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Impact of SO_2 Emission on the Gross Domestic Product Growth of China

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ABSTRACT

Applying a structural panel vector autoregression (VAR) model to panel datasets for 108 cities between 2000 and 2015, we evaluate the effect of SO_2 on China's gross domestic product (GDP) growth by calculating the costs associated with this pollutant and its health effects. The results indicate that SO_2 emissions promote GDP growth on a national scale but exhibit high regional heterogeneity in terms of cost. Specifically, although the costs exceed 20% in central China, implying that this environmental pollution contributes more than one-fifth of the GDP, and equal approximately 5% in western China, they have already begun to hinder economic growth in the eastern part of the nation. We also find that the health costs total approximately 2%, 3%, and 1% of the GDP per capita for the eastern, central, and western regions, respectively, revealing that rapid economic growth has been achieved at the expense of health.

Keywords: Structural panel VAR; Pollution costs; Health costs.

INTRODUCTION

China's industrialization initiated in the early 1980s has brought economic prosperity over the past decades (Zhang *et al.*, 2016). Meanwhile, a side effect has loomed out of the rapid growth: The air pollution has become ever more severe, which has attracted considerable attention from academics and government agencies across the world (Banister, 1998; Cai *et al.*, 2018; Wang *et al.*, 2018; Alonso-Carrera *et al.*, 2019; Lin *et al.*, 2019; Liu *et al.*, 2019). There is little disagreement that air pollution, as a factor to both respiratory and cardiovascular diseases, poses a major environmental risk to human health (Lee *et al.*, 2014; Abe *et al.*, 2018; Guttikunda and Jawahar, 2018; Hung *et al.*, 2018; Widiana *et al.*, 2019; Chen *et al.*, 2020). For example, Chay and Greenstone (2003) find a strong correlation between air pollution and mortality, where respiratory-related incidents usually increase as air quality deteriorates. Despite its direct effect on health, air pollution also exerts an indirect impact on economic development. As Bloom *et al.* (2004) point out, pollution leads to inflating medical costs, therefore reduces the capital available to production.

These findings prompt us to investigate the possible interactions among economic growth, industrialization, air pollution, and health in China. In particular, this paper tries to answer the question: *Given these interactions, how high price has China paid for its economic prosperity?*

To achieve that, this paper applies a structural panel vector autoregression (PVAR) model to measure the magnitudes of the costs. In contrast to cross-section, time series and single-equation panel data models, PVAR approach not only allows us to solve the endogenous problem, but also controls for the invisible time-invariant individual features. In doing so, this paper relates to a rapidly growing literature on the interaction between economic development, air pollution and health. The increase in energy consumption has boosted economic growth, but also increased pollution. This fact can be seen in Fig. 1 which shows four different energy consumption in China. Coal still contributes to over 60% of total energy consumption from 1978 to 2018, and this trend is probably to be persistent in the future (Liu *et al.*, 2016).

Accompanying the heavy consumption of coal, SO_2 emissions are inevitably correlated with coal consumption. Fig. 2 depict the unconditional correlation between coal consumption and SO_2 emissions at the national level as well as the separated area levels from 2000 to 2015. Along with the emissions of SO_2, mortality may also rise. From Fig. 2, the three areas display similar pattern in coal emissions nexus, but this result masks considerable heterogeneity. For instance, the degree of industrialization and intensity of environmental regulation in east and west are bound to be heterogeneous. Therefore, knowledge of the relationship between growth, industrialization, SO_2 emissions and mortality is of considerable interest. Figs. 3(a) and 3(b) report the relationship between mortality and SO_2 emissions for the whole country and central China, respectively. Clearly, these two variables are positively correlated in central China.

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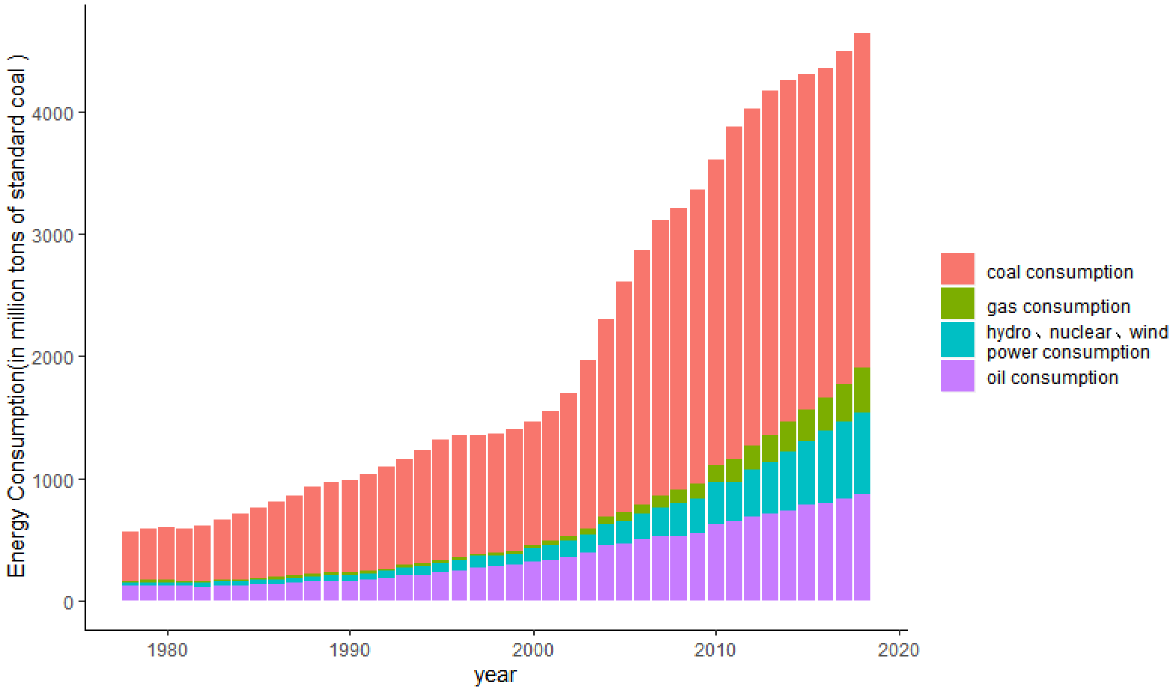


Fig. 1. Energy consumption. Source: National Bureau of Statistics of China.

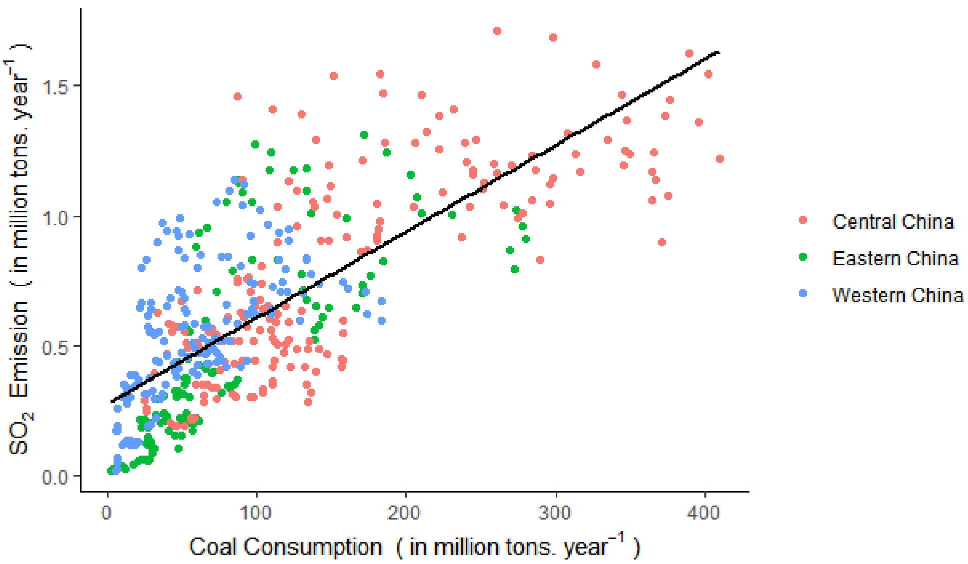


Fig. 2. Coal consumption and SO_2 emissions for the whole country (2000–2015). Source: National Bureau of Statistics of China.

