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Research paper

Reexamining the relationships among urbanization, industrial structure, and environmental pollution in China—New evidence using the dynamic threshold panel model

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ABSTRACT

Since China's reform and opening up, the urban economy has substantially developed, and the nation's urbanization process has advanced to gradually enter a "new normal" phase. In this process, China's population and industries continue to inundate its cities, and environmental pollution has become a critical problem. This study uses panel data spanning 1998 to 2015 from 29 Chinese provinces and a comprehensive framework of well-designed generalized method of moments (GMM) models to accurately examine the relationships between urbanization and per capita sulfur dioxide (PSO_2), per capita industrial soot (PSOOT), and per capita industrial waste gas (PIWG). A newly developed dynamic threshold panel model that incorporates GMM characteristics is utilized to explore how urbanization affects environmental pollution under different industrial structures. This study finds evidence of a comprehensive relationship among urbanization development, the industrial structure, and environmental pollution. Urbanization has contributed to increased environmental pollution. A nonlinear relationship exists between urbanization and environmental pollution in China. Further, urbanization increasingly promotes environmental pollution with an increase in the proportion of secondary industries; however, such promotion decreases with an increase in the proportion of tertiary industries.

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1. Introduction

With progressive urbanization, China's economy has continuously developed in recent years. However, its population and industries have inundated its cities, with more energy and resources consumed, and environmental pollution has become increasingly serious. China's sulfur dioxide (SO_2) emissions and soot or dust emissions were approximately 18.59 and 15.38 million tons in 2015, respectively, according to China's *Statistical Yearbook*. Although these pollutants have decreased since 2014, their emissions levels have remained high (Fig. 1). Clearly, the contradiction between urbanization and environmental pollution has brought significant challenges to China's economic and social development. However, the nation's economic development still relies more on an extensive growth model that includes high energy consumption, emissions, and pollution. The secondary sector, especially the manufacturing industry, accounts for a substantial part, while the tertiary sector accounts for a low percentage of the nation's development, with an unreasonable industrial structure. Nevertheless, industrial institutions closely relate to urbanization, economic growth, and environmental pollution. Therefore, this study explores whether adjusting the industrial structure facilitates the coordinated development of urbanization and the ecological environment.

Currently, China considers the construction of an ecological civilization as an important strategic position in governing the

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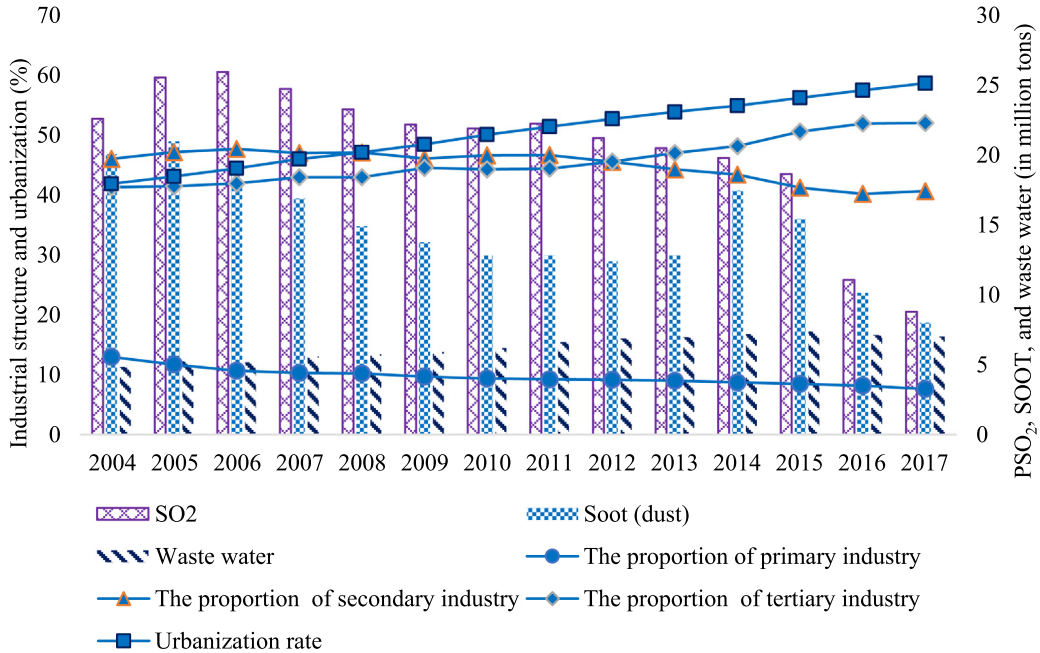

Fig. 1. The urbanization rate, industrial structure, and environmental pollution in China.
Source: National Bureau of Statistics (http://www.stats.gov.cn/).

country; as China's president, Xi Jinping has often emphasized that "Clear waters and green mountains are as good as mountains of gold and silver.", or that protecting the environment involves protecting productivity, while improving the environment will develop productivity. The shift in population and industry caused by urbanization has led to an increase in energy and resource consumption, which may exacerbate environmental pollution. As a type of health cost, environmental pollution affects the population's health, living environment, and labor supply; this can result in population outflows and damage to labor enthusiasm and social welfare, which could hinder the further advancement urbanization. Subsequently, the urgent need exists to study the connections among urbanization, the industrial structure, and environmental pollution. However, significant policy implications could manifest in resolving the contradictions among these factors.

