran’s I index is positive or the value of Geary’s C index is less than 1, the similarities between a city and its neighboring cities are examined by the agglomeration of either high-pollution cities or low-pollution cities. A negative Moran’s I index or Geary’s C index exceeding unity indicates diversity, which reflects the presence of high-pollution cities in the vicinity of low-pollution cities. However, a Moran’s I index of zero or a Geary’s C index of unity indicates no spatial autocorrelation.

As Table 2 and Fig. 3 reveal, based on different spatial distance matrices and spatial autocorrelation indexes, all the spatial autocorrelations of pollution emissions are significantly positive. In other words, there are clear spillover effects of both urban industrial pollution and haze pollution, and the spatial models are therefore appropriate for estimating and analyzing the characteristics of EKC.

5.1.2. Local spatial autocorrelation

Fig. 4 provides LISA (i.e., Local Indicator of Spatial Association) scatter diagrams of urban industrial wastewater, industrial SO\(_2\), industrial smog, and haze pollution emissions based on the economic-geographical distance matrix (using Stata). The horizontal axis represents the standardized value of industrial pollution emissions and PM\(_{2.5}\) concentration, while the vertical axis represents the corresponding spatial lag value. According to the descriptions in some studies (e.g., Zhao et al., 2014; Long et al., 2016; Zhang et al., 2016; Cheng, 2016; Dong et al., 2019), each Moran’s I index scatter plot can be divided into four quadrants. Each quadrant corresponds with different types of spatial autocorrelations: the first indicates the existence of high-high positive autocorrelation, the third indicates low-low positive autocorrelation, and the second and fourth represent the atypical observation area with negative spatial autocorrelation. According to the local spatial autocorrelation tests, urban industrial pollution and PM\(_{2.5}\) pollution in most cities have a significantly positive spatial autocorrelation, with high-high and low-low clustering. In short, these pollution indicators have a significant spatial dependence.

For spatial visualization, Fig. 5 provides the LISA maps of pollution conducted by ArcGIS with the geographical distance matrix (W1). The maps also indicate the positive spatial autocorrelation is relatively evident in terms of high-high or low-low clustering among many Chinese cities, which endorses the above findings of global spatial autocorrelation and the LISA scatter plots.

5.2. Spatial regression analysis

To further examine the spatial autocorrelations and dynamic relationships between industrial/haze pollution and economic growth, dynamic spatial panel models (including both SLM and SDM) are used for the empirical analysis of the general EKC patterns and heterogeneity.

5.2.1. Full sample estimates

Table 3 and Fig. 6 provides the dynamic SLM results based on the full sample data. It is shown that, first, in general, from the temporal perspective, the time lag coefficients are significant at the 1%
significance level based on two different spatial weight matrices, which indicates that the urban pollution emissions have autocorrelations. That is, the lag effect exists.

Furthermore, from the spatial perspective, except for the estimates of industrial wastewater emissions, the spatial lag coefficients are significant at the 1% significance level based on two different spatial weight matrices. The estimates of spatial effects are also significant, which indicates that urban haze pollution and industrial pollution is spatially correlated. In other words, there are spillover effects of explained variables, which suggests that a strategy of regional joint prevention and control should be adopted to control the haze and industrial pollution – otherwise, the spillover effects of urban pollution between regions would invalidate any ‘unilateral’ environmental policies.

The results also indicate that, focusing on PM$_{2.5}$ concentration and the composite index of industrial pollution, the coefficients of the linear term of per capita GDP are positive, while the quadratic term coefficients are negative, based on different spatial distance matrices. Thus, the EKC for the industrial pollution and haze pollution has ‘inverted U’ characteristics. This corresponds with the Kuznets curve preliminary settings, with ‘the joint growth first, and then a decoupling’ between economic growth and industrial pollution/PM$_{2.5}$ concentration. Specifically, the nexus between industrial smog emissions and economic growth displays a similar ‘inverted U shape’. However, the relationship between industrial wastewater emissions and economic growth presents an ‘N-shaped’ curve (i.e., the coefficients of the per capita GDP linear term and the cubic terms are positive, while the quadratic term coefficient is negative). That is, they change with the trend of ‘joint growth first, then decoupling, and finally mutual growth again’, whilst industrial SO$_2$ emissions and economic growth show an ‘inverted N-shaped’ relationship (i.e., the coefficients of the per capita GDP linear term and the cubic terms are negative, while the quadratic term coefficient is positive). These two do not follow a Kuznets-type

Fig. 5. LISA maps of Moran’s index of industrial pollution (2018) and PM$_{2.5}$ pollution (2016) based on the geographical distance matrix (W1).
trajectory, which suggests that the EKC hypothesis is only one of the scenarios and models describing the growth-environment relationship and per capita GDP is not the only determinant of the two specific types of industrial pollution emissions. Such other factors as environmental policies, technology innovations, energy prices, international trade, and FDI will also affect specific industrial pollution, and further lead to deviations from the steady EKC state in a non-linear ‘inverted U shape’ trajectory, which suggests that the EKC hypothesis is only one of the -