Figs. 3(a) and 3(b) depicts the relationship between mortality and SO_2 emissions. A large number of epidemiological studies show that air pollution is harmful to human health (Lee *et al.*, 2011; Abe *et al.*, 2018; Guttikunda and Jawahar, 2018; Hung *et al.*, 2018), such as the occurrence of respiratory diseases directly caused by air pollution (Chen *et al.*, 2017; Abdolahnejad *et al.*, 2018). SO_2 is a common irritant that may cause diseases like bronchitis and bronchial asthma, leading to health damage (Hansell *et al.*, 2011; Cerón-Bretón *et al.*, 2018). SO_2 emissions, accompanying the increasing coal consumption, adversely affect health and enhance mortality. This can be reflected in Figs. 3(a) and 3(b), especially in central China, where SO_2 emissions increase and mortality increases.

Historically, many studies analyze the impact of air pollution on health. For example, Pope *et al.* (2002) find that SO_2 is significantly associated with mortality. Luechinger (2014) finds an elasticity of 0.07–0.13. Maji *et al.* (2017) show that environmental pollution in Agra is becoming increasingly serious and the burden of health economic costs is increasing. Abe *et al.* (2018) find environmental pollution (PM_{10}) has a significant impact on mortality burden of

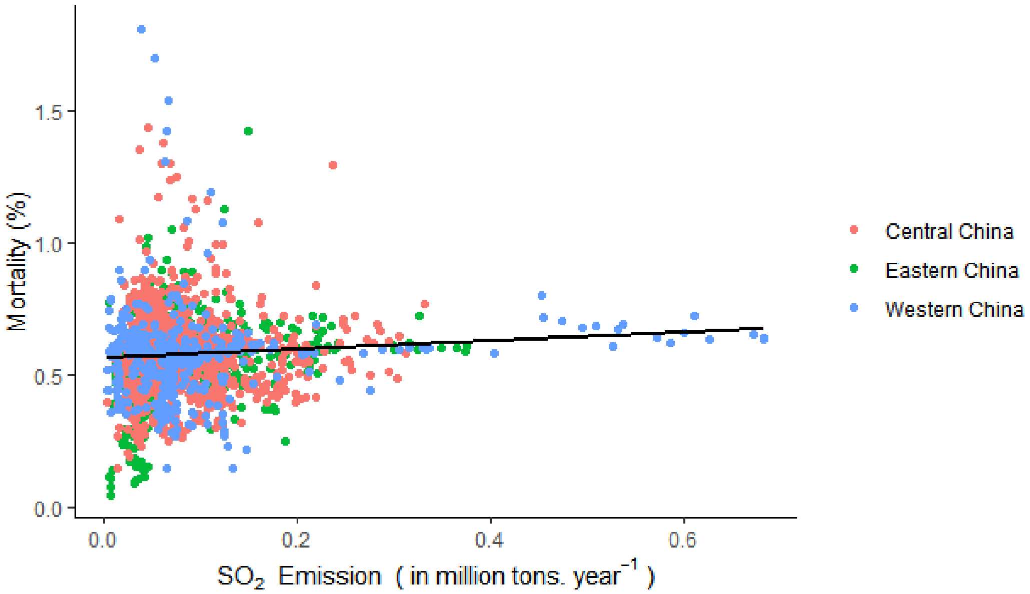


Fig. 3(a). Mortality and SO_2 emissions for the whole country (2000–2015). Source: National Bureau of Statistics of China.

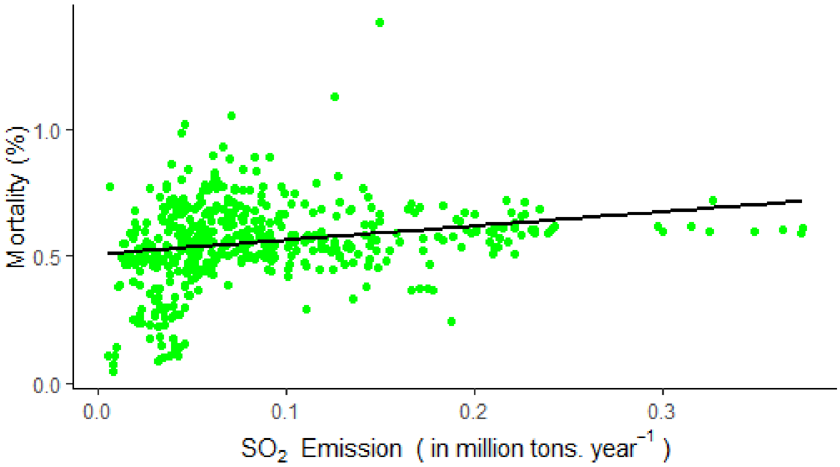


Fig. 3(b). Mortality and SO_2 emissions for central China (2000–2015). Source: National Bureau of Statistics of China.

cardiovascular and respiratory diseases. Zhou *et al.* (2020) find that, compared with $PM_{1\text{-}2.1}$ and $PM_{2.1\text{-}9.0}$ particles, $PM_{1.1}$ particles cause more serious harm to human health in China. Kao *et al.* (2020) show that $PM_{2.5}$ affects the neurodevelopment of infants in southern Taiwan. Vormittag *et al.* (2018) show that improving air quality can reduce government public health fiscal expenditure and save economic costs.

There are very informative literatures have analyzed the relationship between SO_2 pollution and mortality, but no conclusion has been reached. Some studies find positive effects (Joyce *et al.*, 1989; Bobak and Leon, 1992; Shinkura *et al.*, 1999; Bobak and Leon, 1999). The chronic effects from prolonged exposure are generally not significant (Chinn *et al.*, 1981; Woodruff *et al.*, 2008).

There are also many reviews analyzing the correlation between development and pollution. The inverted U-shaped relationship between environmental pollution and income per capita - now what we call the environmental Kuznets curve (EKC) is hotly discussed and empirically tested. The early studies are found to support the EKC hypothesis. While later, among various studies, such as Wagner (2015), Apergis (2016), and many others, reach mixed conclusions. The work of Shafik (1994) even indicate that rising income levels will increase pollutant emissions. Lee and Rosalez (2017) indicate that a high-energy price can improve the energy structure by inciting energy efficiency use and result in decoupling CO_2 emissions from economic growth. Cheng *et al.* (2019) show that the potential sources of CO_2 and SO_2 are similar, mainly distributed in poor countries or regions, such as India and Pakistan, and Inner Mongolia and Gansu and Guizhou Provinces in China.