In summary, this study offers three primary contributions. First, it integrates urbanization, the industrial structure, and environmental pollution into a unified research framework that comprehensively considers the interactions among these three factors. Second, the industrial structure among China's different regions is considered in studying the nonlinear relationship between urbanization and environmental pollution. Third, a newly developed dynamic threshold panel model incorporates the characteristics of the generalized method of moments (GMM) method. This model is utilized to explore how urbanization affects environmental pollution under different industrial structures. Specifically, the dynamic threshold panel model combines instrumental variable regression with the existing threshold regression technology. This can not only facilitate an analysis of nonlinear problems, but also effectively solve potential endogeneity issues.

The remainder of this paper is organized as follows: Section 2 describes the construction of the econometric model and the selection of related variables. Section 3 provides the empirical results, while Section 4 discusses the estimation results. Section 5 offers related policy implications and concludes.

2. Literature review

The literature has extensively investigated the relationship between urbanization, the industrial structure, and environmental pollution. In the late 19th century, Howard (2014) recognized the ecological problems in the urbanization process and attempted to use reasonable planning methods to coordinate urbanization and ecological issues. Grossman and Krueger (1995) discovered that the urban economy and ecological environment exhibited an inverted U-shaped relationship, then proposed the environmental Kuznets curve (EKC) hypothesis. Subsequently, many scholars have conducted a series of studies based on this theory to both qualitatively and quantitatively verify whether a relationship exists between economic growth and environmental pollution, and if so, what kind of relationships exist (Panayotou, 1997; Stern and Common, 2001).

With the development of industrialization, some studies have begun to incorporate the industrial structure into an analysis framework of economic growth and environmental pollution. Based on the IPAT model, York et al. (2003) developed the STIRPAT and IMPACT models to introduce a di-logistic model that can be decomposed to empirically analyze the relationship between urbanization and environmental quality. They then explored the mechanism of the model's positive effects. Oosterhaven and Broersma (2007) used an econometric analysis to posit that optimizing and upgrading the industrial structure would be an important way to improve the ecological environment's quality. Martínez-Zarzoso and Maruotti (2011) empirically analyzed urbanization's effect on carbon dioxide emissions in developing countries from 1975 to 2003 by calculating semi-parametric, mixed-model estimates; their results revealed that the relationship between urbanization and carbon dioxide emissions exhibited an inverted U shape. Sushinsky et al. (2013) argued that urbanization led to serious environmental degradation, which existed worldwide, and its size and intensity were still growing. Al-Mulali et al. (2015) examined 23 countries in Europe from 1990 to 2013; their fully modified ordinary least squares method indicated that GDP growth, urbanization, and financial development increased CO_2 emissions in the long term, but a high degree of trade openness could decrease such emissions. Kasman and Duman (2015) confirmed an inverted U-shaped relationship between their sampled countries' environment and income by investigating the causal relationship between energy consumption,

carbon dioxide emissions, economic growth, trade openness, and urbanization among new EU member and candidate countries from 1992 to 2010. Bekhet and Othman (2017) utilized ecological modernization and augmented Cobb–Douglas production theories to study the interaction between carbon dioxide emissions and urbanization in Malaysia from 1971 to 2015. They then used an F-bounds test and VECM Granger causality to examine the dynamic relationship among variables and the inverted U-shaped relationship between CO_2 emissions and urbanization in the long term. Long et al. (2017) studied Korean enterprises in China to find that environmental innovation has a greater impact on environmental than economic performance.

Some scholars have also studied the relationship between urbanization, industrial structure, and environmental pollution in China. Wang et al. (2008) monitored cross-sectional data on Shanghai from 1982 to 2005 and an integrated pollution index to study the changes in surface water quality in urban, suburban, and rural areas. Their results indicated an inverted U-shaped relationship between Shanghai's economic growth and surface water quality. Zhang et al. (2014) quantitatively studied the impact of China's economic growth, industrial structure, and urbanization on carbon emissions' intensity from 1978 to 2011. They found that an increase in the share of tertiary industry and economic growth decisively determined carbon emissions' intensity, but urbanization might cause carbon emissions' increased intensity.

Moreover, economic growth is the main factor affecting changes in carbon emissions' intensity during the sample period. He and Shen (2015) used Chinese provincial panel data from 1995 to 2011 to examine the regional differences in environmental pollution caused by urbanization based on economic development levels. They found an inverted U-shaped relationship between urbanization and CO_2 emissions in China's major regions. Li and Lin (2015) divided the balanced panel datasets from 73 countries spanning 1971 to 2010 into four groups according to their annual income levels. They also constructed dynamic panel threshold regression models to conclude that advanced urbanization and industrialization would increase CO_2 emissions in low-, middle-low-, and high-income groups. Zi et al. (2016) noted a direct relationship between urbanization and carbon dioxide emissions in China from 1979 to 2013. When the threshold point exceeded 0.43 or residents' income increased, carbon dioxide emissions also increased.

Some scholars have also studied the impact of specific indicators of the urbanization process on environmental pollution. Long et al. (2018a,b) studied 192 thermal power plants in the Yangtze River Delta to discover that the intensity of coal consumption negatively impacted environmental benefits. From 2009 to 2010, the nation's environmental efficiency improved, ultimately decreasing in 2011. Luo et al. (2017) observed a strong decoupling between carbon dioxide emissions and agricultural output value in eastern China from 1997 to 2014. Domestic and foreign scholars have conducted a series of meaningful discussions to lay the foundation for this study, but the literature still has some shortcomings: First, current research on the relationship among urbanization, industrial structure, and environmental pollution typically tend to study only the simple relationships between these factors. Second, previous studies have often used linear models to study the relationship between urbanization and environmental pollution, often overlooking the nonlinear relationship between them. Third, previous studies reveal that urbanization and environmental pollution mutually influence each other (Lim et al., 2012; Chen et al., 2017; Han et al., 2018; Ali et al., 2019). This two-way causality leads to endogeneity issues that have not been effectively addressed.