<table>
<thead>
<tr>
<th>Table 3</th>
<th>The dynamic Spatial Lag Model (SLM) results based on the full sample data.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>W1</td>
</tr>
<tr>
<td>lnpm(-1)</td>
<td>0.4322***</td>
</tr>
<tr>
<td>w^lnpm1:1</td>
<td>-0.4098***</td>
</tr>
<tr>
<td>lnpollution</td>
<td>0.7649***</td>
</tr>
<tr>
<td>w^lnpollution</td>
<td>-0.1572***</td>
</tr>
<tr>
<td>lnwater(-1)</td>
<td>0.6670***</td>
</tr>
<tr>
<td>w^lnwater</td>
<td>0.0197</td>
</tr>
<tr>
<td>lnso2(1)</td>
<td>0.5458***</td>
</tr>
<tr>
<td>w^lnso2(1)</td>
<td>0.1572***</td>
</tr>
<tr>
<td>lnmg(-1)</td>
<td>0.6029***</td>
</tr>
<tr>
<td>w^lnmg</td>
<td>-0.1614***</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>0.0181***</td>
</tr>
<tr>
<td>(lnpcgdp)^2</td>
<td>0.1418***</td>
</tr>
<tr>
<td>(lnpcgdp)^3</td>
<td>0.5439***</td>
</tr>
<tr>
<td>Control variables</td>
<td>Yes</td>
</tr>
<tr>
<td>Spatial effect</td>
<td>1.0827***</td>
</tr>
<tr>
<td>R^2</td>
<td>0.0289</td>
</tr>
<tr>
<td>Observations</td>
<td>4350</td>
</tr>
<tr>
<td>EKC pattern</td>
<td>Inverted U shape</td>
</tr>
</tbody>
</table>

Note: The asterisks ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are the corresponding standard errors. (1), (2), (3), (4), and (5) denote the models with dependent variables of PM2.5 concentration, composite industrial pollution, industrial wastewater emissions, industrial SO2 emissions, and industrial smog emissions, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.

5.2.2. Regional subsample estimates

In China, different regions and cities differ from initial economic conditions such as geographical location, economic structure, technological development level, market maturity, infrastructure investment, and resource endowment. Thus, EKC heterogeneity for industrial and haze pollution is investigated among the eastern, central, and western regions. Through analyzing and comparing the shapes, turning points, and status in different regions, the EKC characteristics and heterogeneity can be tracked and examined. Therefore, the following regression analysis is conducted based on subsamples from different regions.

5.2.2.1. EKC for haze pollution. Based on the PM2.5 concentration data, Table 4 shows that EKC haze pollution has significant ‘inverted U-shaped’ characteristics for cities in the eastern and western regions but is ‘N-shaped’ for those in the central region. Specifically, under the setting of the geographical distance matrix and economic-geographical distance matrix, the ‘inverted U’ pattern of EKC for haze pollution in eastern China is more significant than that in the western region.

According to the coefficient estimates based on the economic-
Fig. 6. Scatter plots (with 95% confidence interval) of the SLM estimated results based on the full sample data and the economic-geographical distance matrix (W2).

Table 4
Results of the dynamic Spatial Lag Model (SLM) based on regional subsamples for haze pollution.

<table>
<thead>
<tr>
<th></th>
<th>Eastern region</th>
<th>Central region</th>
<th>Western region</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Western region</td>
<td>Western region</td>
<td>Western region</td>
</tr>
<tr>
<td>lnpm</td>
<td>W1</td>
<td>W2</td>
<td>W1</td>
</tr>
<tr>
<td>lnpm(-1)</td>
<td>0.2238*** (0.0243)</td>
<td>0.2338*** (0.0242)</td>
<td>0.0589*** (0.0245)</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>0.1915** (0.0885)</td>
<td>0.2590*** (0.0983)</td>
<td>99.9050*** (0.8645)</td>
</tr>
<tr>
<td>lnpm(-1)</td>
<td>0.0094** (0.0043)</td>
<td>0.0133*** (0.0048)</td>
<td>10.2833*** (0.0063)</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>0.3513*** (0.0030)</td>
<td>0.2459*** (0.0036)</td>
<td>0.0018* (0.0009)</td>
</tr>
<tr>
<td>lnpm(-1)</td>
<td>0.9102*** (0.0115)</td>
<td>0.9123*** (0.0131)</td>
<td>1.2259*** (0.0082)</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>0.7863</td>
<td>0.5898</td>
<td>0.0001</td>
</tr>
<tr>
<td>Observations</td>
<td>1515</td>
<td>1515</td>
<td>1500</td>
</tr>
</tbody>
</table>

Note: The asterisks ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are the corresponding standard errors. (1), (2), (3), (4), and (5) denote the models with dependent variables of PM$_{2.5}$ concentration, composite industrial pollution, industrial wastewater emissions, industrial SO$_2$ emissions, and industrial smog emissions, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.
2001, the real economic growth of 52 central cities was on the right side increased to 98, which means that almost all eastern cities entered the central cities have passed the first turning point since 2014. In addition, when real per capita GDP reaches CNY 9500 and CNY 32,370, respectively; while, at the turning point for haze pollution in the western region, the corresponding real per capita GDP is around CNY 143. All 100 western cities have passed the turning point since 2014. In addition, almost all 89 western cities crossed the turning point in 2001–2016.

