Volume 23, Number 3 – September 2021
China Accounting and Finance Review
中国会计与财务研究
2021 年 9 月　第 23 卷　第 3 期

One Size Fits All? Re-examining the Environmental Kuznets Curve of Eleven Pollutant Emissions in China*

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Received 20th of April 2021　Accepted 24th of May 2021

Abstract

Environmental protection is a complex issue. Different types of pollutants behave differently, and different locations may present different environmental problems. This is particularly true in China, which is a vast country with significant pollution problems that vary across regions. This study undertakes a comprehensive analysis of the emission levels of 11 environmental pollution indicators to provide evidence on the relationship between these 11 indicators and economic development in China, measured by per capita, applying the environmental Kuznets curve (EKC) hypothesis to data derived over the period 1999 to 2010. Our study also closely examines the data on the 11 pollutants in three regions of China to determine the presence of an EKC for each pollutant on a regional basis. Our results have important policy implications. We suggest that the best way to address China's complex and variable pollution problems is to supplement national environmental policy with policies that target specific regions and take into account both economic development and the emission levels of the specific pollutants present in each region.

***Keywords*: China, Pollution Indicators, Environmental Kuznets Curve**

* We would like to thank Prof. Albert Tsang (editor) and the anonymous reviewers for their helpful comments. We would also like to thank Kenn Webb, Shareholder of the law firm Ferguson Braswell Fraser Kubasta PC of Plano, Texas, for his valuable insights and editorial contributions.

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I. Introduction

Pollution is usually one of the biggest concerns for many countries and is particularly so for China, which has seen rapid economic development in recent decades. As a result, during the past decades, corporate social responsibility (CSR) performance, which measures firms' commitment to both environmental and social activities, has become a critical issue globally and is now a primary corporate governance concern and business practice for many firms. Research in accounting, business, and management generally finds a positive relationship between CSR and firm value (Dhaliwal *et al*., 2011; Dhaliwal *et al*., 2012; Chen *et al*., 2016; Radhakrishnan *et al*., 2018; Clarkson *et al*., 2019; Muslu *et al*., 2019; Liao *et al*., 2020; Ryou *et al*., 2020; Tsang *et al*., 2021).

Meanwhile, the empirical literature has investigated the relationship between economic growth and environmental quality. These studies are motivated by a desire to provide scientific evidence with important public policy implications. Among these studies, the environmental Kuznets curve (EKC) hypothesis has been extensively analysed (e.g. Dinda and Coondoo, 2006; Song *et al*., 2008 Tamazian *et al*., 2009; Pao *et al*., 2011; Shahbaz *et al*., 2012; Tiwari *et al*., 2013; Farhani *et al*., 2014; Apergis and Ozturk, 2015; Begum *et al*., 2015; Jebli and Youssef, 2015; Al-Mulali *et al*., 2016; Dogan and Turkekul, 2016; Liu *et al*., 2017; Liu *et al*., 2019). The EKC hypothesis states that the environment deteriorates during the initial stages of economic growth but improves once the economy reaches a level of development that is evidenced by higher personal income levels (Grossman and Krueger, 1991; Grossman and Krueger, 1995).

Studies using the EKC in China have been a heated topic of discussion in recent years as China is facing the challenges of accelerated economic growth and rapidly worsening environmental quality. Environmental deterioration and resource exhaustion are common problems in developing countries when those countries experience rapid economic growth. According to the World Bank, China's economy has enjoyed an annual growth rate of almost 10% in GDP since major economic reforms started in 1978. China's gross national income (GNI) per capita was $293 in 1985 and reached $10,410 in 2019 (World Bank). However, the fast-growing economy has come with significant costs, namely, overuse of natural resources and declining environmental quality. Total sulphur dioxide (SO_2) emissions in China, for example, were 23 million tons in 1995 and 25 million tons in 2005, the highest volume in the world at those times. Every year, over one hundred thousand Chinese people suffer from, and many die of, respiratory diseases. The serious air pollution problem has become a heavy burden to China's future sustainable economic development. The Chinese government did not pay serious attention to the problem until 2000. As pressure to address these environment issues increased, the Chinese government started implementing a series of environmental regulations. According to China's 13th five-year plan, the Chinese government aims to reduce carbon dioxide (CO_2) emissions per unit of GDP by at least 40% by 2020 compared to 2015 levels. In addition, under the Paris Agreement, which it signed in 2016, China has pledged to reach peak CO_2 emissions by 2030. Policymakers in China need more scientific evidence to develop effective policies to achieve these targets.

