March 2019

Working Paper

005.2019

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Economic Theory
Series Editor: Matteo Manera

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Summary

This paper examines the long-run relationship between income and urban air pollution using a joint distribution dynamics approach. This approach enables to estimate the transition process and long-run distribution and to examine the mechanisms behind the evolution process. The approach is applied to a unique panel data of CO2, SO2 and PM2.5 (particulate matter smaller than 2.5μm) for 286 Chinese cities over the period 2002-2014. Strong persistence in the transition dynamics suggests that this convergence process may require a long time. The distribution dynamics analyses indicate that multiple equilibria are the major characteristics in the long-run relationship between income and urban air pollution in China, which implies that inter-regional technology spillover may be an important way to accelerate convergence. Our results further support the existence of poverty-environmental trap in PM2.5 concentrations. Thus, new environmental models are expected to be developed to explain this new stylized fact. The findings provide strong support for taking more aggressive measures that consider income and urban environment simultaneously to reduce poverty and air pollutions together in the Chinese cities.

Keywords: Income, Urban Air Pollution, Poverty-environment Trap, Distribution Dynamics Approach, China

JEL Classification: O13, O44, Q43, Q53, Q56, Q58

This work is financially supported by the National Natural Science Foundation of China (grant Nos. 71874070, 71573258 and 71373055). Research results and conclusions expressed here are those of the authors and do not necessarily reflect the views of the grant providers. The authors bear sole responsibility for any errors and omissions that may remain.

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Does China Fall into Poverty-Environment Traps?

Evidence from Long-term Income Dynamics and Urban Air Pollution*

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Abstract: This paper examines the long-run relationship between income and urban air pollution using a joint distribution dynamics approach. This approach enables to estimate the transition process and long-run distribution and to examine the mechanisms behind the evolution process. The approach is applied to a unique panel data of CO_2, SO_2 and $PM_{2.5}$ (particulate matter smaller than 2.5μm) for 286 Chinese cities over the period 2002-2014. Strong persistence in the transition dynamics suggests that this convergence process may require a long time. The distribution dynamics analyses indicate that multiple equilibria are the major characteristics in the long-run relationship between income and urban air pollution in China, which implies that inter-regional technology spillover may be an important way to accelerate convergence. Our results further support the existence of poverty-environmental trap in $PM_{2.5}$ concentrations. Thus, new environmental models are expected to be developed to explain this new stylized fact. The findings provide strong support for taking more aggressive measures that consider income and urban environment simultaneously to reduce poverty and air pollutions together in the Chinese cities.

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This work is financially supported by the National Natural Science Foundation of China (grant Nos. 71874070, 71573258 and 71373055). Research results and conclusions expressed here are those of the authors and do not necessarily reflect the views of the grant providers. The authors bear sole responsibility for any errors and omissions that may remain.

1. Introduction

During the past two decades, the income-pollution relationship has attracted the attention of policymakers, theorists, and empirical researchers. Stern (2017) indicates that economic growth has increased both pollution emissions and concentration in the past decades. The income-pollution nexus has been examined in several strands of literature. The environmental Kuznets curve (EKC) has been the dominant approach among economists to model aggregate pollution emissions and ambient concentrations over the last decades. Since the EKC might mislead policy-makers to incorrectly de-emphasize environmental policy and instead pursue economic growth as a solution, thus more and more studies have thrown doubt on the idea that economic growth may eventually reduce environmental impacts (Carson, 2010; Kaika and Zervas, 2013; Chow and Li, 2014; Wagner, 2015). In recent years, convergence approaches provide further insight in the income-pollution nexus. A convergence effect predicts that higher initial levels of pollution are generally associated with slower growth in pollution. However, empirical studies have failed to reach conclusive results to reconcile the EKC and convergence literature (Stern et al., 2017). There is no theoretical or empirical consensus in the existing studies on the relationship between economic development and pollutant emissions (Jaforullah and King, 2015; Sanchez and Stern, 2016; Stern et al., 2017).

As the world second largest economy, China is confronting serious environmental deterioration in the last decades. China is now the largest greenhouse gas emitter in the world. Chinese cities have long been entangled with SO_2 emissions and acid rain. In 2013, 99.6 percent of China's population was exposed to $PM_{2.5}$ air pollution levels above the guidelines of the World Health Organization (WHO) (Brauer *et al.*, 2016). According to a report from the Asian Development Bank, more than 99 percent of the 500 county-level cities in China cannot meet the air quality standards of the WHO (Zhang and Crooks, 2012). However, the causes and consequence of urban air pollution in China are quite complicated. There is no consensus on the drivers of changes in urban pollution emissions and ambient concentrations in China. Different from most studies using a simple indicator of environmental pollution emissions or ambient concentrations, this paper uses CO_2 emissions, SO_2 emissions, and $PM_{2.5}$ concentration as environmental variables. This enables us to provide a comprehensive examination of the urban income-environment relationship.

This paper aims to examine the relationship between income and urban air pollution using a novel dataset for 286 Chinese prefectural-and-above (PAA) level cities over the period 2002-2014, which has never been used previously in any existing literature. We employ a combination of a new nonparametric joint distribution dynamics approach to provide a comprehensive picture of the relationship in the long-run.

This study contributes to the income-environment nexus in several important ways. First, the nonparametric approach enables us not only to reveal divergence/convergence trend among Chinese cities in the long-run, but also the formation of multiple equilibria, such as poverty and/or environmental traps, which are examined in a few theoretical and empirical studies (John and Pecchenino, 1994; Xepapadeas, 1997; Ikefuji and Horii, 2007; Mariani *et al.*, 2010; D'Alessandro *et al.*, 2010; Varvarigos, 2010; Bassetti *et al.*, 2013). Understanding the future distribution of urban air pollution can help policy-makers design better policy to accelerate convergence in urban air pollution. Second, this paper constructs a novel dataset for 286 Chinese PAA level cities. Due to the unavailability of urban air pollution data, most studies in the existing literature use provincial dataset, which is only approximately one tenth of the size of the PAA level cities. Large sample size guarantees the robustness of our parametric and nonparametric estimation results. Thus, our data set provides more research opportunities in a broad context. Third, given the fact that air pollution in Chinese cities is extremely high, our research on the heterogeneous relationship between income and three pollutions, namely CO_2, SO_2 emissions and $PM_{2.5}$ concentrations, provides valuable information for both the general public and policymakers.