An assessment of the existing literature suggests that most studies focus either on the nexus of development-pollution or pollution-health where little effort has been made to test these links under the same framework. This study is an attempt to fill the gap. China is the largest developing country in the world, and it has experienced both high growth, severe pollutant emissions and health costs in the past decades. Hence, this paper proposes a structural PVAR model to gauge the magnitudes of the pollution and health costs by examining the dynamic relationships between economic development, pollution and health.

This paper formulates and estimates a structural PVAR model using the generalized method of moments (GMM) by treating economic development, industrial structure, SO_2 emissions, and mortality as endogenous variables. This paper proposes a novel method to approximate the pollution and health costs, and the paper is arranged as follows. First of all, the basic structural PVAR framework including model specification and identification is introduced. And then, the data and empirical results are reported. Finally, the conclusion is summarized.

ECONOMETRIC METHODOLOGY

Model Specification

To analyze how economic growth and pollution affect health, Ruhm (2000), and Chay and Greenstone (2003) consider a fixed-effect panel data model:

$$H_{it} = \pi_1 E_{it} + \pi_2 P_{it} + \delta_t + \alpha_i + \varepsilon_{it} \tag{1}$$

where H_{it} is a proxy for health of individual i in period t, such as life expectancy or mortality; E_{it} is economic development, such as GDP per capita; P_{it} is a proxy for pollution, captured by the emissions of a specific pollutant; α_i is the individual fixed effect, δ_t is the time fixed effect, and ε_{it} denotes the idiosyncratic disturbances.

Eq. (1) is a static model, which fails to capture the simultaneous and dynamic effects of these variables. Coondoo and Dinda (2002) find that in Asian countries, pollutant emissions and income affect each other. Likewise, Xu *et al.* (1994) find that lagged deaths can explain current mortality in Beijing, China. As a result, when accounting for the pollution or health costs incurred by economic development, a static model like Eq. (1) will give rise to biased estimates.

To remedy this, this paper extends Eq. (1) to a structural PVAR model:

$$A\begin{pmatrix} S_{it} \\ P_{it} \\ E_{it} \\ H_{it} \end{pmatrix} = \sum_{l=1}^{k}\begin{pmatrix} \phi_{l,11} & \phi_{l,12} & \phi_{l,13} & \phi_{l,14} \\ \phi_{l,21} & \phi_{l,22} & \phi_{l,23} & \phi_{l,24} \\ \phi_{l,31} & \phi_{l,32} & \phi_{l,33} & \phi_{l,34} \\ \phi_{l,41} & \phi_{l,42} & \phi_{l,43} & \phi_{l,44} \end{pmatrix}\begin{pmatrix} S_{it-l} \\ P_{it-l} \\ E_{it-l} \\ H_{it-l} \end{pmatrix} + \begin{pmatrix} \alpha_i^S \\ \alpha_i^P \\ \alpha_i^E \\ \alpha_i^H \end{pmatrix} + \begin{pmatrix} u_{it}^S \\ u_{it}^P \\ u_{it}^E \\ u_{it}^H \end{pmatrix} \tag{2}$$

where the matrix A captures the contemporaneous relationship between the variables; u_{it}^S, u_{it}^P, u_{it}^E and u_{it}^H are the structural shocks to industrial structure, pollution, development and mortality, and are assumed to be orthogonal to each other.

Multiply both sides of Eq. (2) by A^{-1}, then:

$$\begin{pmatrix} S_{it} \\ P_{it} \\ E_{it} \\ H_{it} \end{pmatrix} = \sum_{l=1}^{k}\begin{pmatrix} \pi_{l,11} & \pi_{l,12} & \pi_{l,13} & \pi_{l,14} \\ \pi_{l,21} & \pi_{l,22} & \pi_{l,23} & \pi_{l,24} \\ \pi_{l,31} & \pi_{l,32} & \pi_{l,33} & \pi_{l,34} \\ \pi_{l,41} & \pi_{l,42} & \pi_{l,43} & \pi_{l,44} \end{pmatrix}\begin{pmatrix} S_{it-l} \\ P_{it-l} \\ E_{it-l} \\ H_{it-l} \end{pmatrix} + \begin{pmatrix} \mu_i^S \\ \mu_i^P \\ \mu_i^E \\ \mu_i^H \end{pmatrix} + \begin{pmatrix} \varepsilon_{it}^S \\ \varepsilon_{it}^P \\ \varepsilon_{it}^E \\ \varepsilon_{it}^H \end{pmatrix} \tag{3}$$

In matrix form, Eq. (3) can be rewritten as:

$$y_{it} = \sum_{l=1}^{k}\Pi_l y_{it-1} + \mu_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim (0,\ \Omega) \tag{4}$$

For the definitions of the variables, please refer to Appendix A.

To analyze the impulse-response functions (IRFs), transform the VAR(k) process into a structural vector moving average (VMA) model with infinite lags:

$$\begin{pmatrix} S_{it} \\ P_{it} \\ E_{it} \\ H_{it} \end{pmatrix} = \begin{pmatrix} \beta_i^S \\ \beta_i^P \\ \beta_i^E \\ \beta_i^H \end{pmatrix} + \sum_{p=0}^{\infty}\begin{pmatrix} \theta_{p,11} & \theta_{p,12} & \theta_{p,13} & \theta_{p,14} \\ \theta_{p,21} & \theta_{p,22} & \theta_{p,23} & \theta_{p,24} \\ \theta_{p,31} & \theta_{p,32} & \theta_{p,33} & \theta_{p,34} \\ \theta_{p,41} & \theta_{p,42} & \theta_{p,43} & \theta_{p,44} \end{pmatrix}\begin{pmatrix} u_{it-p}^S \\ u_{it-p}^P \\ u_{it-p}^E \\ u_{it-p}^H \end{pmatrix} \tag{5}$$

In compact form:

$$y_{it} = \beta_i + \sum_{p=0}^{\infty}\Theta_p u_{it-p} \tag{6}$$

Identification

Rewrite the error term in Eq. (3) as:

$$\begin{pmatrix} \varepsilon_{it}^S \\ \varepsilon_{it}^P \\ \varepsilon_{it}^E \\ \varepsilon_{it}^H \end{pmatrix} = \begin{pmatrix} B_{11} & B_{12} & B_{13} & B_{14} \\ B_{21} & B_{22} & B_{23} & B_{24} \\ B_{31} & B_{32} & B_{33} & B_{34} \\ B_{41} & B_{42} & B_{43} & B_{44} \end{pmatrix}\begin{pmatrix} u_{it}^S \\ u_{it}^P \\ u_{it}^E \\ u_{it}^H \end{pmatrix} \tag{7}$$

In matrix form:

$$\varepsilon_{it} = Bu_{it},\ Var(u_{it}) = I,\ BB' = \Omega \tag{8}$$

Here, $B = (B_{ab})$, a, b = 1, 2, 3, 4 is a 4 × 4 matrix with 16 unknowns, and $B = A^{-1}$. Since the covariance matrix Ω is symmetric, $BB' = \Omega$ induces only 10 equations about B_{ab}; in other words, 6 additional restrictions are needed to identify B.