3. Methodology and data

3.1. Econometric methodology

3.1.1. The construction of a benchmark regression model

According to the Environmental Kuznets Curve (EKC) hypothesis, an inverted U-shaped relationship exists between environmental pollution and economic growth. Specifically, environmental pollution will first increase with economic development and environmental quality will continue to decline. When the economy grows to a certain stage, environmental pollution and the degree of environmental degradation will both peak at an inflection point. Subsequently, environmental pollution will continue to decline as the economy continues to develop, and environmental quality will continue to improve (Panayotou, 1993). Therefore, this paper establishes an EKC-based econometric model for studying economic activities and environmental pollution.

This paper tests whether an EKC relationship exists between China's level of economic development and the environment by introducing the per capita GDP and its square term in the model. Additionally, previous studies note that rapid urbanization has accelerated energy consumption and triggered a series of environmental problems (Wu et al., 2019). Therefore, urbanization is also included as the main variable in this paper's econometric model. Simultaneously, the country's environmental quality in an open economy is also affected by import and export trades as well as educational levels and energy consumption. Therefore, import and export trades, educational input, and energy intensity are added to the model as control variables to obtain the following basic econometric model:

$$\begin{aligned} lnPollution_{it} &= \beta_0 + \beta_1 lnUR_{it} + \beta_2 lnPGDP_{it} \\ &+ \beta_3 lnPGDP^2{}_{it} + \beta_4 lnIETVR_{it} \\ &+ \beta_5 lnEI_{it} + \beta_6 lnPE_{it} + \alpha_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{1}$$

Such environmental pollutants as SO_2 have certain time-lag effects, in that environmental pollution in the current period may be affected by variables of the previous period. Therefore, this econometric model introduces the environmental pollution lag phase variable $lnpollution_{it-1}$. The basic linear regression model is calculated as follows:

$$\begin{aligned} lnPollution_{it} &= \beta_0 + \beta_1 lnPollution_{it-1} + \beta_2 lnUR_{it} \\ &+ \beta_3 lnPGDP_{it} + \beta_4 lnPGDP^2{}_{it} \\ &+ \beta_5 lnIETVR_{it} + \beta_6 lnEI_{it} + \beta_7 lnPE_{it} + \alpha_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where ln denotes the logarithm; i and t represent the province and time, respectively ($i = 1, 2, 3, \ldots, 29$; $t = 1998, 2007, \ldots, 2015$); μ_i and ν_t indicate the provincial and time effects, respectively; ε_{it} signifies the idiosyncratic error term; $Pollution_{it}$ indicates the amount of environmental pollution emissions; UR_{it} is the level of urbanization; $PGDP_{it}$ indicates the level of economic development; $IETVR_{it}$ denotes the import and export trade; EI_{it} is the energy intensity; and PE_{it} indicates the educational level. As the first-phase dependent variable lags are added to the model, any endogeneity issue will lead to a bias in the previous fixed effects, hereafter "FE". Generally, the fixed effects estimators are biased downward, as the regressors may correlate with the unobserved fixed effects (Nickell, 1981). The instrumental variable estimators – and specifically, the generalized method of moments (GMM) approach – can properly address any endogeneity (e.g., Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Therefore, the GMM method is used in the actual analysis to solve for any potential endogeneity in estimating Model (2).

3.1.2. The construction of a dynamic threshold panel model

The benchmark regression analysis only verifies the linear relationship between urbanization and environmental pollution. Thus, we aim to explore whether this relationship will always exist in China with longitudinal changes over time and lateral changes in space. Levels of urbanization substantially vary from region to region in China due to the nation's imbalanced regional economic development. Recently, the various regions' industrialization and urbanization processes have accelerated, with a gradually more optimized industrial structure. Therefore, urbanization's impact on environmental pollution may be characterized by temporal nonlinearity or spatial heterogeneity. Specifically, the differences in the proportion of secondary and tertiary industries in various regions may lead to a "threshold effect" from urbanization's impact on China's environmental pollution. Additionally, the relevant literature reveals that urbanization significantly increases environmental pollution (Han et al., 2018; Ali et al., 2019). Further, Han et al. (2018) argued that urbanization has contributed to the increase in $PM_{2.5}$ in China, and especially in larger cities with high population densities. Ali et al. (2019) used the ARDL and causality VECM models to test the short- and long-term relationships between urbanization and carbon emissions in Pakistan. Their results indicate that urbanization has increased Pakistan's long-term carbon emissions.

Simultaneously, some studies have found that environmental pollution affects urbanization (Lim et al., 2012; Chen et al., 2017). For example, Lim et al. (2012) studied the Korean Urban Elderly Community Center to discover that air pollution can affect the moods of the urban elderly. Chen et al. (2017) studied air pollution's impact on China's population migration to demonstrate that air pollution causes a significant number of changes in China's urban population inflows and outflows. This endogeneity problem, caused by a two-way causal relationship between variables, will lead to biased estimation results in the previous fixed effects model. This paper further verifies the above hypothesis and avoids potential endogeneity issues by drawing on work by Wu et al. (2019) to combine the threshold model and GMM method to construct a dynamic threshold panel model. We further revised Model (2) to illustrate the following dynamic threshold panel model[1]:

$$\begin{aligned} lnPollution_{it} &= \alpha + \beta_1 lnPollution_{it-1} + \beta_2 lnUR_{it} \\ &\cdot I\left(q_{it} \le c\right) + \beta_3 lnUR_{it} \\ &\cdot I\left(q_{it} > c\right) + \sum_{k=1}^{5} \delta_k X_{kit} + \alpha_i + \upsilon_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where q_{it} represents the threshold variable, or the proportion of secondary (*SIR*) and tertiary industries (*TIR*); further, I(·) indicates the indicator function and c is the specific threshold value, while X_{kit} represents a series of control variables, including $PGDP_{it}$, $IETVR_{it}$, EI_{it}, and PE_{it}.