We arrive at several interesting conclusions. First, our results show strong evidence for the existence of multiple equilibria in the long-run relationship between income and urban air pollution. Moreover, to the best of our knowledge, this paper is the first one that empirically proves the existence of poverty-environment trap (low income and high pollution), which has been predicted by some theoretical studies (John and Pecchenino, 1994; Xepapadeas, 1997; Ikefuji and Horii, 2007; Mariani *et al.*, 2010; D'Alessandro *et al.*, 2010; Varvarigos, 2010). Second, global and local pollutants show significant difference in the distribution dynamics in relation to income. This suggests that different environmental policies should be imposed upon these pollutants. Third, our results show strong persistence in the transition dynamics, indicating that this convergence process towards the stead state is very slow.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. Section 3 outlines the empirical methodology. Section 4 introduces data used in the paper. Section 5 presents the empirical results. Section 6 provides concluding remarks and policy implication.

2. Review of the related literature

The relationship between income and pollutions has been examined in three strands of closely related literature. This section provides a brief review of these literature.

The first strand is the EKC literature. The EKC is hypothesized to be an inverted U-shaped relationship between various environmental pollutions and income per capita. The EKC has been the dominant approach among economists to modeling pollution emissions and ambient concentrations after Grossman and Krueger (1991) first introduced the EKC concept in their study of the potential environmental impacts of the NAFTA (North American Free Trade Agreement). The drivers of the EKC can be decomposed into three effects, namely, scale, composition, and technique effects. These three proximate factors may be driven by variables such as environmental regulation, innovation policy, and even more fundamental variables. For example, Auffhammer *et al.* (2016) examine the channels through which the inflow of FDI and environmental regulations affects CO_2 emissions after decomposing CO_2 emissions into scale, composition and technique effects. However, the empirical evidence for the EKC effect is quite mixed. Many studies have found evidence for the EKC[†], while some other studies find a monotonically increasing

† Such as Stern and Common (2001), Brannlund and Ghalwash (2008), Halicioglu (2009), Iwata et al. (2010), Tamazian and Rao (2010), Jalil and Feridun (2011), Jayanthakumaran and Liu (2012), Ozturk and Acaravci (2013), Kasman and

impact of income on pollution.‡ There are also some studies that examine the existence of EKC in China. Yin *et al.* (2015) examined the EKC hypothesis in CO_2 emissions using a panel date for the period 1999-2011. Their results support the existence of EKC in China. Hao and Liu (2016) analyze the EKC in $PM_{2.5}$ using a dataset of 73 Chinese cities in 2013. They find evidence for the existence of EKC. Song et al. (2008) examined the EKC hypothesis using Chinese provincial data for the period 1985-2005. The results support the existence of EKC in waste water, waste gas and solid waste. In fact, the evidence for the EKC is sensitive to the selection of samples and econometric techniques (Stern, 2017). Relatively, local pollutants ($PM_{2.5}$, SO_2, etc.) are more likely to display an EKC relationship than global pollutants (CO_2 emissions, etc.) (Sanchez and Stern, 2016; Stern, 2017).

The second strand is the convergence analysis of pollution emissions and concentration. In recent years, convergence approaches to modeling pollution emissions and concentrations become more and more popular. The research on environmental convergence has been inspired by the economic convergence literature. The economic convergence hypothesis supposes that high income countries have low economic growth, while low income countries have high economic growth. This leads to the convergence in income level in the long-run. Similarly, the environmental convergence hypothesis proposes that pollution declines faster in high pollution countries than in low pollution ones. In some cases, high pollution countries have a decline trend, while low pollution countries have an increase trend. In the long-run, all countries would converge into similar environmental quality level. Bulte *et al.*, (2007) and Brock and Taylor (2010) provide basic theoretical frameworks for environmental convergence. The EKC hypothesis postulates an inverted U-shaped relationship between income and environmental pollutions. This implies that low income countries have a positive pollution growth, while high income countries have negative pollution growth. Thus the EKC hypothesis also predicts convergence in pollution emissions and ambient concentration. Correspondingly, the drivers of EKC are also the important factors that drive the convergence in pollution emissions and ambient concentration. Three types of convergence, namely, sigma-convergence, beta-convergence, and stochastic convergence, are most popularly examined in existing studies. Sigma convergence examines the dispersion of a variable in question over time using variance, coefficient of variation, or Gini coefficient. Bata convergence examines whether the growth rate of a variable in question is negatively correlated with the initial level. The stochastic convergence examines the evolution trend of the variable in question using cointegration approach.

The earliest studies (List, 1991; Strazicich and List, 2003) examine the environmental convergence, followed by many studies on both cross-national and cross-regional analysis on the convergences of various pollution emissions and ambient concentrations (Pettersson *et al.*, 2013). The empirical research on the convergence of cross-national CO_2 emissions shows evidence of convergence among developed countries, while evidence of persistence or divergence is found at the global level (Westerlund and Basher, 2008). Similar to the studies of the EKC, the results on the convergence of environmental variables are also affected by the choice of econometric approaches, samples, and statistical tests. Therefore, this empirical literature is far from being conclusive. Pettersson *et al.* (2013)

Duman (2015), Linh and Lin (2015), Tang and Tan (2015).

‡ Such as Shafik (1994), Akbostanci et al. (2009), Jaunky (2011), Esteve and Tamarit (2012a), Alkhathlan and Javid (2013), Azlina et al. (2014), and Jaforullah and King (2015).

provide a comprehensive review of the studies of convergence of CO_2 emissions. Although the convergence of CO_2 emissions is the most popularly studied topic in this literature, the environmental convergence analyses are also applied to a wide range of issues from NO_x (Bulte *et al.*, 2007; Ordás Criado *et al.*, 2011; Camarero *et al.*, 2013a), SO_2 (List, 1991; Bulte *et al.*, 2007; Nourry, 2009; Payne *et al.*, 2014), $PM_{2.5}$ (Stern and Zha, 2016; Stern and Van Dijk, 2017; Stern, 2017) and energy intensity (Markandya *et al.*, 2006; Mulder and de Groot, 2012; Herrerias, 2012). There are also some studies that focus on the environmental convergence in China. For example, Hao *et al.* (2015) examine the convergence of SO_2 emissions using a city-level panel data for the period 2002-2012. They find absolute and conditional convergence in per capita SO_2 emissions. Huang and Meng (2013) investigate the convergence of per capita CO_2 emissions for the period 1985-2008. They find convergence among provincial urban areas. Similarly, Zhao et al. (2015) find convergence in CO_2 emission intensity among 30 Chinese provinces for the period 1990-2010. Using a dataset of 50 Chinese cities for the period 2013-2014, Stern and Zha (2017) examine the convergence of $PM_{2.5}$ and PM_{10}. They find clear evidence of convergence with concentrations falling faster in more highly polluted cities.