The results from the current literature are quite conflicting. According to the meta-analysis study conducted by Saqib and Benhmad (2021), 57% of the results from the current literature support the validity of the EKC hypothesis, while 43% do not. Dinda (2004) summarises prior studies and suggests that the EKC hypothesis applies only to environmental problems that are easy to resolve, well documented, and well known. He points out that the EKC hypothesis is valid for SO_2 and carbon monoxide (CO) emissions, but other pollutants follow either monotonicity or have an N-shaped relationship with economic development. Using a sample of many countries, Selden and Song (1994) find that SO_2 emissions per capita is a monotonic function of income; however, SO_2 emissions show an inverted U-shaped relationship to income when using a subsample of high-income countries. Taking diagnostic statistics and specification tests into account and using appropriate techniques, Perman and Stern (2003) reject the existence of an EKC in the case of SO_2 emissions and then cast doubt on the general applicability of the EKC hypothesis.

Studies applying EKC analyses in China also fail to reach a definitive conclusion. Yaguchi *et al.* (2007) compare emissions of SO_2 and carbon dioxide (CO_2), as well as energy consumption in Japan and China, for the last few decades, and they conclude that an inverted U-shaped EKC exists only in the case of SO_2 emissions in Japan, although they acknowledge that it is possible that China is on the flat turning portion of the EKC. Using China data, Liu *et al.* (2007) show that production-induced pollutants support the EKC hypothesis while consumption-induced pollutants do not. Li *et al.* (2016) find evidence in support of the EKC hypothesis in China for CO_2, waste water, and solid waste, and Riti *et al.* (2017) also find support for the hypothesis for CO_2 in China. More recently, Ahmad *et al.* (2021) confirm the existence of an EKC for CO2 at the aggregate level, but results for the provincial level vary. These inconsistent results make it hard for policymakers to make appropriate policy decisions.

In this study, we make two primary contributions to the literature. First, we analyse a comprehensive list of 11 emissions that represent the three major areas of pollution: air, water and solid waste. Second, we examine disaggregated data for each of three major regions in China to provide evidence to assist regional governments in developing policies targeted specifically to their regions.

The 11 emissions included in our analysis are (1) industrial waste gas emissions, (2) SO_2 emissions by industry, (3) SO_2 emissions by consumption, (4) soot emissions by industry, (5) soot emissions by consumption, (6) industrial dust emissions, (7) CO_2 emissions, (8) waste-water discharge from industry, (9) waste-water discharge from consumption, (10) solid waste by industry, and (11) solid waste by consumption. To the best of our knowledge, this is the first study to analyse the emissions of a comprehensive list of pollutants in China.

Carefully examining all the pollutants serves us in two ways. First, our findings provide more detailed information that the government can use to make effective environment policies that address more precisely the pollution problems presented by different pollutants. The key to solving any complex problem is having a thorough and nuanced understanding its causes. We need to understand the relationship between economic growth and the emission levels of each pollutant to find solutions for China's pollution problem since every pollutant has a different EKC. Indeed, after analysing the emission levels of seven pollution indicators to investigate the relationship between economic growth and the contribution of such indicators to air pollution, our results confirm that three of the indicators, CO_2, industrial SO_2, and industrial waste gas emissions per capita, show a statistically significant inverted U-shaped EKC relationship with GDP per capita.