[1] The traditional threshold panel model is a static threshold panel model that uses fixed effects for a regression analysis (Hansen, 1999, 2000). In fact, the fixed-effects estimators are biased downward because the regressors may correlate with unobserved fixed effects (Nickell, 1981). The instrumental variable estimators – and specifically, the GMM approach – can well address any endogeneity issues (e.g., Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; Caner and Hansen, 2004). The newly developed dynamic threshold panel model, which incorporates characteristics of the GMM method and existing time-series techniques on threshold models, can effectively solve potential endogeneity issues (Dang et al., 2012). Specifically, potential endogenous variables are regressed against the selected instrumental variables in the dynamic threshold panel model's estimation process; the endogenous variables' estimated values, rather than actual, are utilized in the estimation. Finally, the two-step first-difference GMM estimator is incorporated, with the previously selected instrumental variables used in estimating the explanatory variables' coefficients (Wu et al., 2019). Although the threshold model is a time-series model and the threshold is unknown (Hansen, 2017), this paper's dynamic threshold regression model is a panel model, and thus, the threshold is known.

3.2. Data source and variable selection

3.2.1. Variable selection

This paper includes 11 variables. First, there are three primary explanatory variables: the urbanization rate, the proportion of the secondary (*SIR*) and tertiary industries (*TIR*), and environmental pollutants. Eight control variables are also included: the per capita GDP, the ratio of import and export trade volumes to GDP, the level of education per capita, and energy intensity. The following theoretical support is provided for the choice of variables:

(1) Explanatory variables: First, the urbanization rate is calculated according to the proportion of urban residents to the total population. The proportion of secondary industry is measured by the ratio of the secondary industry's output value to GDP, and the proportion of tertiary industry is calculated by the ratio of the tertiary industry's output value to GDP (Liu and Lin, 2019; Zhu et al., 2019).

This paper follows the literature in defining environmental pollution as the volumes of SO_2, soot (dust), and industrial waste gas emissions per capita (e.g., Hao et al., 2015; Liu et al., 2018a,b; Dong et al., 2018; Omri et al., 2019; Wang, 2019). SO_2 is a major conventional atmospheric pollutant and can dissolve in water to form sulfurous acid (H_2SO_3), the main component in acid rain (Hao et al., 2015). Excessive discharges of SO_2 can lead to economic losses and residents' deteriorated health. Wei et al. (2014) found that the costs of agricultural losses due to SO_2 pollution was estimated at US$1.43 billion across 899 Chinese counties. SO_2 also severely affects human health and could potentially cause pulmonary dysfunction, airway inflammation, and respiratory diseases (e.g., Xu et al., 1995; Venners et al., 2003). Soot is another significant air pollutant generated during processes that involve the burning of materials and industrial production, and could substantially impact human health; it contains several contaminants, including PM2.5. Studies have found that exposure to fine particulates, whether in the long or short term, may significantly increase the incidence of cardiovascular, respiratory, and cerebrovascular diseases, as well as their corresponding mortality rates (Fang et al., 2016; Song et al., 2017).

Industrial waste gas refers to the various types of pollutant gases discharged into the air in the fuel combustion and production processes in production plants. The excessive discharge of industrial waste gas can cause disorders of the human immune system, which can lead to notable health risks regarding severe chronic diseases, including hypertension, heart disease, chronic pulmonary disease, and diabetes (Lu et al., 2016). A few relevant studies also involve a Chinese context. For example, Li et al. (2016a,b) measured the economic loss related to health problems from waste gas emissions and discovered that such losses from PM_{10} and SO_2 accounted for 1.63% and 2.32% of the GDP in 74 cities, respectively. Similarly, Liu et al. (2018a,b) evaluated the healthcare burden from waste gas emissions and heavy metals in the spring and winter of 2016.

Fig. 2 illustrates the geographical distribution of this study's primary variables – the classification of urbanization rates, GDP per capita, and volume of SO_2 emissions per capita – at the beginning (1998) and end (2015) of the sample period. Clearly, these three variables significantly differ across provinces and regions, and these differences remain constant for the entire sample period.