Specifically, in 2001, the real per capita GDP of 53 eastern cities was on the right side of the turning point while, in 2016, this number increased to 96, which means that almost all eastern cities entered the stage of EKC for haze pollution with a downward trend. In addition, in 2001, the real economic growth of 52 central cities was on the right side of the ‘N-shaped’ EKC’s first turning point for haze pollution, of which only Daqing passed the second turning point; in 2016, all cities in this region passed the first turning point, with 44 crossing the second. In summary, it is concluded that, until 2016, all the eastern and western cities and half the central cities have presented the characteristics of ‘decoupling’ between urban haze pollution and economic growth. However, there is a need to pay sufficient attention to the mutual growth trend between haze pollution and economic growth in 44 central cities.

In addition, the estimates of the lag terms and the spatial effect coefficients are significant, which also supports the significant spillover effects of haze pollution in different regions. Regarding the control variables, the reduction effect of the expenditure science and technology concentration, composite industrial pollution, industrial wastewater emissions, industrial SO2 emissions, and industrial smog emissions, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.

Table 5
Results of the dynamic Spatial Lag Model (SLM) based on regional subsamples for composite industrial pollution.

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Eastern region</th>
<th>Central region</th>
<th>Western region</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnw</td>
<td>0.5779*** (0.023)</td>
<td>0.5813*** (0.034)</td>
<td>0.8771*** (0.0219)</td>
</tr>
<tr>
<td>w*lnw</td>
<td>-0.1410*** (0.0362)</td>
<td>-0.1418*** (0.0269)</td>
<td>0.0283 (0.0435)</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>13.4240** (5.4901)</td>
<td>13.6605** (5.5165)</td>
<td>244.6914** (5.7191)</td>
</tr>
<tr>
<td>(lnpcgdp)^2</td>
<td>-1.2896** (0.5445)</td>
<td>-1.3425** (0.5473)</td>
<td>-25.2794** (0.4493)</td>
</tr>
</tbody>
</table>

Control variables

Note: The asterisks ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are the corresponding standard errors. (1), (2), (3), (4), and (5) denote the models with dependent variables of PM2.5 concentration, composite industrial pollution, industrial wastewater emissions, industrial SO2 emissions, and industrial smog emissions, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.

Table 6
Results of the dynamic Spatial Lag Model (SLM) based on regional subsamples for specific industrial pollutions.

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Eastern region</th>
<th>Central region</th>
<th>Western region</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnw</td>
<td>0.5717*** (0.023)</td>
<td>0.7681*** (0.0132)</td>
<td>0.7575*** (0.0156)</td>
</tr>
<tr>
<td>w*lnw</td>
<td>-0.0057 (0.0269)</td>
<td>0.0307 (0.0425)</td>
<td>0.4281*** (0.0186)</td>
</tr>
<tr>
<td>lnpcgdp</td>
<td>0.4573*** (0.0185)</td>
<td>0.5612 (0.0378)</td>
<td>0.0103*** (0.0034)</td>
</tr>
<tr>
<td>(lnpcgdp)^2</td>
<td>-0.0560** (0.0284)</td>
<td>-0.0069* (0.0312)</td>
<td>0.6543*** (0.0016)</td>
</tr>
<tr>
<td>lnsmog</td>
<td>0.5471*** (0.0160)</td>
<td>0.5241*** (0.0214)</td>
<td>0.5241*** (0.0214)</td>
</tr>
<tr>
<td>w*lnso2</td>
<td>-0.1116*** (0.0299)</td>
<td>-0.0383 (0.0421)</td>
<td>0.0031 (0.0062)</td>
</tr>
</tbody>
</table>

Control variables

Note: The asterisks ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are the corresponding standard errors. (1), (2), (3), (4), and (5) denote the models with dependent variables of PM2.5 concentration, composite industrial pollution, industrial wastewater emissions, industrial SO2 emissions, and industrial smog emissions, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.
Ecological Indicators 130 (2021) 108128

5.2.2.2. EKC for industrial pollution. Table 5 summarizes the relationships between urban industrial pollution and economic growth from the perspectives of both composite index and specific pollutants. It is shown that, firstly, the EKC for composite industrial pollution of eastern and central cities has significant ‘N-shaped’ characteristics, while it is ‘inverted U-shaped’ in the western region.