Differing from the EKC and convergence literature, the third strand of literature focuses on the multiple equilibria in the long-run relationship between pollution emissions and income per capita. Many studies have shown that convergence clubs or multiple equilibria may exist in pollution emissions or ambient concentrations (Panopoulou and Pantelidis, 2009; Ordás Criado and Grether, 2011; Camarero *et al.*, 2013b; Wu *et al.*, 2016). Convergence clubs may be formed on geographical factors, income levels or a combination of several factors. Many studies found environmental convergence clubs among countries/regions with similar income levels (Ordás Criado and Grether, 2011; Bassetti *et al.*, 2013). Moreover, some studies (John and Pecchenino, 1994; Xepapadeas, 1997; Ikefuji and Horii, 2007; Mariani *et al.*, 2010; D'Alessandro *et al.*, 2010; Varvarigos, 2010) further indicate that there may exist a poverty-environment trap, in which countries remain persistently trapped in a state of low income and low environmental quality. Empirically, it is difficult to test the existence of a poverty-environment trap using traditional parametric approaches. The study of Bassetti *et al.* (2013) is one of few studies that examine the existence of poverty-environment trap using a discrete distribution dynamics approach. However, their results provide evidence for the existence of multiple steady states, namely, a poverty trap (low income and low pollution) and an environmental trap (high income and high pollution). They found no evidence for the existence of a poverty-environment trap in the long-run stationary state.

No conclusive results have been reached on the income-pollution nexus both theoretically and empirically in existing literature. There is still much scope for developing more reasonable dynamic models of the joint-evolution of the economic growth and pollution emissions. There is also scope for the empirical work to test alternative theoretical models and even to find new stylized fact.

3. Research methodology

Most early studies on the EKC and convergence have suffered from various statistical pitfalls (Wagner, 2008; Vollebergh *et al.*, 2009; Carson 2010; Kaika and Zervas 2013; Chow and Li, 2014; Wagner, 2015; Stern, 2010; Stern *et al.*, 2017; Stern, 2017). The conventional econometric techniques only provide information on the convergence behavior of an average or representative economy (Quah, 1996). However, they provide little information on how air pollutions of different cities evolve relative to each other in the long-run. They are silent on many crucial questions in the long run distribution of air pollutions in Chinese cities. For example, they shed little light on the catch-up and convergence among cities. It provides little information on the stratification and polarization in the long run steady distribution. In addition, traditional approaches seldom focus on the mechanisms behind the transition process and long-run steady distribution. To address these questions, one needs to know the entire shape of distribution dynamics of air pollution in the sample.

The distribution dynamics approach is developed mainly by Quah in a series of papers (Quah, 1993, 1996, 1997) to examine the long-run evolution behavior of income across countries. The distribution dynamics approach has several advantages over the traditional econometric approaches. First, the distribution dynamics approach is completely data-driven and thus can avoid the possible estimation bias due to model specification errors, which are common in traditional econometric approaches. Second, it uses a nonparametric kernel density approach to estimate the transition process and long-run distribution and thus can provide more insights on the law of motion in an entire distribution shape of the air pollution. Third, it can also be used to examine the mechanisms behind the evolution process, such as the formation of convergence clubs, EKC hypothesis, and policy effects. Thus it can provide comprehensive information on the multiple equilibria, polarization, persistence and poverty-environmental traps.

Let us use $f_t(x)$ and $f_{\mathrm{t+\tau}}(y)$ to denote the cross-city distribution of air pollution at time *t* and *t*+*τ*. Assuming that the evolution of the distribution is time-invariant and first-order, that is, the distribution of air pollution $f_t(x)$ at time *t* will evolve into the $\boldsymbol{\tau}$-period-ahead distribution of $f_{\mathrm{t+\tau}}(y)$ at time *t*+*τ*, where $\tau >$ 0. The relationship between the two distributions $f_t(x)$ and $f_{t+\tau}(y)$ can be described as follows:

$$f_{t+\tau}(y) = \int_0^\infty \mathrm{g}_\tau(y|x) f_t(x) \mathrm{d}x \tag{2}$$

where $g_\tau(y|x)$ is the conditional density function mapping the transition process of the distribution of air pollution across cities from time *t* to time $t + \tau$. For any *x*, we have $\int_0^\infty g_\tau(y|x)dy = 1$.

The long-run stationary (ergodic) distribution (denoted by $f_\infty(y)$) can be estimated as the solution to:

$$f_\infty(y) = \int_0^\infty g_\tau(y|x) f_\infty(x) dx \tag{3}$$

Most early studies in the literature use discrete distribution dynamics approach, which discretizes the variables into several state spaces (normally 5 or 7). As indicated in Quah (1997), Bulli (2001) and Johnson (2005), the process of discretizing the state space of a continuous variable is inevitably arbitrary and can change the revealed probabilistic properties of the data. Differing from the discrete distribution dynamics approach, this paper adopts a continuous distribution dynamics approach. This continuous approach estimates the transition probability and its ergodic distribution using a stochastic kernel density method. The joint natural kernel estimator of $f_{t,t+\tau}(y,x)$ and marginal kernel $f_t(x)$ can be defined as follows:

$$f_{t,t+\tau}(y,x) = \frac{1}{nh_x h_y}\sum_{i=1}^{n} K_x\left(\frac{x\text{-}x_i}{h_x}\right)K_y\left(\frac{y\text{-}y_i}{h_y}\right) \quad (4)$$

$$f_t(\mathrm{x}) = \frac{1}{nh_x}\sum_{i=1}^{n} K_x\left(\frac{x\text{-}x_i}{h_x}\right) \quad (5)$$

where x_i and y_i are the air pollution of the cities at time *t* and time $t+\tau$. n is the total number of cities. We use h_x and h_y to denote the bandwidth of *x* and *y* respectively, which are estimated with the adaptive method proposed in Silverman (1986). Then the conditional density can be estimated as follows:

$$g_\tau(y|x) = \frac{f_{t,t+\tau}(y,x)}{f_t(x)} \quad (6)$$

In the continuous distribution dynamics approach, the transition probability can be presented with three-dimensional surface plots and contour plots, in which the intra-distribution mobility is measured by the deviation from the 45 degree diagonal. Thus it can provide important information on convergence and persistence. In many cases, the aggregate transition tendency at each air pollution level is more informative. To provide information on the aggregate transition tendency of the distribution at each point, we further estimate the net transition probability (NTP) $\varphi(x)$ as follows:

$$\varphi(x) = \int_x^\infty g_\tau(z|x)dz \text{ - } \int_0^x g_\tau(z|x)dz \quad (7)$$