However, the results show that these pollutants are in different stages according to our EKC analysis. For CO_2 and industrial SO_2, China has reached and passed its EKC peak and emissions are declining in relation to GDP per capita. Industrial waste gas emissions, however, are still on an upward trend, far away from reaching the EKC turning point. For the other four air pollution indicators, SO_2 emissions by consumption, soot emissions by industry and consumption, and industrial dust emissions, we find no significant relationship between per capita emissions of those indicators and GDP per capita. The policy implications from these results are clear: It is time for government to take serious action to control industrial waste gas emissions to reach the turning point more quickly and flatten the EKC, while for CO_2 emissions and industrial SO_2 emissions, our analysis shows that prior policies have taken effect and there is no urgent need to promote new policies. For the other four air pollution indicators, the policy implications are unclear and further research may be needed to provide guidance for effective policy decisions.

Our EKC analysis of the two water pollution indicators shows that industrial waste-water emissions are declining in relation to GDP per capita. Interestingly, however, consumption waste water does not show any sign of declining. It is important for the government to closely monitor consumption waste water and make new policies or revise prior policies to stop consumption waste water's upward trend. For solid waste pollution, our EKC analysis does not demonstrate any statistically significant relationship between GDP per capita and the two indicators we examined, per capita solid waste disposals by industry and by consumption. We suggest more research on this topic is necessary to provide evidence to guide near-term policy development.

In addition, applying an EKC analysis to each of the 11 pollutants enhances our study in that it helps explain the conflicting findings in the current literature. The findings of previous studies are variable and often ambiguous, which impairs the government's ability to develop precise and effective environmental policies. Since each pollutant has unique characteristics from an EKC perspective, examining the relative contributions by the individual pollutants can provide clear conclusions.

The second primary contribution of our study to the literature on the relationship between economic growth and environmental quality is our use of disaggregated data to provide evidence that each local government can use to develop environmental policies that address the specific circumstances of their region. To the best of our knowledge, this is the first study to analyse EKC at a regional level. As Xu (2018) points out, aggregation bias arises in EKC studies in China because results from disaggregated data fail to support conclusions reached using aggregated data. To alleviate the problem of aggregation bias, we divide the 30 provinces into three regions according to each province's geographical location and economic structures. Geographical location is the best and easiest proxy for industry type, which directly correlates with the presence of the specific environmental pollutants. With respect to economic structures, China is a vast country with uneven economic development across regions. As expected, our results show the following: The most EKC relationships between GDP per capita and the emission levels of the 11 studied pollutants are observed in the eastern region, which has the highest level of economic development; the fewest EKCs are observed in the western region, which has the lowest GDP per capita; and in the central region, which has the median GDP per capita, the number of EKCs observed is between the numbers of EKCs found in the other two regions.

A one-size-fits-all policy will not resolve China's pollution problems. It is important for each local government to understand the environmental problems that are characteristic of its region; only then will they be able to develop policies that effectively address each individual problem and, as a result, improve overall environmental quality.

The remainder of this paper is organised as follows: Section II presents our empirical model and data, section III discusses the results of our data analysis, and section IV summarises our study and concludes the paper.

II. Empirical Model and Data

Although there are a wide variety of specifications for the EKC, the basic model usually takes the following form: an indicator of pollutant emissions is the dependent variable; per capita income or GDP, its squared term, and a set of control variables are the explanatory variables.

$$EM_{it} = \alpha_i + \beta_1 \mathrm{GDP}_{it} + \beta_2 \mathrm{GDP}_{it}^2 + \sum \beta_k Z_{kit} + \varepsilon_{it}, \tag{1}$$

where EM represents per capita pollutant emissions, GDP_{it} is per captia GDP, t is the time index and i is the regional index, Z_{kit} denotes other control variables, and ε_{it} is the error term.

Instead of using the traditional fixed-effects model for panel data, we estimate the econometric model using the dynamic panel data estimator proposed by Arellano and Bond

(1991).[4] The advantage of using the dynamic panel data estimator is that it produces an unbiased estimator for panel data with short time periods, which is the case in this paper. In the dynamic panel data model, the lagged dependent variable is used as an instrument to address the potential endogeneity issue. Such specification is preferred since pollution is dynamic in the sense that current pollution level depends on its own past realisation.

$$\ln(EM_{it}) = \alpha_i + \ln(EM_{it-1}) + \beta_1 \ln(\mathrm{GDP}_{it}) + \beta_2 \ln(\mathrm{GDP}_{it})^2 + \beta_3 \mathrm{Trade}_{it} + \beta_4 \mathrm{Urban}_{it} + \beta_5 \mathrm{Energy}_{it} + \beta_6 \mathrm{EnvInv}_{it-1} + \varepsilon_{it}, \qquad (2)$$

where EM represents per capita pollutant emissions, GDP_{it} is per capita GDP, t is the time index and i is the region/province index, and ε_{it} is the error term.