According to the coefficient estimates based on the economic-geographical distance matrix, at the turning points of ‘N-shaped’ EKC for composite industrial pollution in the eastern region, real per capita GDP reaches CNY 14,271 and CNY 52,470, respectively; those of the ‘N-shaped’ trend in the central region are CNY 8258 and CNY 33,928, respectively; while the turning point of the curve in the western region corresponds to real per capita GDP at around CNY 438. Similarly, all 100 central cities passed the first turning point in 2014, and almost all 89 western cities crossed the turning point in 2001–2018. Specifically, in 2001, the real per capita GDP of 60 eastern cities had passed the first turning point of the ‘N-shaped’ EKC for composite industrial pollution in the eastern region, real per capita GDP reaches CNY 14,271 and CNY 52,470, respectively; those of the ‘N-shaped’ trend in the central region are CNY 8258 and CNY 33,928, respectively; while the turning point of the curve in the western region corresponds to real per capita GDP at around CNY 438. Similarly, all 100 central cities passed the first turning point in 2014, and almost all 89 western cities crossed the turning point in 2001–2018.

Table 6 summarizes the results of analyzing the regional EKC heterogeneity for industrial wastewater pollution, industrial SO\(_2\) pollution, and industrial smog pollution. It is indicated a significant ‘N-shaped’ trend between industrial wastewater emissions and real per capita GDP in the eastern and central regions, but an ‘inverted N’ relationship in the western region. Moreover, the EKC for industrial SO\(_2\) is a significant ‘inverted U’ curve in the central region and an ‘inverted N shape’ in the eastern and western regions. Finally, regarding the EKC for industrial smog pollution, the heterogeneity of three regions is relatively clear. The EKC relevant to urban industrial smog emissions in the eastern, central, and western regions varies most, showing a significant ‘inverted N-shaped’, ‘N-shaped’, and ‘inverted U-shaped’ pattern, respectively. Furthermore, considering spatial autocorrelations, three models with different settings are commonly used in the previous studies: the Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). Therein, SLM and SDM can be carried out dynamically with different settings of lag terms, whilst SDM combines the settings and strengths of the other two (see, Rios et al., 2017; Luo and Wang, 2017; Wang and Zhou, 2017; Shao et al., 2019; Feng and Wang, 2020). The dynamic SDM is also used for robustness check. The results are elaborated in the appendix, which provide evidence and verify the robustness of the above empirical findings.
5.2.3. Other subsample estimates

It is believed that environmental policies and regulations play crucial roles in both pollution control and economic growth (see, Foulon et al., 2002; Lanoie et al., 2008; Kijima et al., 2011; Cao et al., 2020), so they have significant impacts on the EKC patterns. After analyzing regional EKC heterogeneity, for policy assessment and implications, the relationships between environmental regulations and the formation of the EKC turning points are worth exploring. Taking the selected pollutants and impacts of environmental policies in China, this research focuses on ‘pollution rights trading (PRT)’, ‘low-carbon city’ and ‘SO\textsubscript{2} emission trading’ for further discussions. The heterogeneity of EKC between pilot and non-pilot cities of these policies is investigated as follows.

Firstly, EKC heterogeneity between PRT pilot cities and non-pilot cities is analyzed. Since 2007, China’s PRT has been established and developed in nine provinces and two cities. In PRT pilot cities\textsuperscript{2}, relevant policies have exerted more pressures on local economic development, with emphases and requirements on emission reduction and pollution trading. Therefore, EKC heterogeneity between pollution rights trading pilot cities and non-pilot cities is predicted to be shown.

The quadratic curve is used to fit the data of two subsamples. Fig. 7a shows that, in 2001–2018, the nexus between urban industrial pollution and urban economic growth in 109 pollution rights trading pilot cities is ‘inverted U-shaped’, and the turning point occurs when real per capita GDP reaches around CNY 393,778. However, as Fig. 7b suggests, this non-linear relationship is not significant in the other 181 non-pilot cities.

Secondly, EKC heterogeneity between low-carbon pilot cities and non-pilot cities is examined. In 2010, 2012, and 2017, a total of 6 provinces and 81 cities (or counties) were nominated as low-carbon pilot cities\textsuperscript{3}. With more specific assignments and higher requirements for saving energy and reducing emissions, the nexus between urban pollution and economic growth in such pilot cities is believed to differ from the non-pilot ones. Therefore, according to relevant government documents released by National Development and Reform Commission, the whole samples are divided into two parts – the low-carbon pilot part containing 124 cities and the non-pilot part comprising the remaining 166 cities in the dataset. Comparing the two parts shows that this regulation has a greater influence on industrial SO\textsubscript{2} emissions and industrial smog pollution than other pollutants.