The net transition probability (NTP) provides the precise values of net upward probability at each point. Intuitively, a positive value of net transition probability at a given point suggests the increase of air pollution, while a negative value at the point implies the decline of air pollution. Thus a downward sloping NTP curve indicates net convergence of air pollution in the long-run, while an upward sloping NTP curve implies divergence of air pollution across cities. As the distribution dynamics approach examines the intra-distribution behavior, following common practices in this literature, this paper uses the relative value of air pollution (RAP), which is the air pollution of each city divided by its yearly average in the analysis. This normalization approach allows for results to be directly comparable from period t to period $t+\tau$, even if the cross-sectional mean of RAPs has changed over the two periods. That is, the distribution of the normalized urban air pollution shows how dispersed the urban air pollution values are from their mean regardless of the level of the cross-sectional mean.

The distribution dynamics approach enables us to investigate the long-run behavior of the relationship between urban air pollution and income per capita. If the ergodic distribution shows only one peak, we can conclude that the variable in question is converging towards a unique stationary equilibrium. On the contrary, the existence of multiple peaks in the ergodic distribution indicates the existence of multiple equilibria.

4. Data

This paper constructs a unique panel data of 286 Chinese PAA level cities for the period 2002-2014. There are 288 PAA level cities in total in China by the end of 2014. As most data for Lasa and Rikaze, the two cities in Tibet, are missing, our data set thereby includes 286 out of 288 PAA level cities (excluding Lasa and Rikaze). A substantial effort has been made to compile a consistent set of PAA-level data of gross city product (GCP), population, CO_2 emissions, SO_2 emissions, and $PM_{2.5}$. Nominal GCP is deflated to constant 2002 Renminbi Yuan using province-specific GCP deflators. Nominal GCP, population, and SO_2 emissions of each PAA city are directly sourced from China City Statistic Yearbook (NBSC, 2003-2015a)[§]. GCP deflators by province are taken from China Statistic Yearbook (NBSC, 2003-2015b).

$PM_{2.5}$ is very hazardous air pollution to human health (WHO, 2013). As indicated by Guan *et al.* (2014) and Zheng *et al.* (2017), $PM_{2.5}$ is the major air pollutant in Chinese cities. Thus this paper uses $PM_{2.5}$ as one of the air pollution indicators in Chinese cities. The official $PM_{2.5}$ data at the PAA city level are only reported after 2013 for partial cities. More importantly, the official data for particulate matters concentration is entangled with the problem of data manipulation (Ghanem and Zhang, 2014). Therefore, this paper uses the $PM_{2.5}$ data extracted from the grid data of global annual $PM_{2.5}$ grid from MODIS and MISR Aerosol Optical Depth.

No CO_2 emissions data are directly available for Chinese PAA level cities. Following Glaeser and Kahn (2010) and Zheng *et al.* (2011), we estimate total PAA level CO_2 emissions from four main sources: electricity, coal gas and liquefied petroleum gas, transportation, and heating. The China City Statistical Yearbook (NBSC, 2003-2015a) provides statistics on the consumption of electricity, coal gas and liquefied petroleum gas. However, it does not report energy consumed in transportation and heating.

Transportation accounts for a large share of energy consumption and CO_2 emissions in Chinese cities. No energy consumption or CO_2 emissions data of transportation is directly available at the PAA level cities. But China City Statistical Yearbooks provide data for freight traffic (ton-kilometer) and passenger traffic (passenger-kilometer) by road, railway, waterway, and aviation. Thus the total energy consumed in the transportation sector at the PAA level cities is estimated from freight traffic (ton-kilometer) and passenger traffic (passenger-kilometer) by road, railway, waterway, and aviation. The China Statistical Yearbook (NBSC, 2003-2015b) provides nationally aggregated data of energy consumption and traffic volume by transportation mode, which allows us to calculate the energy intensity

§ The industrial SO_2 emissions are the only available SO_2 emissions data at the PAA city level and they account for the majority of total SO_2 emissions. Thus we use industrial SO_2 emission as a replacement for total SO_2 emissions in a city.

of each transportation mode. Following Li *et al.* (2013), we can further estimate the PAA-level energy consumption data by transportation mode assuming uniform energy intensity by transportation mode nation-wide.

Heating is an important source of CO_2 emissions in China's total CO_2 emissions in the northern Chinese cities, especially in winter. In China, winter heating is officially provided between November 15 and March 15 in the following year in all cities northern to the Qinling Mountains–Huai River line. Winter heating is primarily provided through centralized heating systems that rely mostly on burning coal. The data on central heating by cities are collected from the China Urban Construction Statistical Yearbook (NBSC, 2003-2014c). Coal consumption for winter heating at the PAA-level is then estimated assuming a 70% thermal efficiency rate (AQSIQ, 2009).

With the energy consumption estimated above, we can further estimate the PAA-level CO_2 emissions from the consumption of coal gas, liquefied petroleum gas (LPG), fuel (transportation), coal (heating) and electricity using the IPCC reference approach (IPCC, 2006). Standard emission factors for coal gas, LPG, fuel, and coal were directly sourced from IPCC (2006). However, Chinese cities differ greatly with respect to natural resources that are used to supply electricity. Following Zheng *et al.* (2011), we thus use region-specific baseline emission factors to estimate CO_2 emissions from electricity consumption (NDRC, 2014). This approach takes into consideration the different portfolios of energy sources used in electricity generation across regions.