(2) Control variable: This study follows previous works in using economic growth, expressed as the GDP per capita (*PGDP*), as a control variable. The levels of import and export trade are calculated as the ratio of import and export trade to GDP. The educational level per capita is based on the average number of years of education: six years of primary school, three years of junior

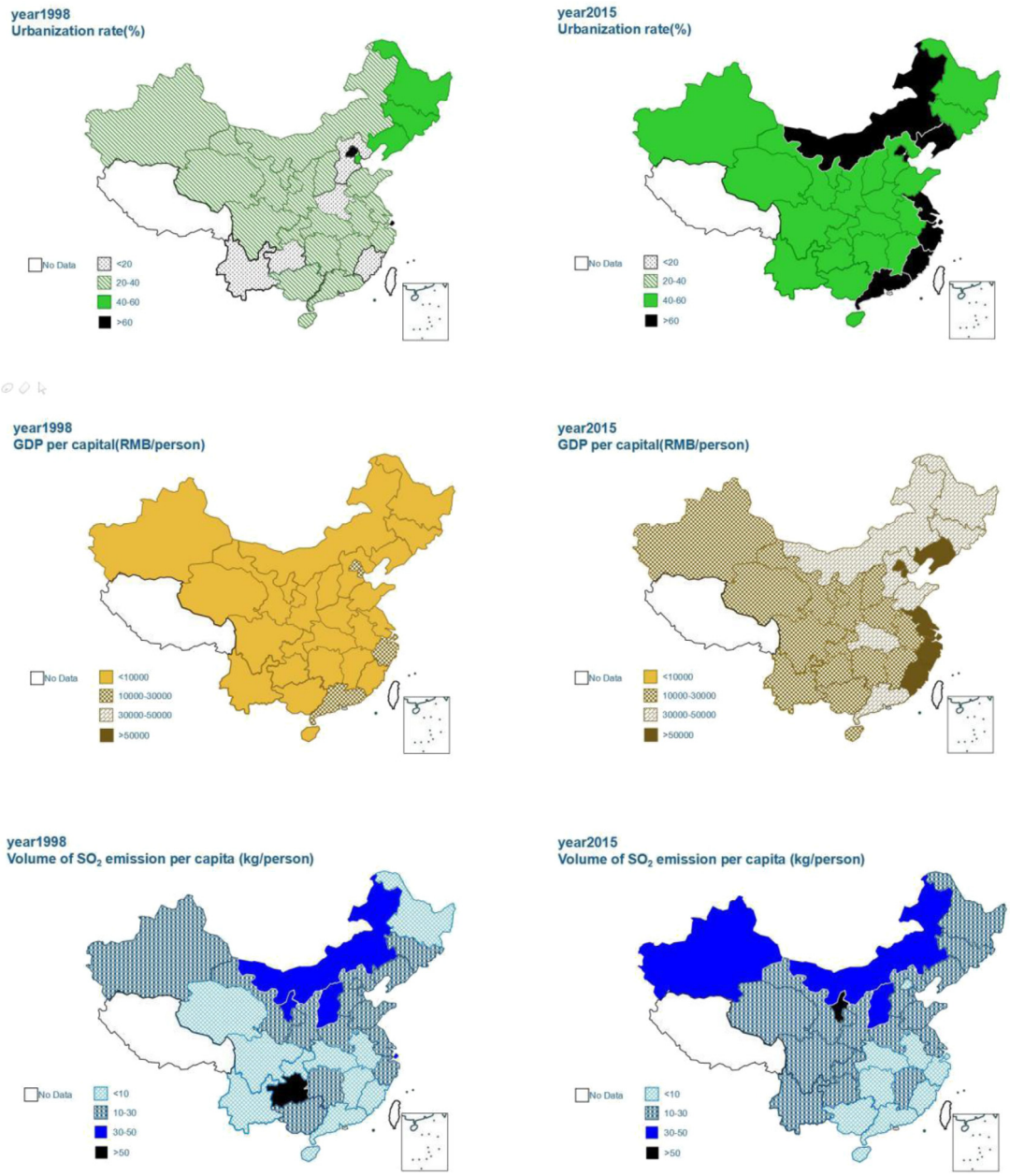

Fig. 2. The geographical distributions of the urbanization rate, GDP per capita, and volume of SO_2 emissions per capita among China's provinces in 1998 and 2015.

high school, three years of high school, and four years of college education. Energy intensity (*EI*), or the energy consumption per unit of GDP, is used to characterize energy efficiency (Wu et al., 2019).

3.2.2. Data sources and processing

This study collects from 29 provinces in China as the study object, and the sample covers panel data from 1998 to 2015. All data are obtained from the *National Bureau of Statistics of the People's Republic of China*, *China Statistical Yearbook on the Environment*, and *China Energy Statistical Yearbook* from 1999 to 2016; and the *Statistical Communiqué of the People's Republic of China on the National Economic and Social Development* and the *Environmental Status Bulletin* from 1998 to 2015. Additionally, this section eliminates the influence of price changes by converting the nominal values of income and GDP-related variables into actual values calculated through 2000 constant prices. We remove the variance issue in our provincial data by taking the natural logarithm of our non-proportional variables.

Table 1 provides the names, definitions, and descriptive statistics of this study's variables. This table indicates significant differences among the variables' observed values, which is possible for the following empirical estimation.

4. Empirical results

4.1. Estimation results from the basic model

According to Table 2, the coefficient of the first-phase lag of environmental pollution is significantly positive at the 1% level, except for the waste gas emissions per capita, indicating that the previous period will affect China's environmental pollution. Therefore, it is necessary to use the GMM method. The residual sequence correlation test reveals that the *p*-value of the AR(2) test is greater than the 10% significance level, and thus, no sequence

Table 1
Variables' descriptive statistics.