To identify the shocks, this paper employs the Cholesky decomposition to ensure identification, namely, imposing a recursive structure on the matrix B. The basic rationales of the recursive identification scheme are that, first of all, the speed of the dynamic adjustment of industrial structure is slow, so that it reacts to economic development, SO_2 emissions and mortality shocks with a lag, hence setting $B_{12} = 0$, $B_{13} = 0$, and $B_{14} = 0$. Secondly, Bovenberg and Smulders (1996) argue that pollution does not increase in proportion to economic growth. Meanwhile, the direction of causality goes from pollution to mortality, rather than the opposite. These facts imply that economic development and mortality have subtle contemporaneous effects on pollution, so sets $B_{23} = 0$ and $B_{24} = 0$. Lastly, Bloom *et al.* (2004) show that improvements in health may increase labor productivity and the accumulation of capital, and then increase the output, implying that the effect of mortality on development may not be instantaneous. Therefore, $B_{34} = 0$.

In sum, this paper postulates that (i) development, SO_2 emissions and mortality shocks have no instantaneous effect on industrial structure, that is, $B_{12} = 0$, $B_{13} = 0$, and $B_{14} = 0$; (ii) development and mortality shocks have no instantaneous effects on SO_2 emissions, namely, $B_{23} = 0$ and $B_{24} = 0$; (ii) mortality shocks show no instantaneous impact on development, $B_{34} = 0$. This leads to a lower triangular matrix B which justifies Cholesky decomposition:

$$\begin{pmatrix} \varepsilon_{it}^{S} \\ \varepsilon_{it}^{P} \\ \varepsilon_{it}^{E} \\ \varepsilon_{it}^{H} \end{pmatrix} = \begin{pmatrix} B_{11} & 0 & 0 & 0 \\ B_{21} & B_{22} & 0 & 0 \\ B_{31} & B_{32} & B_{33} & 0 \\ B_{41} & B_{42} & B_{43} & B_{44} \end{pmatrix} \begin{pmatrix} u_{it}^{S} \\ u_{it}^{P} \\ u_{it}^{E} \\ u_{it}^{H} \end{pmatrix} \tag{9}$$

Bootstrapping Standard Errors

Due to the correlation between the lagged dependent variables in the panel VAR system, the standard errors of the estimated coefficients are not efficient. Therefore, this paper uses the bootstrap method to obtain the correct standard errors.

Denote p the lag order of the panel VAR model, T the total time periods, and $\hat{\varepsilon}_{it}$ the estimated residual from the reduced model:

$$y_{it} = \sum_{l=1}^{k} \Pi_l y_{it-1} + \mu_i + \varepsilon_{it}$$

Step 1: For each individual i, resampling with replacement for d times, generating a new bootstrap error series $\left\{\varepsilon_{it}^{d}\right\}_{t=p+1}^{T}$.

Step 2: Generate an artificial sample of the dependent variable $\left\{y_{it}^{d}\right\}_{t=p+1}^{T}$ according to the following equation:

$$y_{it}^{d} = \begin{cases} \hat{\mu}_i + \varepsilon_{it}^{d}, & t = 1 \\ \sum_{l=1}^{t} \Pi_l y_{it-1}^{d} + \hat{\mu}_i + \varepsilon_{it}^{d}, & 2 \le t \le p \\ \sum_{l=1}^{p} \Pi_l y_{it-1}^{d} + \hat{\mu}_i + \varepsilon_{it}^{d}, & t \ge p \end{cases}$$

Step 3: For each bootstrap sample $\left\{y_{it}^{d}\right\}_{t=p+1}^{T}$, estimate the following model by GMM:

$$y_{it}^{b} = \sum_{l=1}^{p} \Pi_l y_{it-l} + \mu_i + \varepsilon_{it}^{d}$$

Step 4: Repeat Steps 1–3 d times, a set of VAR coefficient estimates $\left\{\widetilde{\Pi}_1^{d}, \ldots, \widetilde{\Pi}_k^{d}\right\}_{d=1}^{D}$ is obtained. Use this bootstrap sample to calculate standard error for all the coefficients and the corresponding elasticities.

EMPIRICAL RESULTS

Data

Our original data covers 120 cites in China across the period 2000–2015. The variables used are collected from the National Bureau of Statistics, which is accessed via Qianzhan Database. 11 cities whose economic scale is too small are dropped; that is, each has a yearly average GDP less than 100 billion yuan. These cities are Yangquan, Zhangjiajie, Sanya, Haikou, Beihai, Panzhihua, Lhasa, Tongchuan, Shizuishan, Jinchang, Karamay. Furthermore, deleting Nanchong, as it is rich in oil and natural gas, violating our assumption that a city relies on coal as its energy source. These deletions result in 108 cities in our final sample.

To control the city heterogeneity, following the 7th Five-Year Plan initiated in 1986, dividing the sample into three parts, east, central and west, and label them as *Group* 1, 2, and 3, respectively. This classification was based on geography, but later approved by the government (Eastern China: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Shandong, Guangdong, and Hainan. Central China: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hunan, and Guangxi. Western China: Sichuan (and the later Chongqing), Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang).

Note that in terms of the volume of SO_2 emissions, cities in Hebei and Shandong are akin to the central provinces. Accordingly, the cities in these two provinces are grouped into the central group (Group 2). The final lists of cities and their geographical distribution are shown in Appendix B. In total, there are 30 eastern cities, 54 central cities, and 24 western cities.

Following previous empirical related studies, the following data are collected:

a. Industrial structure, S_{it}: In most of the literature, industrial structure is often measured by the proportion of the secondary industry in the GDP. China is experiencing rapid industrialization and urbanization to date, and the secondary industry is still the foundation of its economy. Meanwhile, the secondary industry consumes more than 70% of total energy, and it is the largest contributor to GDP. Hence, define S_{it} as the proportion of the secondary industry output in GDP.
b. Pollution, P_{it}: Chen and Xu (2010) and Tanaka (2015) show that three quarters of China's aggregate power are coal; hence, SO_2 is directly linked to coal combustion. According to National Bureau of Statics, SO_2 emissions are categorized by its sources, which include those from industry, agriculture, urban living, automobile, and

pollution abatement. However, only SO_2 from industry can be traced back to 1994. Consequently, P_{it} is defined as the log of industrial SO_2 emissions (originally in 10,000 tons) per capita.

c. Economic development (GDP), E_{it}: Following most of the literature, the real GDP in 2000 is used as an endogenous variable, and it is adjusted by the population of city i and taken logs.
d. Health, H_{it}: The log of mortality per 100,000 persons is used to proxy health. In the literature, many authors use infant mortality to proxy for health, but due to the availability of data, here the overall mortality is used.

Empirical Evidence

The first step describes the dataset employed, the presence of panel unit root using LLC test is conducted. The results are shown in Table 1. The nulls of panel unit root test are all highly rejected, indicating the variables are stable.

Next, employing the model selection criteria proposed by Andrews and Lu (2001). The results are shown in Table 2. Based on results of MMSC-AIC, MMSC-BIC, MMSC-HQIC, an order of one are appropriate for all the models.

Long-run Elasticity

As indicated above, the lag order of our PVAR model is one. The standard errors of the coefficients are obtained by bootstrap with 500 iterations, and the algorithm is detailed in Section *Bootstrapping Standard Errors*.

Table 1. LLC panel unit root test.