Table 1 Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
CO_2 emission intensity (ton/ten thousand RMB)	3718	1.314	1.265	0.200	25.045
pm_{25} (μg/m^3)	3718	53.481	22.929	6.500	118.600
SO_2 emission intensity (ton/ten thousand RMB)	3718	0.128	0.179	0.000	2.439
Income (ten thousand RMB per capita)	3718	2.000	1.597	0.169	12.833

Source：Authors own estimation.

5. The empirical results

5.1 The static distribution of urban air pollution in China

To examine the evolution trend of urban air pollution over time, Figure 1 presents the kernel density distribution of the three relative air pollution (RAP) variables in representative years. The distributions of CO_2 and SO_2 emission intensity are significantly right-skewed unimodal in our sample period. Most cities (87% for CO_2 emissions and 90% for SO_2 emissions) collect in the region with below 2 times of mean pollution level; and only a small number of cities scatter around the region between 2 to 10 times of mean pollution level. Strong persistence can be observed in the distributions of CO_2 and SO_2

emissions in the representative years. However, significant bimodality can be observed in the distributions of $PM_{2.5}$ concentrations in most of the representative years, implying the possible existence of convergence clubs at different $PM_{2.5}$ concentration levels. Approximately two-thirds of the cities cluster into the peak at 0.8 times mean value, while the remaining one-third situates around the peak at 1.5 times mean pollution value. In general, the distribution of CO_2 and SO_2 emissions are much more dispersed than that of $PM_{2.5}$ concentrations.

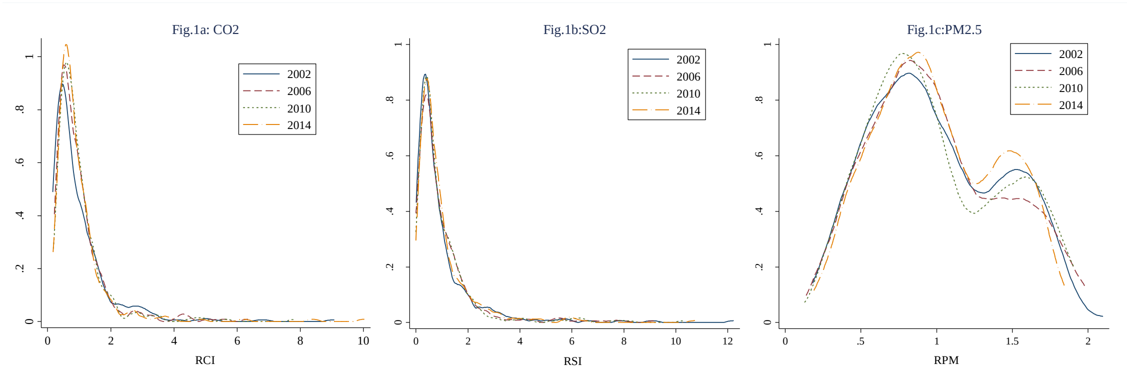

Figure 1 The distribution of air pollution in representative years for the period 2002–2014

Figure 2 presents the three-dimensional and contour plots of the joint distribution of the relative income (RI) and RAP for the 286 Chinese cities in the initial and final years in the sample period. We can observe that a major peak and a small peak exist in all three air pollution variables. Interestingly, the small peaks of CO_2 and SO_2 emission intensity locate in the high-income region with low pollution, while those of the $PM_{2.5}$ concentrations locate in the low-income region with high pollution. This may imply the existence of rich and clean city clubs in terms of CO_2 and SO_2 emission intensities, and poverty-environment trap in terms of $PM_{2.5}$ concentrations. This unveils the fact that cannot be revealed using the traditional econometric approach.

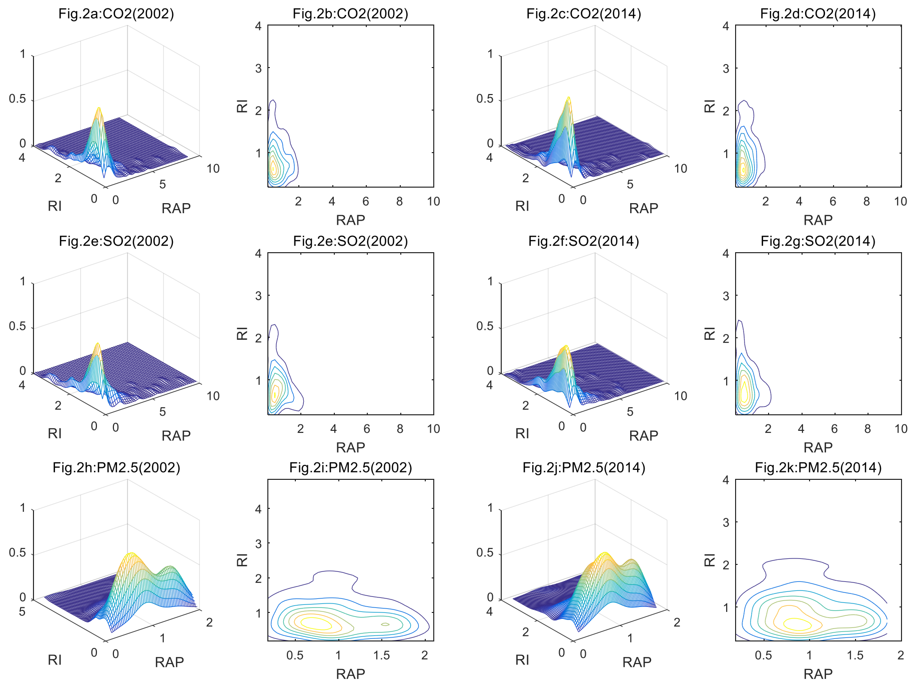

Figure 2 The joint-distribution of income and urban air pollution in 2002 and 2014

5.2 The distribution dynamics of urban air pollution over time

Figure 3 presents the distribution dynamics of three urban air pollution variables for the period 2002-2014. The contour plots in the first column of Figure 3 show the transition probability from *t* period to *t+1* period. To provide intuition, suppose that we choose a point 4 in axis marked *t* and slice the contour plot parallel to axis marked *t+1*, this slice indicates the probability density distribution of this city transition to other positions in the period *t+1*. Therefore, if the transition probability mass distributes along the 45 degree diagonal, this indicates a strong tendency of persistence in relative position changes. The distributions of urban air pollution for the cities tend to remain where they begin. On the other hand, the deviation from the diagonal indicates high mobility. The distribution of transition probability density parallels to the axis marked *t* indicates a tendency of convergence. This implies that the 'clean' cities become dirtier and the dirty cities get cleaner, and finally all cities cluster to the similar pollution level. We can observe that strong persistence existence in the transition probability of $PM_{2.5}$ concentration. However, for CO_2 and SO_2 emission intensity, the low pollution cities show strong persistence, while high pollution cities have high mobility in the intra-distribution dynamics.