We include the following control variables other than GDP: trade openness, denoted by *Trade* and measured by the total of exports and imports as a percentage of GDP; level of urbanisation, denoted by *Urban* and measured by the percentage of the population within province that lives in urban areas; energy consumption, denoted by *Energy* and measured by per capita electricity consumption; and environmental investment, denoted by *EnvInv* and measured as investment in pollution treatments as a percentage of GDP.

Per capita GDP and per capita emissions enter the model after natural log transformation. Also, we include environmental investment as a lagged variable for two reasons. First, it may take time for pollution treatment to make an impact on pollutant emissions. Second, decisions on environmental investment can rely on the emission levels of various pollutants; thus, including it as a lagged term can alleviate endogeneity.

Data in this paper are obtained mainly from the China Statistical Yearbook. Data on GDP, population, exports and imports, urban population, energy consumption, environmental investment, and 10 of the 11 pollutant emissions are collected for 30 provinces in China from 1999 to 2010 (excluding Inner Mongolia, Hong Kong, Macao, and Taiwan).[5] Due to the lack of official CO_2 emission data, we use the provincial CO_2 emission data published in Shan *et al*. (2018). The 11 pollutant emissions represent three types of emissions: air, water and solid waste. Table 1 provides descriptions of the 11 emissions, and Table 2 provides summary statistics for all the data. All emission, GDP, and energy consumption data are converted into per capita values.

Table 1 Variable Descriptions

Table 1 defines all the variables used in this study. Eleven emissions are classified into three categories: air, water, and solid.

Pollutant		Variable	Unit
AIR	*I-Gas*	Industrial waste gas emission	1000 m^3 per capita
	I-SO2	Industrial sulphur dioxide emission	Kg per capita

[4] Fixed-effects model estimation results are available upon request.

[5] Data on certain emissions are no longer collected after 2010, and thus our sample size is limited to 12 years of data.

	C-SO2	Consumption sulphur dioxide emission	Kg per capita
	CO2	Carbon dioxide emissions	Million tons per capita
	I-Soot	Industrial soot emission	Kg per capita
	C-Soot	Consumption soot emission	Kg per capita
	I-Dust	Industrial dust emission	Kg per capita
WATER	*I-Water*	Industrial waste water discharge	Tons per capita
	C-Water	Consumption waste water discharge	Tons per capita
SOLID	*I-Solid*	Industrial solid waste produced	Kg per capita
	C-Solid	Consumption waste collected	Tons per capita

Table 2 Summary Statistics

Table 2 presents the descriptive statistics of all the variables used in this study during the sample period of 1999 to 2010. Emissions, GDP, and energy consumption are per capita values. All the data except CO_2 come from the China Statistical Yearbook. CO_2 emission data are adopted from Shan *et al*. (2018).

Variable	N	Mean	Std Dev	Minimum	Maximum
I-Gas	360	24.95	21.87	4.48	257.90
I-SO2	360	15.80	9.90	2.42	57.95
C-SO2	360	3.43	3.58	0.00	22.91
CO2	356	178.24	136.33	8.10	766.60
I-Soot	360	7.00	5.08	0.75	27.12
C-Soot	360	2.24	1.96	0.00	8.59
I-Dust	360	6.47	4.44	0.42	31.14
I-Water	360	16.86	9.48	3.08	57.86
C-Water	360	23.41	15.89	6.29	98.56
I-Solid	360	16.64	34.04	0.00	224.00
C-Solid	240	0.13	0.08	0.04	0.39
GDP	360	17.12	13.91	2.46	78.33
Trade	360	62.84	80.78	6.08	368.96
Urban	360	45.27	15.58	21.71	89.30
Energy Consumption	360	0.27	0.18	0.05	1.17
Envir. Invt.	360	30.14	28.74	1.25	178.62