Similarly, focusing on PM\textsubscript{2.5} concentration, Fig. 8 shows that, in 2001–2016, the EKC for haze pollution in both the pilot and non-pilot cities displays the significantly ‘inverted U-shaped’ characteristics. For the pilot cities, the turning point is at real per capita GDP CNY 30,240, while that for the non-pilot cities is CNY 225,002.

In short, it is concluded that with the relevant regulations being conducted in the pilot cities, the trading system contributes to reaching the turning point for both urban industrial pollution and haze pollution earlier, and further promoting emission reduction without economic loss.

\textsuperscript{2} The lists of pilot cities are from the relevant documents released by the State Council of China, which are available at http://www.gov.cn/zhengce/content/2014-08/25/content_9050.htm.

higher level of real per capita GDP to reach the turning point. Similar conclusions can also be drawn from Fig. 10 concerning urban industrial smog pollution. At the turning point, real per capita GDP in the pilot cities is around CNY 149,043, which is much smaller than that in the non-pilot cities. Therefore, it is evident that the policies appertaining low-carbon cities are conducive to reducing the emissions of both industrial SO$_2$ and smog.

Thirdly, when it comes to SO$_2$ emission trading policies, since 2002, 4 provinces and 3 cities have been selected as SO$_2$ emission trading pilot provinces and cities by Ministry of Ecology and Environment of the People’s Republic of China$^4$. A more efficient trading market and more control of emissions should impact on the interactions between urban pollution (especially industrial SO$_2$ pollution) and economic growth. Shanghai, Tianjin, Liuzhou, and the cities in Shandong, Shanxi, Jiangsu, and Henan compose the subsample of SO$_2$ emission trading pilot cities for comparison with the EKC for urban industrial SO$_2$ pollution of the non-pilot cities.

Fig. 11 demonstrates that, in 2001–2018, the relationship between urban industrial SO$_2$ emissions and urban economic growth in 61 SO$_2$ emission trading pilot cities is significantly ‘inverted U-shaped’. At the turning point, real per capita GDP is around CNY 34,826. However, such a nonlinear relationship does not exist in the other 229 non-pilot cities, where the trend in urban industrial SO$_2$ emissions is to continually increase with urban economic growth. In other words, the establishment and development of an SO$_2$ emission trading system results in fewer industrial SO$_2$ emissions overall.

6. Discussions

This study provides both empirical support and a challenge or extension to the initial homogeneous configuration of EKC. First, at the national level, the EKC heterogeneity of different types of pollution is significant (Mazzanti et al., 2007). The ‘inverted U-shaped’ relationship between composite industrial pollution and economic growth is examined in China. Specifically, only the EKC for industrial smog pollution is verified, which accords with the findings of Zhao et al. (2005), Bao and Peng (2006), and Zhu et al. (2010). Moreover, the departure of industrial wastewater emissions and industrial SO$_2$ emissions from EKC has also been recorded elsewhere in the literature (e.g., Panayotou, 1997; Peng and Bao, 2006; Park and Lee, 2011). Furthermore, the evidence of EKC for haze pollution also corresponds with several previous studies (e.g., Xie et al., 2019; Zhang et al., 2020).

Second, at a meso level, echoing the arguments of Brock and Taylor (2004), this research uses newly constructed, more heterogeneous, and longer datasets at the city level and further for in-country subsamples in homogeneous relevant areas, rather than international cross-country datasets. These may produce very different results and reveal some vital ones about the heterogeneity. In the Chinese context, on the one hand, the shapes and turning points of EKC vary between the eastern, central, and western regions. On the other hand, the significant heterogeneity also exists between cities piloting environmental regulations and those that are not.

6.1. Regional heterogeneity

The sources of heterogeneity are rather complex (Nguyen Van and Azomahou, 2007). As the largest developing country in the world, China’s regional EKC heterogeneity has been considered to be the outcome of the disparities of resource endowment, economic development level, development mode, environmental policy, etc. (Li and Zhang, 2008). The regional heterogeneity of environmental regulation (ER) and socioeconomic drivers leads to a more complicated formulation of energy and environment policy (Wang et al., 2020). However, in practice this is often ignored or paid inadequate attention, which further results in compromised policy effectiveness or even invalidation. Moreover, local governments have competing policy priorities, in which pro-growth initiatives take precedence over environmental protection (Wen, 2020). This could explain the failure of environmental regulation in China, and the balance between economic growth and environmental protection has been increasingly highlighted for sustainable development. Therefore, an increasing emphasis on environmental issues and trade-offs between growth and the environment together with policy flexibility according to local conditions is recommended. Tailor-made and targeted policies for a specific development stage and geographic units are needed to address the dilemma of environmental regulations through better controlling and mitigating pollution with less economic loss. Furthermore, increased environmental governance and supervision could contribute to narrowing the gap between environmental regulation and regulatory enforcement and further guarantee the effectiveness of environmental policy.