Variable	Units of measurement	Sample period	Obs.	Mean	Std. Dev.	Min.	Max.
UR	Urbanization level (%)	1998–2015	522	46.8	16.1	14.0	89.6
PGDP	GDP per capita (RMB/person)	1998–2015	522	19,231.600	15,084.650	2,341.610	85,036.410
PSO_2	Volume of SO_2 emissions per capita (kg/person)	1998–2015	522	18.667	12.280	2.546	64.471
PSOOT	Volume of industrial soot (dust) emissions per capita (kg/person)	1998–2015	522	15.460	10.682	1.690	82.896
PIWG	Volume of industrial waste gas emissions per capita (10 thousand m^3/person)	1998–2015	522	3.308	2.880	0.416	25.790
SIR	Ratio of secondary industry to GDP (%)	1998–2015	522	0.466	0.077	0.197	0.615
TIR	Ratio of tertiary industry to GDP (%)	1998–2015	522	0.399	0.078	0.286	0.797
IETVR	Ratio of import and export trade to GDP (%)	1998–2015	522	0.316	0.393	0.032	1.721
PE	Educational level per capita (years/person)	1998–2015	522	8.392	1.221	4.906	20.144
EI	Energy intensity (tce/10,000 RMB)	1998–2015	522	1.672	0.937	0.496	5.102

correlation exists in the random error term. Hansen's test reveals that the model's instrumental variable selection is valid; Wald's statistic also indicates that the model is highly significant overall. Therefore, the dynamic panel regression results are credible. In estimating the model's main variables, the estimated coefficient for urbanization is significantly positive in the regression results for PSO_2, *PSOOT*, and *PIWG* as dependent variable equations, indicating that increasing urbanization promotes an increase in the emission of these three pollutants. However, the coefficients differ for the dependent variables of urbanization levels with different pollutants. Among them, the estimated coefficient of the urbanization level is the largest when the per capita PSO_2 is the dependent variable.

Moreover, among the other influencing factors the baseline model estimates, the primary coefficient of the economic development level is significantly positive when PSO_2 and *PIWG* are used as pollutants, and the quadratic coefficient is significantly negative, indicating an inverted U-shaped relationship between environmental pollution and economic growth in China. However, the regression results with *PSOOT* as a dependent variable indicate a U-shaped relationship between the same two factors. Simultaneously, the coefficient for import and export trade is positive in the model with PSO_2, *PSOOT*, and *PIWG* as the dependent variables. When *PSOOT* and *PIWG* are the dependent variables, the estimated coefficient for import and export trade is significantly positive at the 1% level, indicating that import and export trade has increased environmental pollution in China. The estimated coefficient of energy intensity is significantly positive in the estimation equations of the three different pollutants, indicating that the increased energy intensity has led to increased environmental pollution in China.

Our results are consistent with those of Salman et al.'s (2019a, 2019b) study of imports' and exports' impacts on carbon emissions in seven countries in the Association of Southeast Asian Nations, which found that exports led to increased carbon emissions. Additionally, the rising population size and energy intensity have increased carbon emissions; specifically, technological innovation significantly reduces carbon emissions by improving energy efficiency. Further, improving per capita education effectively reduces environmental pollution.

4.2. The dynamic threshold panel model's estimation results

A threshold effect test is conducted with PSO_2, *PSOOT*, and *PIWG* as dependent variables using Stata 15.0 software, based on the dynamic threshold panel model with Wald's test and a self-sampling (bootstrap) method, with the assumption of no threshold effects. Table 3 indicates that the dynamic threshold model

Table 2
Baseline regression model.

Variable	$\ln PSO_2$	lnPSOOT	lnPIWG
$lnPollution_{it-1}$	0.208***	0.428***	0.047
	(4.910)	(15.765)	(0.782)
lnUR	2.064***	1.887***	1.072***
	(7.726)	(5.137)	(2.715)
lnPGDP	3.209***	−11.371***	2.294**
	(4.548)	(−20.126)	(2.398)
$(lnPGDP)^2$	−0.186***	0.570***	−0.076*
	(−5.143)	(19.458)	(−1.703)
lnIETVR	0.005	0.154***	0.063***
	(0.476)	(8.076)	(2.684)
lnEI	0.842***	0.903***	0.508***
	(7.730)	(15.697)	(8.177)
lnPE	−0.124***	−0.207***	−0.136***
	(−4.653)	(−3.412)	(−3.762)
Curve Shape	Inverted U	U	Inverted U
AR(1)	−0.00	−2.62	−2.79
	[0.998]	[0.009]	[0.005]
AR(2)	0.19	0.47	−0.89
	[0.851]	[0.642]	[0.373]
Hasen Test	23.51	28.20	26.65
	[0.431]	[0.207]	[0.113]
Wald Test	30 062.19***	5458.90***	2762.92***
	[0.000]	[0.000]	[0.000]
N	464	464	464

Note: The prefix "ln" before the explanatory variables denotes a logarithmic form. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses indicate *z*-values of the coefficients and *p*-values of the corresponding test statistics.

with three different pollutants as the explained variables rejects the null hypothesis with no threshold effect at the 1% significance level, and the threshold is obvious. Therefore, urbanization's impact on environmental pollution is characteristically non-linear characteristic due to the difference between the proportions of secondary (*SIR*) and tertiary industries (*TIR*) in China.

The sample is then divided into regions with large or small proportions of secondary industry, and high or low proportions of tertiary industry, according to whether the threshold variable crosses the threshold value. The data used in this paper span 1998 to 2015; for brevity, this paper only presents the 2015 grouping results from 29 provinces in China. The statistical results in Table 4 demonstrate that when PSO_2 is the dependent variable and the proportion of secondary industry (*SIR*) is the threshold variable, the proportions of secondary industries in 20 provinces crosses the threshold. The top five are Inner Mongolia (0.505), Shaanxi (0.504), Jiangxi (0.503), Fujian (0.503), and Qinghai (0.499), and most of these provinces are concentrated in China's central and western regions. Nine provinces have a

Table 3
The different threshold variables' threshold values and confidence intervals.