III. Results and Discussion

3.1 Main Model

We start our analysis with the results from our main model, which are shown in Table 3. In addition to the 11 individual pollutant emissions, we also consider total SO_2, soot, waste water, and solid waste, in each case from both industry and consumption. The autocorrelation (AR) tests at lag 1 shown in Table 3 confirm a serial correlation of order one, and thus including the lagged dependent variable is necessary. The AR tests at lag 2 suggest no serial correlation and thus no deeper lags are needed.

Table 3 Regression Results for National Data Set

Table 3 presents the results at national level from the dynamic panel data model on 11 emissions in year *t* as the dependent variable and with the lagged dependent variable *Lag(emission)* as instruments:

$$\ln(EM_{it}) = \alpha_i + \ln(EM_{it-1}) + \beta_1 \ln(\mathrm{GDP}_{it}) + \beta_2 \ln(\mathrm{GDP}_{it})^2 + \beta_3 \mathrm{Trade}_{it} + \beta_4 \mathrm{Urban}_{it} + \beta_5 \mathrm{Energy}_{it} + \beta_6 \mathrm{EnvInv}_{it-1} + \varepsilon_{it}$$

Standard deviations are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Variable	(1) I-Gas	(2) I-SO2	(3) C-SO2	(4) CO2	(5) I-Soot	(6) C-Soot	(7) I-Dust
Lag (emission)	0.087 (0.113)	0.658*** (0.067)	0.647*** (0.139)	0.530*** (0.163)	0.710*** (0.100)	0.570*** (0.094)	0.544*** (0.063)
ln(GDP)	1.047*** (0.305)	0.677*** (0.213)	0.190 (0.252)	0.728*** (0.159)	0.247 (0.169)	0.288 (0.244)	0.336 (0.299)
ln(GDP)2	-0.101** (0.039)	-0.136*** (0.032)	-0.094* (0.051)	-0.096*** (0.019)	-0.074** (0.029)	-0.064 (0.041)	-0.164*** (0.050)
Urban	0.000 (0.001)	0.001** (0.000)	-0.002** (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	0.001* (0.001)
Trade	0.024** (0.009)	0.005 (0.009)	0.014 (0.015)	0.008 (0.010)	0.006 (0.009)	0.017 (0.020)	0.027** (0.012)
Energy	0.388** (0.158)	0.233 (0.197)	0.911** (0.385)	0.339 (0.212)	0.255 (0.225)	-0.247 (0.560)	0.616** (0.273)
Lag (Env. Inv.)	-0.000 (0.001)	-0.001*** (0.000)	0.000 (0.001)	-0.000 (0.000)	-0.002*** (0.001)	0.001* (0.001)	-0.002** (0.001)
AR test (p-value)	0.103	0.382	0.191	0.163	0.263	0.774	0.344

Table 3 (Continued)

Variable	(8) I-Water	(9) C-Water	(10) I-Solid	(11) C-Solid	Total SO2 (2)+(3)	Total Soot (5)+(6)	Total Waste Water	Total Solid Waste
Lag (emission)	0.619*** (0.077)	0.292** (0.125)	0.148 (0.133)	-0.061 (0.142)	0.653*** (0.071)	0.684*** (0.088)	0.300* (0.157)	0.583*** (0.123)
ln(GDP)	0.243** (0.119)	0.392*** (0.121)	-0.344 (1.254)	-0.224 (0.170)	0.636*** (0.174)	0.327* (0.185)	0.294*** (0.112)	-0.495 (0.794)
ln(GDP)2	-0.077*** (0.019)	-0.030 (0.019)	-0.059 (0.285)	0.036 (0.037)	-0.123*** (0.025)	-0.072** (0.029)	-0.042** (0.017)	-0.068 (0.142)
Trade	-0.000 (0.000)	0.000*** (0.000)	-0.007 (0.005)	0.001** (0.000)	0.001** (0.000)	0.000 (0.001)	0.000** (0.000)	-0.005 (0.004)
Urban	0.008 (0.006)	0.001 (0.004)	-0.064 (0.069)	0.010 (0.006)	0.002 (0.006)	-0.007 (0.010)	0.004 (0.005)	0.015 (0.030)
Energy	0.637*** (0.154)	0.010 (0.095)	-0.673 (2.097)	-0.056 (0.462)	0.111 (0.167)	0.248 (0.182)	0.285*** (0.103)	0.683 (0.822)
Lag Env. Inv.	-0.000 (0.001)	0.000 (0.000)	0.004 (0.005)	-0.001* (0.000)	-0.001** (0.000)	-0.001* (0.000)	0.000 (0.000)	-0.002 (0.002)
AR test (p-value)	0.252	0.611	0.462	0.602	0.445	0.835	0.456	0.258