Specifically, based on the EKC for haze pollution and composite industrial pollution, at the early stage of economic development, both PM$_{2.5}$ concentration and industrial pollution increased with economic growth in all the three regions. At the turning point, real per capita GDP in the eastern region is much greater than that in the western region, and greater than that in the central region at the first turning point. It is indicated that, to realize sustainable development with economic growth and emission reduction, the economic development threshold is much higher in the eastern cities. This may be a result of the high industrialization level and a more radical and extensive development mode in this region. According to the regional EKC above, until 2016 the mutual growth trend between haze pollution and economic growth has only occurred in 44 central cities, while until 2018 the mutual growth trend between industrial pollution and economic growth has found in 39 eastern cities and 43 central cities. Therefore, there is a need for more

$^4$ Named the National Environmental Protection Administration (NEPA) before 2008; relevant documents of SO$_2$ trading pilot cities are available at https://www.china.com.cn/tzt/2002-05/31/content_5153447.htm.
emphasis on environmental protection and emission reduction in the eastern and especially central regions.

6.2. Heterogeneity relevant to environmental regulations

Stringent and systematic environmental regulations can change the EKC characteristics (Zhang et al., 2009). Command-and-control (CAC) policies (such as emissions and technology standards) and, to a lesser extent, market-based instruments (MBIs) such as emissions fees and tradable permits, consist of the common tools of environmental regulators (Blackman et al., 2018). In particular, as MBIs, the effectiveness of China’s PRT and emission trading scheme (ETS) for controlling haze pollution and urban industrial pollution are examined in this study and have also been acknowledged in other research (for instance, Cheng et al., 2016a; Ge et al., 2019; Yan et al., 2020; etc.). According to the empirical findings, nearly half the existing list of PRT pilot cities are in the central region, while around one third are in the eastern region. Thus, far from ‘decoupling’ pollution and growth, improvements in the implementation of PRT in these pilot cities are expected, and some policy preferences are recommended for other non-pilot cities in these two regions in the future.

Focusing on the specific industrial pollutants, industrial SO\(_2\) emissions until 2018 increased with urban economic growth in 50 eastern and 3 western region cities. Furthermore, both the SO\(_2\) emission trading system and low-carbon nominations are effective in promoting industrial SO\(_2\) emission reductions. Of the existing pilot cities of these two environmental policies, the eastern cities comprise the relatively dominant proportion. Therefore, to reach the second turning point of the ‘inverted N-shaped’ EKC for SO\(_2\) emissions earlier, there is a need to implement these two policies in the eastern region, together with more and better environmental regulations and supervisions. Moreover, it is important to note that only one of 61 SO\(_2\) emission trading pilot cities is located in the western region. Thus, more cities in the western region need to establish and develop SO\(_2\) emission trading systems. On the other hand, until 2018 industrial smog emissions have increased with urban economic growth in 27 eastern region cities, 17 central region cities, and 3 western region cities. To some degree, it could be concluded that, as an effective CAC instrument for controlling industrial smog emissions concurrently with economic growth, the promotion of low-carbon cities could be involved in environmental policy making more widely in China.

In short, to dance with ‘shackles’, the importance of market-based regulations (especially through trading systems) for haze pollution and industrial pollution would benefit from greater government recognition. More specifically, the SO\(_2\) emission trading system is a targeted and effective tool for abating urban SO\(_2\) emissions, and its combination with the CAC instrument (in terms of low-carbon policy) could further reduce industrial SO\(_2\) emissions. On the other, as the crucial stakeholder of environmental governance, government and central planning need play a dominant role in reducing industrial smog emissions. Regarding the heterogeneous stages and characteristics of the growth-pollution curves between regions in China, increased supervision of the implementation of existing environmental regulations in both eastern and western regions and extension of CAC regulations in the western region should help in striking a balance between urban emissions reduction and long-term economic growth and further the goal of sustainable development.

Finally, the spillovers of haze pollution or industrial pollution in China also correspond with the findings of other research (for example, Eitan et al., 2010; Cheng et al., 2016a; Chen and Ye, 2018; Zhang et al., 2020; and Chen et al., 2019), which claims that a city’s environmental pollution status depends not only on itself, but also on other surrounding cities (Wang and Zhao, 2018). As a result, unilateral pollution control may become futile, while the establishment of regional joint prevention and control of pollution by cities is recommended and highlighted. In China, the Joint Prevention and Control of Atmospheric Pollution (JPCAP) is believed to be an effective way to improve regional air quality (Wang and Zhao, 2018), which has been reflected and supported by the ‘APEC blue’ in 2014 (Wang et al., 2016). Along with the regional heterogeneity of environmental pollution, economic development, and the economic-environmental relationship, such collaborative efforts and regimes can be region-oriented or even city-oriented, through considering local conditions and been given distinct priority (echoing Wu et al., 2015; Wang et al., 2016; and Chen et al., 2019).