Variable	Test Statistic	p-value
S_{it}	–5.0802***	0.0000
P_{it}	–5.7461***	0.0000
E_{it}	–19.2616***	0.0000
H_{it}	–3.3780***	0.0004

Note: The null of LLC test is: For each city i, every time series contains a unit root.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Because development, SO_2 emissions and mortality are measured in logs, the coefficients in the VMA can be interpreted as short-run elasticity. Likewise, the sum of the VMA coefficients yields the long-run elasticity. For example, the development equation E_{it} can be approximated as:

$$E_{it} = \beta_i^E + \sum_{p=0}^{\infty}\theta_{p,31}u_{i,t-p}^S + \sum_{p=0}^{\infty}\theta_{p,32}u_{i,t-p}^P + \sum_{p=0}^{\infty}\theta_{p,33}u_{i,t-p}^E + \sum_{p=0}^{\infty}\theta_{p,34}u_{i,t-p}^H \tag{10}$$

Note that $\sum_{p=0}^{\infty}\theta_{p,31}$, $\sum_{p=0}^{\infty}\theta_{p,32}$, $\sum_{p=0}^{\infty}\theta_{p,33}$ and $\sum_{p=0}^{\infty}\theta_{p,34}$ can be explained as the long-run elasticity of industrial structure, SO_2 emissions, development and mortality on development, respectively. Table 3 reports the results from estimating Eq. (5). Note that here the numbers presented in Table 3 are cumulative effects that are transformed to one unit shock rather than one standard deviation shock. To do this, first calculate the estimates of the standard errors of the structural shocks, and then use the impulse response values to divide by these estimates.

Referring to the third row and the second column (GDP to SO_2) of Table 3, the income elasticity of pollution is negative across all regions: –1.15, –0.28 and –0.27 for eastern, central and western cities, respectively. This suggests that China may already be on the second stage of the inverted *U*-shape EKC, where SO_2 emissions reduce as the income goes across a high threshold value.

From Column 3 in Table 3, 1% increases in SO_2 emissions raises GDP per capita by –0.06 in the east, 0.92 in the central cities, and 0.20 in the west. This result indicates that central and western China is still at a stage that pollution can promote economic growth, but in the east, it seems that pollution already begins to hinder economic growth.

This result needs some scrutiny. In 1999, the State Council of China launched the Western Development Strategy, by which 11 policy-targeted provinces experienced quick growth

Table 2. Lag-order selection statistics for PVAR estimated using GMM.

East	MMSC-AIC	MMSC-BIC	MMSC-HQIC
1	–3325.7	–10,097.1	–6303.5
2	–3294.4	–9862.3	–6193.7
3	–3240.0	–9535.5	–6030.4
4	–3136.0	–9093.0	–5787.8
Central	MMSC-AIC	MMSC-BIC	MMSC-HQIC
1	–3299.8	–11,056.4	–6604.4
2	–3266.5	–10,807.8	–6492.6
3	–3199.5	–10,447.2	–6313.6
4	–3105.7	–9984.3	–7075.3
West	MMSC-AIC	MMSC-BIC	MMSC-HQIC
1	–3330.9	–9728.4	–6176.2
2	–3308.3	–9506.7	–6075.0
3	–3240.0	–9174.0	–5898.9
4	–3136.0	–8743.1	–5658.6

Table 3. Long-run elasticity.

Group 1	Industrial Structure (S_{it})	SO_2 Emissions (P_{it})	GDP (E_{it})	Mortality (H_{it})
Industrial Structure	1.8089*** (11.3493)	0.1018*** (6.6744)	–0.0885*** (–5.4443)	0.0026 (1.1486)
SO_2 Emissions	3.7996** (2.0461)	1.1719*** (7.1941)	–0.0587 (–0.2720)	–0.0015 (–0.0867)
GDP	–13.4434*** (–6.1476)	–1.1485*** (–5.5468)	1.7802*** (10.0136)	0.0042 (0.1240)
Mortality	–1.6892 (–0.3360)	–0.7598 (–1.7325)*	0.4010 (0.8000)	1.0119*** (10.2960)
Group 2	Industrial Structure (S_{it})	SO_2 Emissions (P_{it})	GDP (E_{it})	Mortality (H_{it})
Industrial Structure	1.0259*** (35.7336)	–0.0028 (–0.6545)	0.0290*** (5.5389)	0.0050*** (3.3872)
SO_2 Emissions	2.8852*** (5.5382)	0.7703*** (15.8248)	0.9181*** (8.1961)	0.0620** (3.2413)
GDP	0.0636 (0.1380)	–0.2793*** (–6.6910)	1.0571*** (28.8402)	0.0491** (3.0467)
Mortality	3.4100** (2.5166)	–0.0078 (–0.0572)	0.5322** (3.3123)	1.0354*** (14.6067)
Group 3	Industrial Structure (S_{it})	SO_2 Emissions (P_{it})	GDP (E_{it})	Mortality (H_{it})
Industrial Structure	1.1853*** (19.2177)	–0.0131 (–1.6114)	0.0460*** (5.8033)	0.0058** (2.4591)
SO_2 Pollution	0.8226 (0.9811)	0.9594*** (15.2107)	0.2001* (1.8789)	–0.0183 (–1.1279)
GDP	4.4868*** (4.9142)	–0.2700** (–3.2710)	1.1890*** (18.7063)	0.0272 (1.2864)
Mortality	3.2918 (1.2839)	–0.2670 (–1.5854)	0.1828 (0.8530)	1.0218*** (8.3032)
Total	Industrial Structure (S_{it})	SO_2 Emissions (P_{it})	GDP (E_{it})	Mortality (H_{it})
Industrial Structure	1.0495*** (12.4492)	0.0113 (0.7607)	0.0201 (1.1231)	0.0047 (0.3011)
SO_2 Emissions	2.4358 (1.2149)	0.8547*** (3.8085)	0.5265 (1.2704)	0.0200 (0.0537)
GDP	–0.8880 (–0.9748)	–0.4007*** (–3.8569)	1.0745*** (6.3796)	0.0336 (0.2093)
Mortality	3.4306 (0.9572)	–0.1469 (–0.1854)	0.3950 (0.4199)	1.0275* (1.6915)

Note: The *t* ratios in the brackets are calculated through bootstrap with 500 iterations.
* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

(Lu and Deng, 2011). However, central and western regions are historically endowed with low physical capital stock. In fact, in the 1990s, more than 50% of the total investment took place in eastern China, 28% in central and only 21% in western China. Meanwhile, the infrastructure in central and west is a heritage of the planned economic system, where efficiency and profits are not of top priority. Thirdly, China's development is compatible with the flying-geese model; that is, low-profit, high-energy-consuming, and labor-intensive industries tend to migrate from east to west. These factors force the central and western regions to adopt capital-saving technology that relied heavily on natural resources. Thus, pollution still plays a role in development.

Column 3 of Table 3 shows that 1% increases in mortality corresponds to a 0.4, 0.53 and 0.18 increase in income of eastern, central, and western China, separately. This implies that the health loss may play a positive role in economic growth.

Pollution and Health Costs

To gauge the pollution costs, first define a concept called *green GDP*. In economic sense, it is the GDP that eliminates the marginal contributions of the environmental (pollution) inputs. So, to quantify how "green" the economy is, the costs of being "non-green," the pollution costs, which are measured as a percentage of GDP need to be examined. Since $\sum_{p=0}^{\infty}\theta_{p,32}$ measures the long-run cumulative effect of the shock to environmental input (SO_2 emissions) on development, $\sum_{p=0}^{\infty}\theta_{p,32}P_{i,t-p}$ captures the increase in GDP brought by pollution costs across p lagged periods. The third line of Eq. (5) calculates the pollution costs as a percentage of GDP as follows:

$$Pollution\ Costs_{it} = \frac{\sum_{p=0}^{\infty}\theta_{p,32}P_{i,t-p}}{E_{it}} \tag{11}$$

Similarly, calculate a *healthy GDP* by eliminating the health loss from GDP. Since $\sum_{p=0}^{\infty}\theta_{p,34}$ represents the long-term effect of health shock on economic growth, $\sum_{p=0}^{\infty}\theta_{p,34}H_{i,t-p}$ represents the increase in GDP inflated by health loss across p lags. Accordingly, the health cost can be defined as:

$$Health\ Costs_{it} = \frac{\sum_{p=0}^{\infty}\theta_{p,34}H_{i,t-p}}{E_{it}} \tag{12}$$

The definitions above avoid assigning subjective prices to the calculations of pollution and health costs, implying that the results here may be more insightful. The results for pollution and health costs are shown in Tables 4 and 5, respectively.