3.1.1 Air pollution

A total of seven air pollution indicators are considered, including CO_2, SO_2 (from industry and consumption), soot (from industry and consumption), industrial waste gas, and dust. SO_2 and CO_2 are the most important indicators monitored and regulated by most countries. Both gases are produced mainly by manufacturing facilities and coal-based power plants, and the latter are the main source of power in China. For both CO_2 and industrial SO_2 emissions, the coefficient of GDP is positive and the coefficient GDP-squared is negative, both being highly significant. This confirms the existence of a EKC for these two emissions, which is in accordance with previous literature. The turning points are 44,330 RMB ($6,926) and 12,049 RMB ($1,854) for CO_2 and industrial SO_2, respectively.[6] In 2020, GDP per capita in China was $10,504. This suggests that, in general, China has reached and passed its EKC peak in CO_2 and SO_2, and both emissions are expected to decline. However, given the vast difference in economic development across different regions of China, it is still possible that certain areas will see increased CO_2 and SO_2 emissions before these emissions can be expected to decline.

Among the remaining emissions, an EKC is confirmed only for industrial waste gas emissions. The turning point is 178,247 RMB ($27,422), which is still much higher than the current GDP per capita in China. The insignificant relationship between GDP and emissions such as SO_2 from consumption, soot and dust may reflect either that economic development has no significant impacts on those emissions or merely that economic development has not yet reached a level at which its impact on those emissions is reflected in an EKC.

3.1.2 Water pollution

For water pollution, we find an inverted U-shaped EKC for industrial waste-water emissions, with GDP and GDP-squared both being highly significant. The turning point is 4844 RMB ($745), which is well below the current GDP per capita. Thus, China has passed the turning point for industrial waste-water emissions and the overall level of emissions is declining with economic growth. In comparison, no EKC is found for waste water from consumption; instead, the positive and significant coefficient of GDP together with the insignificant coefficient of GDP-squared suggests that consumption waste water has been continuously increasing as China's economy grows. Additional policies or modifications of existing policies may be needed to better address the issue.

3.1.3 Solid waste

For solid waste, no EKC is found for either industrial or consumption emissions, as the coefficients of both GDP and GDP-squared are insignificant. It is possible that these results are inconclusive because economic development during our sample period is not high enough to demonstrate a significant relationship between GDP and solid waste emissions.

3.1.4 Total industrial and consumption emissions

Regardless of whether emissions are from industry or consumption, they are essentially

[6] Turning points are calculated as $TP = e^{-\beta 1/(2\beta 2)}$ since GDP is included in the model with natural log transformation.

the same emissions discharged into the environment. Therefore, we aggregate industrial and consumption emissions of SO_2, soot, waste water, and solid waste and consider them as the total emissions of each type.

We find an inverted U-shaped EKC for all total emissions except total solid waste. When considered individually, industrial or consumption soot emissions do not exhibit any U-shaped curve. However, when total soot emissions are examined, we do observe an EKC, which suggests that as a total discharge into the air, soot emissions increase during the initial stages of economic growth but gradually improve after the peak. In terms of total solid waste, instead of a U-shaped EKC, we find it to be monotonically increasing with GDP. Such a relationship calls for more stringent and specific environmental policies to better address increasing solid waste discharges.