7. Conclusions and implications

After experiencing rapid economic growth for over 30 years, China has encountered increasingly prominent ecological and environmental problems that could impede sustainable development and reduce social welfare. In this context, ‘the construction of Ecological Civilization’ and ‘high-quality development’ have been highlighted. To understand the nexus and pursue the balance between economic growth and environmental protection, the Environmental Kuznets Curve has been widely examined and analyzed. However, due to the specifications of empirical models, measures of environmental status, and heterogeneity of analysis units, the EKC trend is not limited to be initially ‘inverted U-shaped’. This study focuses on the heterogeneity of EKC, not only for various pollution emissions, but also among different regions and cities with different environmental regulations. Dynamical spatial models are employed based on the geometrical distance matrix and economic-geographical distance matrix for relatively robust analyses and syntactical insights of EKC in the Chinese context. Based on the panel data of 290 cities, the main findings are:

1. There are spillover effects of both industrial pollution and haze pollution in China. Most of the cities have high-high clustering and low-low clustering of urban industrial pollution and PM\(_{2.5}\) pollution. In short, there is a significant spatial autocorrelation of pollution emissions.

2. At the national level, the EKC for industrial and haze pollution has ‘inverted U’ characteristics, and all the cities have been experiencing a ‘decoupling’ between urban pollution and economic growth. To be specific, the industrial smog emissions EKC is also ‘inverted U-shaped’. However, EKC for industrial wastewater emissions is ‘N-shaped’, while that for industrial SO\(_2\) emissions is ‘inverted N-shaped’. All the cities have entered the second stage of these three curves.

3. At the regional level, there is significant heterogeneity of the EKC for haze pollution between regions, with an ‘inverted U shape’ in the eastern and western regions, and an ‘N-shaped’ relation in the central region. Furthermore, at the turning point, real per capita GDP is CNY 16,930 in the eastern region, compared to CNY 143 in the western region. Two turning points of the ‘N-shaped’ EKC for haze pollution in the central region correspond to the level of economic growth reaching CNY 9,500 and CNY 32,370, respectively. Until 2016, all the eastern and western cities and half the central region cities have displayed ‘decoupling’ characteristics between urban haze pollution and economic growth. However, the mutual growth of haze pollution and economic growth has emerged in 44 central cities.

4. There is also significant heterogeneity of the EKC for industrial pollution between regions, with the ‘N-shaped’ nexus in the eastern and central regions, and an ‘inverted U shape’ in the western region. In addition, at the turning points of the ‘N-shaped’ curves, real per capita GDP reaches CNY 14,271 and CNY 52,470, respectively, in the eastern region; in the central region these are CNY 8,258 and CNY 33,928, respectively, while the turning point in the western region is CNY 438. Until 2018, 59 eastern cities, 57 central cities, and all western cities were in the stage of EKC for industrial pollution with a downward trend. However, mutual growth between industrial pollution and economic growth has occurred in 39 eastern and 43 central cities.
Table 7

Results of the dynamic Spatial Durbin Model (SDM) for haze pollution and composite industrial pollution.

<table>
<thead>
<tr>
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<th>(1)</th>
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<th>(2)</th>
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<tr>
<td></td>
<td>Full sample</td>
<td>Eastern region</td>
<td>Central region</td>
<td>Western region</td>
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<td>lnpm(-1)</td>
<td>0.3799***</td>
<td>0.2246***</td>
<td>-0.1574***</td>
<td>0.4769***</td>
<td>(0.0149)</td>
<td>(0.0245)</td>
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<td>w*lnpm(-1)</td>
<td>-0.2678***</td>
<td>-0.2004***</td>
<td>-0.1927***</td>
<td>-0.4010***</td>
<td>(0.0202)</td>
<td>(0.0302)</td>
</tr>
<tr>
<td>lnpollution(-1)</td>
<td>0.7535***</td>
<td>0.5668***</td>
<td>0.8315***</td>
<td>0.8177***</td>
<td>(0.0089)</td>
<td>(0.0135)</td>
</tr>
<tr>
<td>w*lnpollution</td>
<td>0.0982***</td>
<td>-0.1629***</td>
<td>0.8177***</td>
<td>0.0041</td>
<td>(0.0222)</td>
<td>(0.0285)</td>
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<td>Lnpcgdp</td>
<td>0.0196***</td>
<td>0.1218***</td>
<td>0.0032**</td>
<td>0.0041</td>
<td>(0.0082)</td>
<td>(0.0262)</td>
</tr>
<tr>
<td>(Lnpcgdp)²</td>
<td>-0.0017**</td>
<td>-0.0099**</td>
<td>0.0016**</td>
<td>0.0041</td>
<td>(0.0007)</td>
<td>(0.0024)</td>
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<tr>
<td>Control variables</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Spatial effect</td>
<td>0.8905***</td>
<td>0.2716***</td>
<td>0.8788***</td>
<td>0.0041</td>
<td>(0.0103)</td>
<td>(0.0195)</td>
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<tr>
<td>R-square</td>
<td>0.8641</td>
<td>0.8772**</td>
<td>0.8372</td>
<td>0.8434</td>
<td>(0.0592)</td>
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<tr>
<td>Observations</td>
<td>4350</td>
<td>4930</td>
<td>1515</td>
<td>1335</td>
<td>9450</td>
<td>9610386</td>
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<td>EKC pattern</td>
<td>Inverted U shape</td>
<td>Inverted U shape</td>
<td>Inverted U shape</td>
<td>Inverted U shape</td>
<td>N shape</td>
<td>N shape</td>
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Note: The asterisks *, **, and *** represent 1%, 5%, and 10% significance levels, respectively. The numbers in parentheses are the corresponding standard errors. (1), (2), (3), (4), and (5) denote the models with dependent variables of PM2.5 concentration, composite industrial pollution, industrial wastewater emissions, industrial SO₂ emissions, and SO₂ emission trading, respectively. Moreover, W1 and W2 represent the two different spatial weight matrices (i.e., the economic distance weight matrix and the economic-geographical distance matrix) introduced earlier.