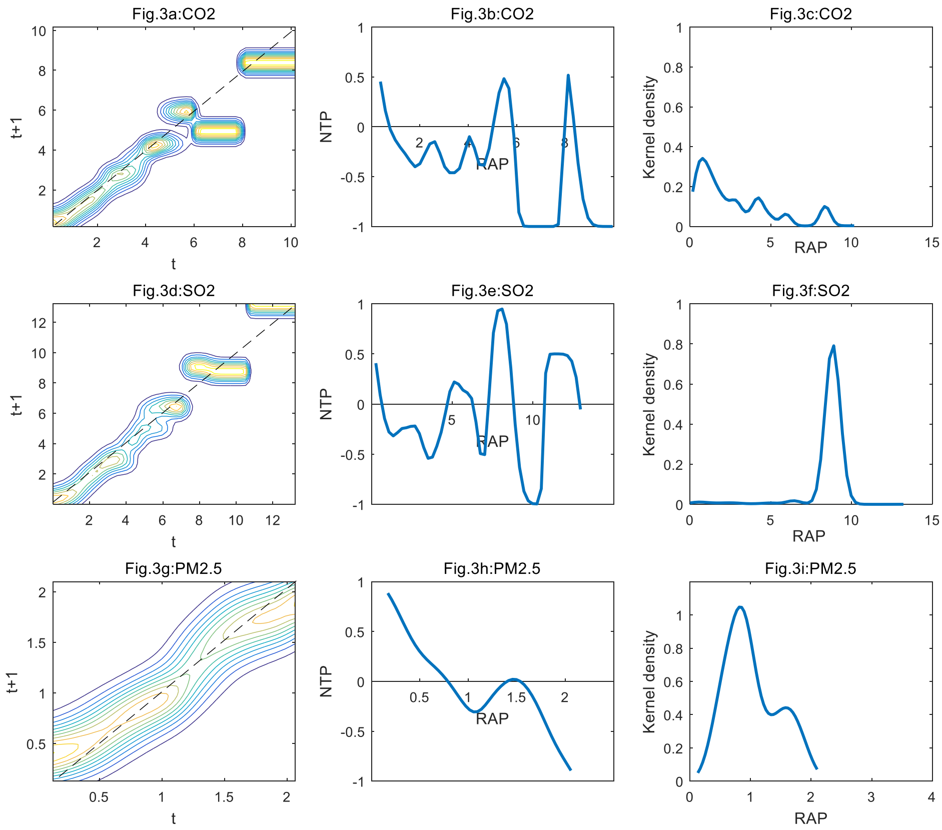

Figure 3 The distribution dynamics of urban air pollution, 2002-2014

The second column of Figure 3 shows the net transition probability (NTP) plot of the three urban air pollution variables. According to the NTP definition, the decline slope of the NTP curve indicates convergence of the variables in question. However, the NTP curves of CO_2 and SO_2 emissions are much complicated. No significant tendency can be implied from these two NTP curves. Therefore, net convergence exists only in $PM_{2.5}$ concentrations. Considering the strong persistence in the transition probability distribution, this convergence may require a long time.

The third column of Figure 3 presents the long-run (ergodic) distribution of the three pollution variables. The three pollution variables differ greatly in the shape of the long-run stationary distributions. Significant multimodality exists in the long-run stationary distribution of CO_2 emission intensity. This implies that keeping the current transition dynamics remains unchanged, Chinese cities will finally evolve into several distinctive clubs at different CO_2 emission intensity levels. However, the long-run stationary distribution of SO_2 emission intensity is unimodal, implying catch-up effect in SO_2 emission intensity. The long-run distribution of $PM_{2.5}$ is right-skewed bimodality, which is quite similar to the current distributions in Fig.1c.

5.3 The joint distribution dynamics of income and urban air pollution

In this subsection, we divide the 286 Chinese cities into three broadly equal groups according to the income in the final years, namely low-income cities (96), middle-income cities (95), and high-income cities (95).[**] Then we estimate the distribution dynamics results of the three pollution variables in the three income groups separately.

Figure 4 presents the distribution dynamics of CO_2 emission intensity in the three income groups. Salient heterogeneity exists in the distribution dynamics of CO_2 emissions among the three income city groups. Significant net convergence can be observed from the contour plots and NTP plots of the low- and middle-income cities. However, no evidence of net convergence can be observed from the transition dynamics of the high-income cities. This suggests the existence of multiple equilibria in the long-run stationary distribution of CO_2 emission intensity with respect to income.

Right skewed unimodality can be observed in the long-run stationary distribution of CO_2 emission intensity for the low-income cities (see Fig.4c). The mass of the long-run distribution of low-income cities concentrates in relatively low pollution region. The long-run distribution of CO_2 emission intensity for the middle-income cities (see Fig.4f) is significantly bimodal. Approximately 62 percent of the middle-income cities collect in the low pollution peak, and the remaining cities collect in the high pollution peak around 4 times average. The long-run distribution of the high-income cities (see Fig.4i) is multimodal, most cities (approximately 71 percent) cluster in the middle peak. However, a considerable number of high-income cities (approximately 26 percent) collect into the low pollution region around the average emission intensity level. This is consistent with the static joint distribution of income and CO_2 emission intensity in Figure 2. The results of long-run distribution in the three income city groups show that income is an important factor in the formation of convergence clubs in CO_2 emission intensity.

[**] The income range for three city groups are, low income, [0.661-2.178], 96 cities; middle income, [2.178-3.552], 95 cities; high income, [3.552-12.833], 95 cities, respectively. The incomes here are the real income based on 2002 prices.