3.1.5 Other control variables

The other control variables included in our model have limited effects on emissions:

- Trade shows positive and significant effects on six of the emissions. The positive effect could be due to the shift of polluting industries to developing countries like China.
- Urbanisation is in general positive and significant in two of the 15 regressions. Previous literature has shown mixed results in terms of how urbanisation can affect emissions. The positive effect found in our study may be due to the growth in population and an increase in the concentration of industry in urban areas (Panayotou, 1997).
- As expected, in accordance with previous literature, we found positive and significant effects of energy consumption on emissions in five of the regressions.
- Lastly, environmental investment shows negative and significant effects on six of the emissions. Such effects are expected as environmental investment is aimed at reducing pollution.

3.2 Regional Models

The data set includes data from all 30 provinces of China, which differ in terms of economic structures, development levels, and natural resources. Thus, it is reasonable to assume that different emission-development relationships exist in different regions. Therefore, we estimate the regional disparity by comparing results across three regions: eastern, central, and western China. The results are shown in Table 4. The “eastern” region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan, a total of 12 provinces along the coast. The “central” region includes Inner Mongolia, Jilin, Heilongjiang, Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan, a total of nine provinces. The “western” region includes Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang, a total of nine provinces. Heilongjiang and Jilin are treated as central provinces due to their production structures and levels of economic development instead of their geographical location. The divisions are basically in accordance with the official divisions, other than merging "north-eastern" into "central" due to their similar economic structures.

Table 4 Regression Results by Region

Table 4 represents the results at regional level from the dynamic panel data model on 11 emissions in year *t* as the dependent variable and with the lagged dependent variable *Lag(emission)* as instruments.

$$\ln(EM_{it}) = \alpha_i + \ln(EM_{it-1}) + \beta_1 \ln(\text{GDP}_{it}) + \beta_2 \ln(\text{GDP}_{it})^2 + \beta_3 \text{Trade}_{it} + \beta_4 \text{Urban}_{it} + \beta_5 \text{Energy}_{it} + \beta_6 \text{EnvInv}_{it-1} + \varepsilon_{it}$$

Standard deviations are reported in parentheses. *p<0.10, **p<0.05, ***p<0.01.

Variables	(1) I-Gas	(2) I-SO2	(3) C-SO2	(4) CO2	(5) I-Soot	(6) C-Soot	(7) I-Dust
Eastern (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan)							
ln (GDP)	1.750***	0.861***	1.734***	1.284***	-0.303	1.952***	0.700**
	(0.566)	(0.217)	(0.621)	(0.427)	(0.199)	(0.613)	(0.321)
ln (GDP)2	-0.199***	-0.174***	-0.360***	-0.164***	-0.014	-0.358***	-0.180***
	(0.074)	(0.035)	(0.117)	(0.050)	(0.030)	(0.085)	(0.041)
Central (Inner Mongolia, Jilin, Heilongjiang, Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan)							
ln (GDP)	0.808**	2.188***	0.052	1.408***	1.583***	0.280**	2.608***
	(0.348)	(0.382)	(0.178)	(0.485)	(0.325)	(0.142)	(0.581)
ln(GDP)2	-0.074	-0.390***	-0.068	-0.180**	-0.337***	-0.058*	-0.600***
	(0.054)	(0.060)	(0.043)	(0.074)	(0.049)	(0.035)	(0.097)
Western (Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang)							
ln (GDP)	0.272	0.385**	0.437	1.005***	-0.176	0.099	0.153
	(0.335)	(0.186)	(0.394)	(0.343)	(0.176)	(0.337)	(0.302)
ln (GDP)2	0.111	-0.122***	-0.164*	-0.153**	0.056	0.029	-0.118
	(0.086)	(0.045)	(0.099)	(0.068)	(0.062)	(0.079)	(0.100)

Table 4 (Continued)