From Table 4, the pollution costs of the eastern and central cities account for –0.3% and 26% of GDP, respectively. The small and negative costs in the east may reflect that the east is slowly transiting to a modern service economy. The high costs for central China may be that cities there still tend to adopt technologies that are more detrimental to environment.

Meanwhile, pollution cost of west is about 5%; it is comparable to the annual economic growth rate, showing that the west is still undergoing an underdevelopment process. These results are in line with the long-term elasticity presented in the second row of Table 3 (SO_2 emissions to GDP), where the elasticity is positive for central and western China, but negative for eastern China. Table 4 reflects the pollution costs in eastern, central and western China. For

Table 4. Pollution costs.

Panel A: Group 1—Pollution costs of eastern cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Beijing	–0.65	–0.12	–1.26	Yangzhou	0.11	–0.82	–0.31	Xiamen	–0.26	–2.24	–0.89
Tianjin	–0.11	0.12	–0.33	Zhenjiang	–0.29	0.81	2.49	Quanzhou	1.16	1.57	0.62
Shanghai	–0.02	–0.53	–0.56	Hangzhou	–0.09	–0.15	–0.22	Guangzhou	–1.06	–0.79	–0.41
Nanjing	–0.10	–0.10	–0.36	Ningbo	–0.65	0.38	–0.60	Shaoguan	0.25	0.64	–1.04
Wuxi	–0.16	–0.61	–0.35	Wenzhou	–0.77	–1.04	–0.20	Shenzhen	–0.64	–4.18	–0.42
Xuzhou	–0.50	0.39	–1.00	Jiaxing	1.07	–0.27	0.13	Zhuhai	–0.14	–0.28	–0.68
Changzhou	0.14	–0.75	–0.25	Huzhou	–0.44	–0.70	–0.15	Shantou	0.12	0.25	–0.25
Suzhou	–0.20	–0.28	–0.09	Shaoxing	–0.01	0.03	0.29	Foshan	–0.06	–0.51	–0.50
Nantong	–0.10	0.11	–0.14	Taizhou	–0.23	0.84	–2.49	Zhanjiang	–0.01	–1.21	–0.83
Lianyungang	–0.80	0.82	0.34	Fuzhou	0.83	–0.14	–1.61	Zhongshan	0.45	–1.31	–0.26
Average	–0.11	–0.34	–0.38			Average for three years: –0.28					

Panel B: Group 2—Pollution costs of central cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Shijiazhuang	29.12	27.65	23.32	Harbin	17.24	20.34	15.43	Kaifeng	22.50	40.6	19.66
Tangshan	34.95	33.86	28.76	Qiqihar	23.52	24.43	16.53	Luoyang	30.42	57.5	23.08
Qinhuangdao	28.86	30.58	27.27	Daqing	26.87	25.26	23.95	Pingdingshan	29.54	55.0	26.36
Handan	31.44	29.99	22.00	Mudanjiang	28.29	22.12	16.11	Anyang	31.16	57.1	29.70
Baoding	18.06	18.80	10.73	Hefei	16.35	17.81	15.32	Jiaozuo	24.75	47.4	22.69
Taiyuan	33.06	30.31	26.60	Wuhu	26.64	20.81	20.12	Sanmenxia	37.15	68.1	33.76
Datong	36.25	36.29	31.68	Maanshan	35.83	29.70	26.64	Wuhan	23.26	41.8	18.28
Changzhi	37.16	36.46	31.98	Nanchang	16.42	17.36	16.38	Yichang	26.39	49.0	23.59
Linfen	30.69	29.94	29.11	Jiujiang	31.22	29.26	24.17	Jingzhou	22.58	40.2	20.26
Huhehaote	36.12	33.13	29.65	Jinan	23.34	25.26	18.40	Changsha	12.31	23.5	8.21
Baotou	40.99	38.90	35.21	Qingdao	23.44	19.80	16.84	Zhuzhou	39.66	70.3	20.35
Chifeng	41.27	33.96	30.11	Zibo	35.70	34.78	30.53	Xiangtan	29.40	53.3	22.07
Shenyang	23.31	22.74	24.17	Zaozhuang	31.85	27.44	22.77	Yueyang	22.07	40.2	19.97
Dalian	25.84	26.63	21.84	Yantai	24.98	22.90	20.09	Changde	20.24	36.5	17.50
Anshan	31.32	31.36	29.70	Weifang	25.55	25.14	22.73				
Fushun	35.91	30.91	28.72	Jining	26.38	26.36	20.99				
Benxi	42.99	36.12	31.48	Taian	26.00	24.70	16.62				
Jinzhou	31.09	26.82	23.35	Weihai	26.71	24.95	19.13				
Changchun	19.55	20.15	17.41	Rizhao	29.25	28.67	21.06				
Jilin	24.40	27.89	24.20	Zhengzhou	29.65	25.10	24.78				
Average	28.70	27.15	22.99			Average for three years: 26.28					

Panel C: Group 3—Pollution costs of western cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Nanning	4.62	3.01	2.88	Guiyang	7.80	6.29	5.64	Lanzhou	6.25	6.83	5.85
Liuzhou	6.39	5.38	4.77	Zunyi	6.98	5.33	5.54	Xining	8.02	7.43	6.82
Guilin	5.27	4.39	3.55	Kunming	6.08	8.97	2.61	Yinchuan	5.08	7.87	6.04
Chongqing	6.97	5.91	5.25	Qujing	6.13	7.75	6.64	Urumqi	7.94	7.62	6.01
Chengdu	4.86	3.10	2.64	Yuxi	3.51	3.38	6.12				
Zigong	5.73	0.52	3.87	Xian	5.46	4.71	3.80				
Luzhou	5.34	5.61	3.49	Baoji	7.07	5.11	3.95				
Deyang	3.64	4.07	3.66	Xianyang	7.46	5.62	4.83				
Mianyang	4.75	4.18	3.84	Weinan	9.98	9.26	6.88				
Yibin	7.29	7.06	5.55	Yanan	4.21	4.23	3.73				
Average	6.12	5.57	4.75			Average for three years: 5.48					

Table 5. Health costs.