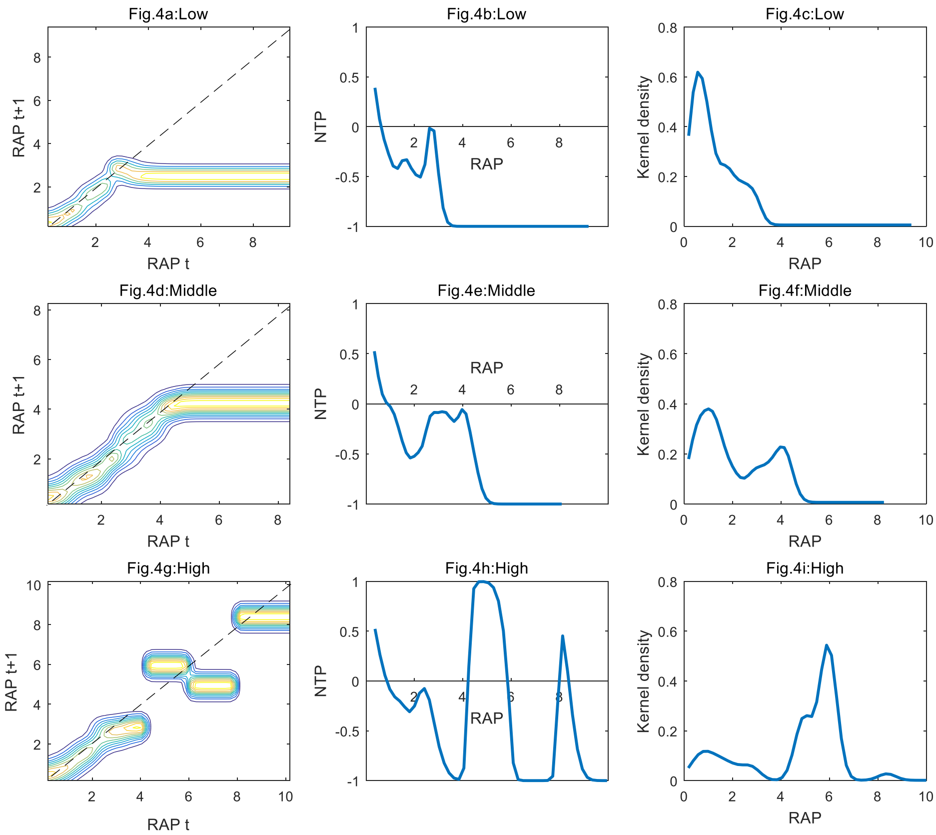

Figure 4 The distribution dynamics of CO_2 emission intensity in the three income city groups

Figure 5 presents the distribution dynamics of SO_2 emission intensity in the three income city groups. The contour plots show that there is more persistence in the low pollution cities than in the high pollution cities in all three income city groups. However, NTP plots for all the three income city groups have no simple decline or increase trend. Thus no evidence of net convergence or divergence can be implied from the NTP plots of the three income city groups. Multimodality can be observed in the long-run distribution of the low- and high-income city groups (see Fig.5c and Fig.5i). However, though two small peaks exist in the low pollution region, the long-run distribution of the middle-income cities is broadly right-skewed unimodal (see Fig.5f). Keeping the current distribution dynamics remains unchanged, the high-income cities will have relative low pollution in the long-run stationary state, while the middle-income cities will have high SO_2 emission intensity, and the low-income cities will be relatively more equally distributed. In general, the high-income cities tend to have lower SO_2 emission intensity than the other two city groups in the future. The middle-income cities tend to collect into high SO_2 emission intensity level. SO_2 emissions are local pollutant that affects most Chinese cities in the past decades. To reduce SO_2 emissions, the Chinese government has imposed stringent SO_2 emission and acid rain control policy (two control zones, TCZs) on the high SO_2 emission and acid rain regions. This policy has reduced SO_2 emissions in most high-income cities. However, the implication of this policy in the middle-income cities is much less stringent than in the high-income cities to reduce its impact on economic growth. Thus, future SO_2 regulation policy should focus on middle income cities and high SO_2 emissions cities in the low income group.

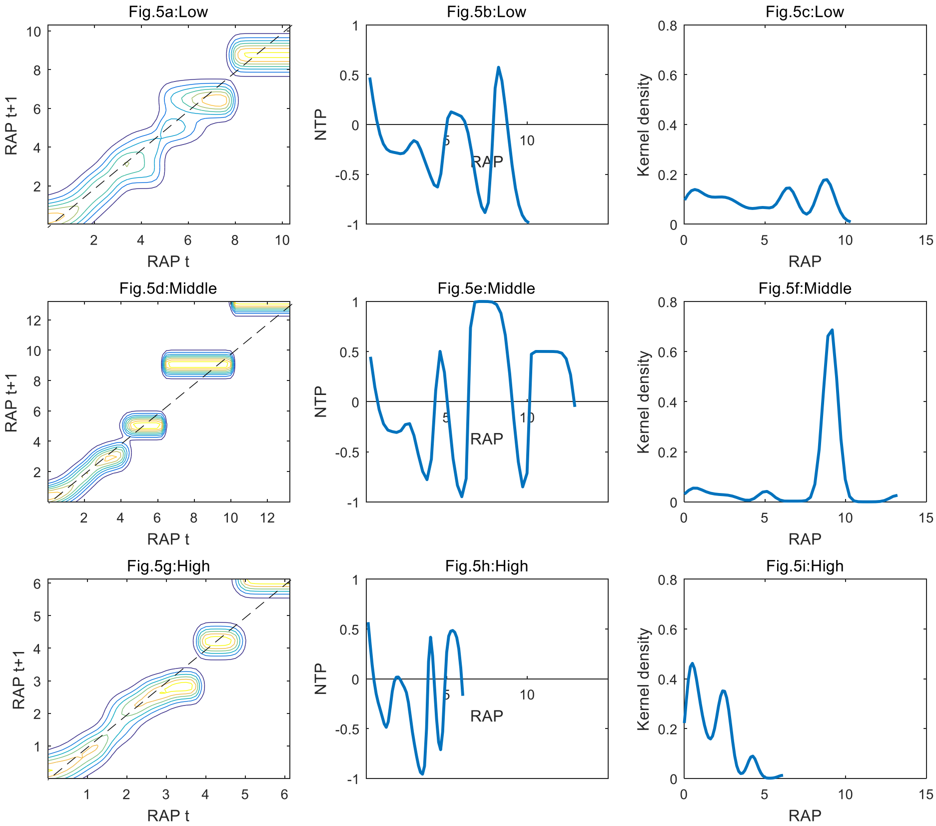

Figure 5 The distribution dynamics of SO_2 emission intensity in the three income city groups