Variables	(8) I-Water	(9) C-Water	(10) I-Solid	(11) C-Solid	Total SO2 (2)+(3)	Total Soot (5)+(6)	Total Waste Water	Total Solid Waste
Eastern (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan)								
ln(GDP)	1.229***	0.316**	-2.404	-0.044	0.811***	-0.283**	0.783***	-3.512***
	(0.318)	(0.145)	(1.930)	(0.281)	(0.197)	(0.138)	(0.186)	(0.943)
ln(GDP)2	-0.255***	-0.044*	-0.150	-0.021	-0.167***	-0.046	-0.112***	0.155
	(0.048)	(0.025)	(0.372)	(0.041)	(0.033)	(0.032)	(0.030)	(0.167)
Central (Inner Mongolia, Jilin, Heilongjiang, Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan)								
ln(GDP)	-0.032	-0.036	-0.085	-0.163	1.621***	1.203***	-0.013	1.590
	(0.313)	(0.127)	(2.287)	(0.526)	(0.356)	(0.300)	(0.182)	(2.563)
ln(GDP)2	-0.017	0.032	0.376	-0.010	-0.350***	-0.257***	0.012	-0.425
	(0.057)	(0.028)	(0.506)	(0.096)	(0.056)	(0.044)	(0.033)	(0.571)
Western (Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang)								
ln(GDP)	-0.015	0.391***	-0.024	-0.143	0.443**	-0.038	0.305*	2.415
	(0.141)	(0.135)	(1.530)	(0.401)	(0.215)	(0.237)	(0.171)	(1.963)
ln(GDP)2	-0.062*	-0.092**	-0.255	0.037	-0.132***	0.040	-0.078**	-0.838**
	(0.034)	(0.038)	(0.320)	(0.117)	(0.040)	(0.055)	(0.033)	(0.408)

For the eastern region, an EKC is found for most emission indicators. The only exceptions are industrial soot emissions and industrial, consumption and total solid waste. Such results are expected as the eastern region is fast growing with relatively high income per capita, and thus our sample can better capture the curve in the relationship. It is worth noting that although no EKC is found for total soot and total solid waste, these two types of emissions decline monotonically with economic development, as shown by the negative and significant coefficients.

The central region of China is usually considered to be in the middle in terms of economic development when compared with the other two regions. For the central region, an EKC is found for almost half of the emission indicators. Yet a concerning finding is that industrial gas emissions seem to increase monotonically with economic development for the central region.

Lastly, the western region shows the fewest EKC relationships. Only industrial SO_2, total SO_2, waste water from consumption, and total waste water show an inverted U-shaped relationship with GDP per capita. The lack of EKCs in the western region is not surprising as the region is still at a relatively low level of economic development. With China's economic policy focusing on the western region, we may observe declining emissions as the economy grows.

The findings of substantial differences across regions not only illustrates how the economy can impact emissions across different regions but also highlights the existence of regional disparities in China's economic growth in general. The fact that these economic disparities will not be fully resolved in the near term further emphasises the need for an increased focus on local environmental policies that address individual regions' specific needs in addition to the national level environmental policy. The cumulative effect of more effective local policies would contribute to improved environmental quality throughout China.

IV. Conclusions

In the economic development process of most developed countries, there seems to be a general rule—degradation then improvement in environmental quality with an increase in per capita income. However, not all developing countries follow this pattern. Environmental policies and regulations, particularly in the areas of natural resource exploration and production, are important factors in preserving and improving environmental quality. This is particularly true in China, which has unified authoritarian economic policies.

The inverted U-shaped EKC relationship to per capita income levels cannot be generalised for all types of pollutants. As shown in our analysis, there is not necessarily an inverted U-shaped relationship for all pollutants across all regions. The shape of the relationship depends on the nature of the pollutants, such as source and duration. Differences in economic structures also change the relationship between economic development and environmental quality. Since the Chinese economy is currently still at the low- to middle-income stage, most regions in China are on the rising section of the relationship curve. Perhaps more than any other factor, environmental policies established by governments often shape the relationship curves greatly. Given the variation in economic development levels and in the relationships between income levels and the emission levels of various pollutants across regions, it is critical to have environmental policies targeting specific regions that take into account a region's economic growth rate and per capita income levels and address the pollutants present in the region individually.

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