Panel A: Group 1—Health costs of eastern cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Beijing	1.68	1.41	1.39	Yangzhou	2.40	2.58	2.71	Xiamen	1.23	2.04	1.55
Tianjin	2.04	1.84	1.82	Zhenjiang	2.41	2.59	2.66	Quanzhou	1.71	2.27	1.68
Shanghai	1.88	1.65	1.55	Hangzhou	1.75	1.62	1.53	Guangzhou	1.55	1.57	1.72
Nanjing	1.91	2.30	2.04	Ningbo	1.93	1.58	1.40	Shaoguan	2.03	1.77	2.27
Wuxi	2.22	2.20	2.08	Wenzhou	1.90	1.74	1.64	Shenzhen	0.34	0.27	0.26
Xuzhou	1.63	3.06	1.42	Jiaxing	2.08	1.81	1.79	Zhuhai	0.93	0.80	0.87
Changzhou	2.17	2.45	2.24	Huzhou	2.05	2.00	2.19	Shantou	1.73	2.08	1.85
Suzhou	2.08	2.02	1.99	Shaoxing	2.25	2.11	2.03	Foshan	1.81	1.88	1.89
Nantong	2.79	2.67	2.73	Taizhou	1.95	1.93	1.79	Zhanjiang	1.99	3.02	2.38
Lianyungang	2.56	2.32	2.34	Fuzhou	1.94	1.84	1.53	Zhongshan	1.12	0.78	0.92
Average	1.87	1.94	1.81			Average for three years: 1.87					

Panel B: Group 2—Health costs of central cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Shijiazhuang	3.58	3.40	2.65	Harbin	2.57	3.17	2.23	Kaifeng	3.53	3.18	2.85
Tangshan	3.89	3.34	2.60	Qiqihar	3.41	2.05	2.35	Luoyang	3.36	2.67	2.99
Qinhuangdao	3.41	3.45	2.89	Daqing	2.27	1.46	1.43	Pingdingshan	3.56	3.06	2.65
Handan	6.03	2.76	2.37	Mudanjiang	2.60	4.84	2.04	Anyang	3.36	3.11	2.73
Baoding	3.90	3.28	2.46	Hefei	2.20	2.71	2.01	Jiaozuo	3.23	2.59	2.72
Taiyuan	2.21	2.27	2.15	Wuhu	3.97	2.42	1.51	Sanmenxia	2.85	2.45	2.04
Datong	2.43	2.47	3.01	Maanshan	2.85	2.33	2.37	Wuhan	2.71	1.96	2.70
Changzhi	3.71	3.18	3.37	Nanchang	3.42	2.89	1.79	Yichang	4.75	4.50	4.42
Linfen	2.23	4.18	1.60	Jiujiang	3.67	3.60	3.42	Jingzhou	2.90	2.23	1.50
Huhehaote	3.06	5.08	1.44	Jinan	3.72	3.21	2.99	Changsha	4.05	3.72	3.34
Baotou	2.62	2.37	1.53	Qingdao	3.72	3.28	3.17	Zhuzhou	4.05	3.76	3.63
Chifeng	3.62	3.28	2.46	Zibo	3.90	2.81	2.58	Xiangtan	4.09	3.88	3.66
Shenyang	3.93	3.13	2.73	Zaozhuang	3.32	2.75	2.08	Yueyang	4.08	3.88	3.72
Dalian	2.91	2.62	2.70	Yantai	4.18	3.41	3.27	Changde	4.13	3.87	3.80
Anshan	3.78	3.43	3.01	Weifang	3.78	3.40	3.08				
Fushun	4.20	3.79	2.96	Jining	3.32	3.49	2.67				
Benxi	3.87	2.97	2.55	Taian	3.88	3.55	3.10				
Jinzhou	4.17	3.10	3.00	Weihai	3.90	3.62	3.42				
Changchun	2.82	3.60	2.37	Rizhao	3.90	3.45	2.97				
Jilin	2.80	2.91	2.75	Zhengzhou	2.42	2.55	2.49				
Average	3.46	3.16	2.67			Average for three years: 3.10					

Panel C: Group 3—Health costs of western cities (%)

City	2007	2011	2015	City	2007	2011	2015	City	2007	2011	2015
Nanning	0.69	0.58	0.92	Guiyang	1.28	1.14	0.85	Lanzhou	0.73	1.05	0.70
Liuzhou	1.84	1.10	0.96	Zunyi	1.31	1.12	1.06	Xining	1.05	0.95	0.88
Guilin	0.89	1.15	0.95	Kunming	1.01	0.94	1.02	Yinchuan	0.91	0.72	0.62
Chongqing	1.33	1.20	1.23	Qujing	1.34	1.00	1.16	Urumqi	0.60	0.60	0.46
Chengdu	0.91	0.98	0.86	Yuxi	1.26	1.00	1.05				
Zigong	1.12	1.34	1.20	Xian	1.03	1.00	0.92				
Luzhou	1.41	1.33	1.24	Baoji	1.03	1.11	1.08				
Deyang	1.31	1.31	1.27	Xianyang	1.12	1.17	1.11				
Mianyang	1.00	1.27	1.21	Weinan	1.26	1.24	1.19				
Yibin	1.31	1.63	1.26	Yanan	0.96	1.06	1.05				
Average	1.11	1.08	1.01			Average for three years: 1.07					

clarification, we average the pollution costs of cities in the same province as the representative of the province, and then use a map to show it. Since the differences among 2007, 2011, and 2015 are not significant, we take 2015 as an example. Fig. 4 shows the pollution costs of 2015 in a much more visual way. It indicates that central and western China are still at a stage that pollution can promote growth and pollution costs are higher in central China, but in the east, pollution is small and negative, which means that it starts to hinder growth.

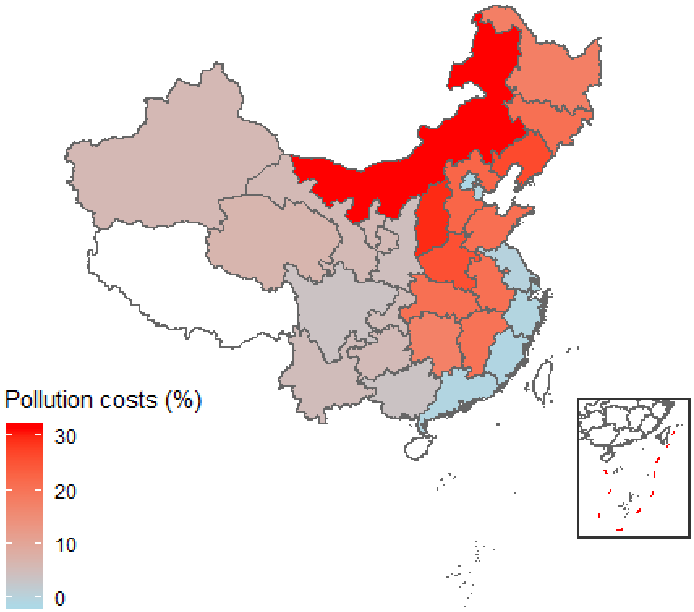


Fig. 4. Pollution costs (2015).

The main conclusions shown from Table 3 and 4 are as follows:

First, SO_2 emissions have promoted GDP growth. These promotions are more pronounced in central and western China, probably because central China has a higher degree of industrialization, mainly the secondary industry, and more resources and environment investment, so it has a greater effect on promoting GDP.

Second, the pollution costs of eastern, central and western China have large heterogeneities. The cost of pollution is highest in central China, reaching more than 20%, which implies that more than one-fifth of the GDP is contributed by environmental pollution. From the perspective of green GDP, its actual amount is only about four-fifths of the original GDP. In western China, pollution cost is about 5%, and the green GDP is about 95% of the original GDP. In eastern China, pollution cost is negative, which means that environmental pollution has a negative effect on economic growth, confirming that the cleaner the production methods, the higher the GDP.