Explanatory variable	Threshold variable	Threshold value	Wald statistics	P-value	BS	95% confidence interval	
						Lower	Higher
PSO2	SIR	0.4171***	0.0002	0.0000	1000	0.3200	0.5326
	TIR	0.4338***	5.1885	0.0000	1000	0.2943	0.5652
PSOOT	SIR	0.4045***	1.7070	0.0000	1000	0.3200	0.5326
	TIR	0.4358***	0.0012	0.0000	1000	0.2943	0.5652
PIWG	SIR	0.3255***	5.4623	0.0000	1000	0.3200	0.5326
	TIR	0.4065***	1.6069	0.0000	1000	0.2943	0.5652

Note: Probability is evaluated from 1000 regression replications. The threshold parameter's confidence interval estimation is based on Hansen's (1999) method. The Wald's statistic is used to determine whether the threshold effect is significant; the smaller the corresponding probability, the more significant the threshold effect.

proportion of secondary industry (*SIR*) less than the threshold; the largest is Shanxi (0.407) and the smallest is Beijing (0.197).

The grouping results with PSO_2 as the dependent variable and the tertiary industry as the threshold variable indicate that this proportion among 18 provinces is greater than the threshold. The top five are Beijing (0.797), Shanghai (0.678), Hainan (0.533), Shanxi (0.532), and Tianjin (0.522), and these provinces are located in China's eastern coastal areas. There are 11 provinces with a proportion of tertiary industry (*TIR*) less than the threshold; the largest is Hubei (0.431) and the smallest is Guangxi (0.388).

In the grouping results with *PSOOT* as the dependent variable and the proportion of secondary industry (*SIR*) as the threshold variable, this proportion exceeded the threshold in 21 provinces and was less than the threshold value in 8 provinces. The grouping result with *PSOOT* as the dependent variable and the proportion of tertiary industry (*TIR*) as the threshold variable is consistent with the grouping result with PSO_2 as the dependent variable and the proportion of tertiary industry (*TIR*) as the threshold variable.

In the group with *PIWG* as the dependent variable and the proportion of secondary industry (*SIR*) as the threshold variable, this proportion was greater than the threshold in 25 provinces, while only 4 provinces exhibited a proportion less than the threshold. In the group with the proportion of tertiary industry (*TIR*) as the threshold variable, this proportion was greater than and less than the threshold in 21 and 7 provinces, respectively.

Table 5 indicates that the lag phase coefficients of PSO_2 and *PSOOT* are both significant at the 1% level, indicating that the previous period will impact current environmental pollution. This conclusion is consistent with the dynamic panel regression results. Further, the residual sequence correlation test reveals that the *p*-value from the AR(2) test is greater than the 10% significance level, and thus, no second-order sequence correlation exists for the random error term. The Hansen's test results indicate that the model's instrumental variable selection is valid, while the Wald's statistic also indicates that the model is highly significant overall. Therefore, this paper's dynamic threshold regression results are credible. The variables' estimation results demonstrate that urbanization significantly increases environmental pollution with PSO_2 and *PSOOT* as the dependent variables, but increases with an increase in the proportion of secondary industry (*SIR*) and decreases with an increase in the proportion of tertiary industry (*TIR*).

With *PIWG* as the dependent variable, the coefficient for urbanization is not significant when the *SIR* falls below a threshold of 0.3255. When the proportion of secondary industry (*SIR*) surpasses this threshold, urbanization significantly promotes an increase in *PIWG*, and the coefficient becomes significantly larger. When the proportion of tertiary industry (*TIR*) is used as a threshold variable, urbanization significantly promotes an increase in *PIWG*, but this effect decreases as this proportion rises.

In summary, urbanization has significantly promoted an increase in environmental pollution in China, and this promotion has gradually risen with an increase in the proportion of the secondary industry (*SIR*). However, improvement in the proportion of tertiary industry (*TIR*) has gradually decreased the promotion effect. Therefore, optimizing and upgrading the industrial structure in the urbanization process effectively conserves energy and reduces emissions.

5. Discussion

This study's empirical results lead to the following discussion: First, urbanization has significantly increased environmental pollution in China (Sun et al., 2019), and the coefficient is the largest with PSO_2 as the dependent variable. This is possibly because urbanization has exacerbated China's environmental pollution, which can be explained from both the macro- and micro-perspectives. This problem from the macro-perspective primarily exists due to the change in industrial structure caused by urbanization (Li et al., 2016a,b). As the early stage of urbanization is driven by industrialization, this attracts a substantial rural labor force to cities, triggering a simultaneous increase in urbanization and industrialization (Riley, 2002; Dong, 1989); the subsequent discharge of waste gases and water as well as industrial waste inevitably lead to environmental disaster. From a micro-perspective, the population's changing lifestyle also induces increased environmental pollution. On the one hand, transportation modes have changed, resulting in urban residents' increasing mobility and range thereof. The shift from manual (bicycle) and animal-based (carriage) transportation to motor transportation (Riley, 2002) has produced automobile exhaust, which is harmful to the environment (Weisbrod and Roberta, 1999). On the other hand, people's need for a better quality of life has also led to a growing demand for such amenities as winter heating and energy-consuming household appliances, which are neither resource-saving nor environmentally friendly. It is noteworthy that urbanization affects SO_2 emissions in more ways than the other two examined pollutants, as industrial boilers and kilns, automobile exhaust, coal-fired heating, and thermal power generation are all sources of SO_2 emissions (Lu et al., 2013). This explains why urbanization has the largest coefficient when using PSO_2 as the explanatory variable.