(1) and (2) denote the models with dependent variables of haze pollution and composite industrial pollution, respectively.

At the city level, there is significant heterogeneity of the EKC for urban pollution between the pilot and non-pilot cities of environmental regulations. The PRT, low-carbon cities, and SO₂ emission trading system contribute to the earlier ‘decoupling’ between urban pollution and economic growth.

Regarding policy implications, the strategy of regional joint prevention and control provides a relatively effective approach due to the significant temporal and spatial autocorrelation of pollution involved. Due to the temporal and spatial differences in the stages of EKC, heterogeneous environmental policies are also recommended. At the national level, ‘decoupling’ between urban pollution and economic growth has emerged, except for industrial SO₂ emissions – thus, there is a need for more emphasis on its control. At the regional level, some eastern and central cities have experienced the mutual growth between haze pollution or industrial pollution and economic growth: there is a need for relevant regulations to be improved and strengthened in these two regions. It is empirically found that expenditure on science and technology has a significant reduction effect on pollution in the eastern and central regions, while an increase of urban green area is shown to be conducive to significant pollution reduction in the central region. Thus, local fiscal expenditure and policy support could present increase preferences for these aspects. Finally, the implementation of policies relating to PRT, low-carbon, and SO₂ emission trading in the eastern and central pilot cities need more attention, and more cities in the western region are recommended to establish and develop SO₂ emission trading systems. The considerations of regional joint control and the diverse effectiveness of regulations in either commanding (such as a low-carbon city) or marketing (such as the PRT and SO₂ emission trading system) way may also inform other (especially developing) economies with a rapid but unbalanced urban economic growth. Furthermore, the crucial role of technology development in increasing the ratio of efficiency to emissions has been examined and highlighted in better developed regions, which is believed to offset the ‘scale effect’ of growth on emissions.

Finally, there are some limitations in this study. For instance, the effects of environmental regulations (including ‘PRT’, ‘low-carbon city’, and ‘SO₂ emission trading’) on pollution abatement have been investigated and evaluated through the heterogeneity analysis between the pilot and the non-pilot cities. However, other regulations and the influencing mechanisms are expected for future study. It is expected that the mechanisms of how environmental regulations would affect pollution abatement from both efficiency and validity aspects should be investigated. Furthermore, except for industrial pollution and haze pollution, carbon emission is another critical subject in the domain of environment management. In this regard, for the common goal of realizing carbon neutrality, relevant research on EKC for carbon emissions and its heterogeneity is worthy of consideration in the future study.

CRediT authorship contribution statement

Li He: Conceptualization, Methodology, Software, Writing - original draft. Xiaoling Zhang: Supervision, Writing - original draft, Writing - review & editing, Funding acquisition. Yaxue Yan: Data curation, Methodology, Validation.

Declaration of Competing Interest

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

Acknowledgements

This work was supported by grants from the National Natural Science Foundation of China (grant numbers 71834005, 71673232); Research Grant Council of Hong Kong, China (grant numbers CityU 11271716); and Hong Kong CityU Internal Funds [grant numbers 9680195, 9610386]. The LISA maps are conducted with the assistance of WANG Jie (a joint Ph.D. student at the City University of Hong Kong and Renmin University of China) on the application of ArcGIS and is greatly
Appendix

Robustness check results

Considering that the increasingly widely-used SDM combines the settings and strengths of SLM and SEM, this study employs dynamic SDM for the robustness check. The results are shown in the following table.

Table 7 reveals that the empirical results and conclusions accord with those of the dynamic SLM. In other words, the findings based on both the full sample and regional subsamples are relatively robust.

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