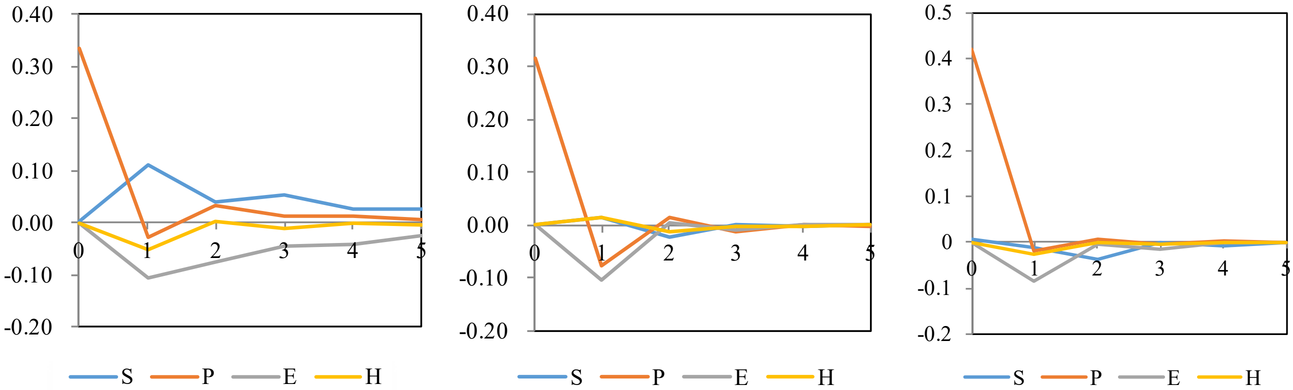
Turning to the health costs in Table 5, the specific numbers of the costs are about 2% for east, 3% for central region, and 1% for west, respectively. Obviously, east and central cities bear higher costs than the west, of which central region undertakes the highest. The reason may be that central region is undergoing industrialization, while east begins to go into the stage of post-industrialization. Both these processes need large physical capital stock and human capital, so that people there bear higher health costs. As regards to west, this region may still stay at the dawn of take-off stage in Rostow's sense. Due to the lake of capital stock and advanced human resources, the health costs are relatively small. This finding is also consistent with the results in Table 3.

Impulse Response Functions

Fig. 5 shows the IRFs of SO_2 emissions to shocks in industrial structure, pollution, development and mortality. When examining the impulse of development on SO_2 emissions, a negative reaction of SO_2 emissions to shocks in income is observed in all the three regions. This shows that the Chinese economy seems to be on the second stage of the EKC. This result reconciles with our long-run elasticity analysis in Section *Empirical Evidence*. Furthermore, we found that the largest effect of development on pollution occurs in eastern China. A possible reason is that people there are more conscious about pollution, and prone to put pressures on the local government when environment deteriorates. Western region, which is lagged in development, is less sensitive to the environmental issues.

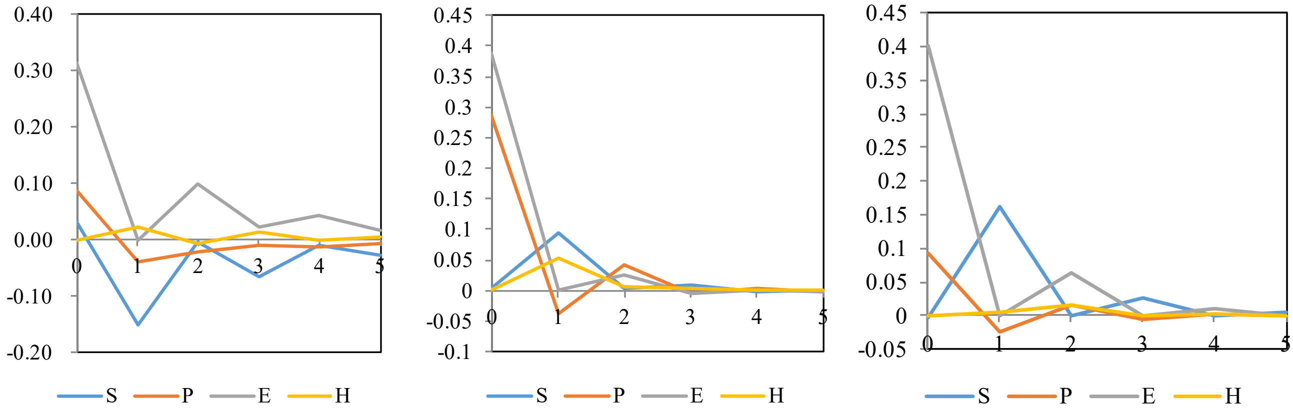
The impulse response function of mortality on SO_2 emissions shows that when there is a positive shock to mortality, SO_2 emissions decreases in east and west. In central China, the effect is a delayed one, with the SO_2 emissions initially increasing, before being affected negatively in a prolonged fashion. When comparing these results, SO_2 emissions decreases more to changes in mortality in the east than in central and west. This seems to be surprising at first glance, but it implies that the east is more concerned about health, the central cities are still at a stage to sacrifice health to exchange for development. For the west, it does not concern much about the negative relationship between mortality and pollution.

Fig. 6 plots the IRFs of development to industrial structure, pollution, development and mortality shocks at a five-year horizon. The response of income to a shock to pollution is negative in the east, though the effect is a delayed one. For the central and western region, following the shock in pollution, income decreases on impact, damping the positive effect and turning to negative. The negative effect reaches the smallest at the first year, and about six months later, it becomes positive in the subsequent years. Three years later, the effect reverts back to zero. Note that for the whole time



(a) (b) (c)

Fig. 5. IRFs of SO_2 emissions in eastern, (b) central, and (c) western cities.



(a) (b) (c)

Fig. 6. IRFs of economic development in (a) eastern, (b) central, and (c) western cities.

horizons, the pattern is quite similar across both the central and the western cities, although the impact of the lagged determinants on the level of development is smaller in the central cities than it is in the western cities. Thus, the findings support the notion that environmental factors are closely related to development. For the east, environmental inputs no longer drive development, but for the central and western region, environment still plays an positive role.

Next, the IRFs illustrate that a shock to development increases income for all the three regions, but the magnitudes of the effects are very different. The effect is largest in the east, and smallest in the central region. This result partly demonstrates that China is caught in the "rich get richer" trap (i.e., the Matthew effect). Furthermore, the unconditional convergence hypothesis seems to be rejected, as no sign of the poorest west converging to the wealthiest east is found. Despite these, there may exist a glimpse of hope. The poorest west is likely to converge to the middle-income central region, a sign of "convergence club." However, the central region shows no sign of converging to the east, a strong signal of middle-income trap.

In addition, the results suggest that the impact of mortality shock on development is positive in all the three regions, though the effect is very small. This result shows that the fast growth is at the expense of health in a way.

CONCLUSION

Our results indicate that SO_2 emissions promote the GDP in China, although the effect displays high heterogeneity between the western, central, and eastern regions. Whereas the costs of this pollutant total approximately 5% in the west, they surpass 20% (the national maximum) in the center, indicating that the latter still tends to adopt more environmentally detrimental technologies. In the east, however, the costs of SO_2 pollution are small or negative, demonstrating that this region is slowly transitioning to a modern service economy. We also find that the health costs total approximately 2%, 3%, and 1% of the GDP per capita for the eastern, central, and western regions, respectively, revealing that rapid economic growth has been achieved at the expense of health.

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SUPPLEMENTARY MATERIAL

Supplementary data associated with this article can be found in the online version at http://www.aaqr.org.

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