Figure 6 presents the distribution dynamics of $PM_{2.5}$ concentration in the three income city groups. Strong persistence can be observed in the contour plots of $PM_{2.5}$ concentrations for all the three income city groups. The NTP plots in Figure 6 indicate that the three income city groups show significant evidence of net convergence in $PM_{2.5}$ concentration. Because the transition dynamics of the three income city groups show much less difference, the corresponding long-run stationary distributions of the three income city groups are similar to each other. This indicates that the distribution of $PM_{2.5}$ concentration may be less affected by income levels. More importantly, the high pollution in low-income cities in the long-run distribution of $PM_{2.5}$ concentrations and strong persistence in relative position changes may indicate the existence of poverty-environment trap among Chinese cities. Differing from the global pollutants such as CO_2 emissions, $PM_{2.5}$ concentrations are local pollutions that can easily scatter around with the wind. Unlike SO_2 emissions, the formation of $PM_{2.5}$ concentrations in China is much complicated and remains unknown. Poor cities may suffer heavily from their rich but high pollution emission neighbors. In fact, 32.9 percent of low-income cities have above average $PM_{2.5}$ in the long-run stationary distribution, while this number for the middle- and high-income groups are 39 and 35.3 percent, respectively. This result also indicates that $PM_{2.5}$ concentration may be a better measure of actual urban air pollution quality than CO_2 and SO_2 emissions.

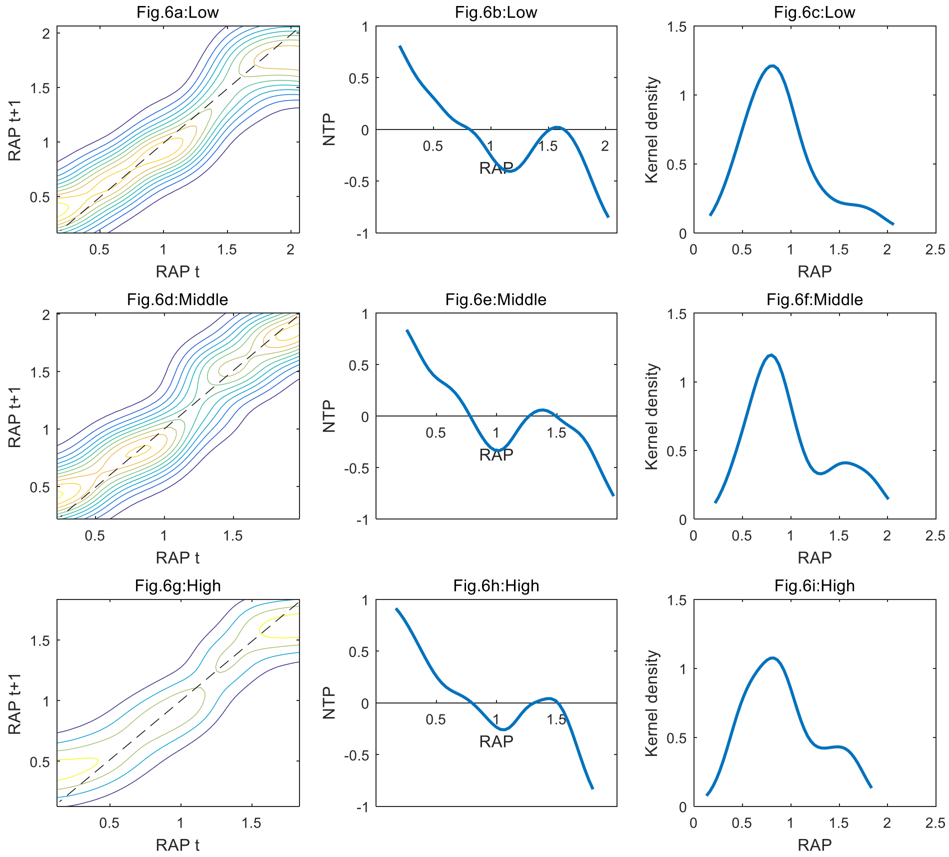

Figure 6 The distribution dynamics of $PM_{2.5}$ concentrations in the three income city groups

6. Conclusions and policy implications

This paper examines the long-run relationship between income and urban air pollution using a new nonparametric joint distribution dynamics approach. This facilitates us to provide more insights on the co-evolution behavior of income and urban air pollutions. We also construct a unique panel data set of three main urban air pollutions, namely CO_2, SO_2, and $PM_{2.5}$, for 286 Chinese PAA level cities for the period 2002–2014.

The results of distribution dynamics approach show that multiple equilibria exist in the relationship between income and urban air pollutions in Chinese cities. Chinese cities with different income levels show salient heterogeneity in the long-run evolution behavior in CO_2 and SO_2 emission intensity, but show little difference in $PM_{2.5}$ emissions. Rich and clean city club exists in terms of CO_2 and SO_2 emission intensities, while poverty-environment trap exists in $PM_{2.5}$ concentrations. This result has important theoretical implication. The existence of multiple equilibria suggests that environment theory faces the task of explaining this new stylized fact, and this is drawing attention anew to models of multiple equilibria rather than the traditional EKC paradigm.

Our results also have important policy implications. Urban air pollutions in China differ greatly in their evolution behavior with respect to income levels. First, the existence of poverty-environment trap in terms of $PM_{2.5}$ concentrations suggests that policy intervention must be taken to promote the economic growth and to reduce $PM_{2.5}$ concentrations in these cities. $PM_{2.5}$ is a pollutant that can easily spread to neighbor regions by the wind. Thus inter-regional coordination efforts should be made to combat $PM_{2.5}$ concentrations. Second, the existence of multimodality and poverty-environment trap in the long-run distribution suggests an unbalanced development. This is consistent with the judgment in the report of the 19th National Congress of the Central Committee of the Communist Party of China, which recognizes that, in the new era, the principal contradiction facing Chinese society is the contradiction between unbalanced and inadequate development and the people's ever-growing needs for a better life. However, the multimodality in the income and pollution distribution also shows a large potential for future air pollution reduction. This also underlines the urgent need for systematic and intense efforts towards less-polluting production technology. Moreover, encouraging inter-regional technological spillover may help reduce disparity in both income and air pollution.

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