Second, urbanization has increased China's environmental pollution as the proportion of secondary industry has increased. This may be due to a growing collection of industries as urbanization accelerates, resulting in the emission of carbon dioxide and SO_2, among other pollutants, consequently destroying the atmospheric ecosystem. An accelerated industrialization process has also changed people's living habits and production methods, and gradually increased the discharge of industrial wastewater and domestic sewage. Simultaneously, China's sewage treatment facilities are inadequate due to their limited technical capabilities

Table 4
The results for different province subgroups.

Explanatory variable	Threshold variable	$q_{it} < C$		$q_{it} \geq C$	
		Provinces	*Nobs*	Provinces	*Nobs*
PSO_2	SIR (C = 0.417)	Shanxi(0.407), Guizhou(0.395), Yunnan(0.398) Xinjiang(0.386), Gansu(0.367), Shanghai(0.318) Heilongjiang(0.318),Hainan(0.237), Beijing(0.197)	9	Neimenggu(0.505), Shaanxi(0.504), Jiangxi(0.503), Fujian(0.503), Qinghai(0.499) Jilin(0.498),Anhui(0.497), Henan(0.484), Hebei(0.483),Ningxia(0.474) Shandong(0.468), Tianjin(0.466), Zhejiang(0.460),Guangxi(0.459), Jiangsu(0.457) Hubei(0.457), Liaoning(0.455),Guangdong(0.448), Sichuan(0.444), Hunan(0.443)	20
	TIR (C = 0.434)	Hubei(0.431), Fujian(0.416), Qinghai(0.414) Shaanxi(0.407), Neimenggu(0.405), Henan(0.402) Hebei(0.402), Jiangxi(0.391), Anhui(0.391) Jilin(0.388), Guangxi(0.388)	11	Beijing(0.797), Shanghai(0.678), Hainan(0.533), Shanxi(0.532) Tianjin(0.522), Heilongjiang(0.507), Guangdong(0.506), Zhejiang(0.498) Gansu(0.492), Jiangsu(0.486), Liaoning(0.462), Shandong(0.453), Yunnan(0.451) Sichuan(0.451), Guizhou(0.449), Xinjiang(0.447), Ningxia(0.445) Hunan(0.441)	18
PSOOT	SIR (C = 0.405)	Guizhou(0.395), Yunnan(0.398) Xinjiang(0.386), Gansu(0.367), Shanghai(0.318) Heilongjiang(0.318), Hainan(0.237), Beijing(0.197)	8	Neimenggu(0.505), Shaanxi(0.504), Jiangxi(0.503), Fujian(0.503), Qinghai(0.499) Jilin(0.498), Anhui(0.497), Henan(0.484), Hebei(0.483), Ningxia(0.474) Shandong(0.468) Tianjin(0.466), Zhejiang(0.460), Guangxi(0.459), Jiangsu(0.457), Hubei(0.457) Liaoning(0.455), Guangdong(0.448), Sichuan(0.444), Hunan(0.443) Shanxi(0.407)	21
	TIR (C = 0.436)	Hubei(0.431), Fujian(0.416), Qinghai(0.414) Shaanxi(0.407), Neimenggu(0.405), Henan(0.402) Hebei(0.402), Jiangxi(0.391), Anhui(0.391) Jilin(0.388), Guangxi(0.388)	11	Beijing(0.797), Shanghai(0.678), Hainan(0.533), Shanxi(0.532) Tianjin(0.522), Heilongjiang(0.507), Guangdong(0.506), Zhejiang(0.498) Gansu(0.492), Jiangsu(0.486), Liaoning(0.462), Shandong(0.453), Yunnan(0.451) Sichuan(0.451), Guizhou(0.449), Xinjiang(0.447), Ningxia(0.445) Hunan(0.441)	18
PIWG	SIR (C = 0.326)	Shanghai(0.318), Heilongjiang(0.318) Hainan(0.237), Beijing(0.197)	4	Neimenggu(0.505), Shaanxi(0.504), Jiangxi(0.503), Fujian(0.503), Qinghai(0.499) Jilin(0.498), Anhui(0.497), Henan(0.484), Hebei(0.483), Ningxia(0.474) Shandong(0.468), Tianjin(0.466), Zhejiang(0.460), Guangxi(0.459), Jiangsu(0.457) Hubei(0.457), Liaoning(0.455), Guangdong(0.448), Sichuan(0.444), Hunan(0.443) Shanxi(0.407) Guizhou(0.395), Yunnan(0.398) Xinjiang(0.386), Gansu(0.367)	25
	TIR (C = 0.407)	Neimenggu(0.405), Henan(0.402) Hebei(0.402), Jiangxi(0.391), Anhui(0.391) Jilin(0.388), Guangxi(0.388)	7	Beijing(0.797), Shanghai(0.678), Hainan(0.533), Shanxi(0.532) Tianjin(0.522), Heilongjiang(0.507), Guangdong(0.506), Zhejiang(0.498) Gansu(0.492), Jiangsu(0.486), Liaoning(0.462), Shandong(0.453), Yunnan(0.451) Sichuan(0.451), Guizhou(0.449), Xinjiang(0.447), Ningxia(0.445) Hunan(0.441) Hubei(0.431), Fujian(0.416), Qinghai(0.414), Shaanxi(0.407)	22

(Jin et al., 2014). Therefore, the discharge of industrial wastewater has polluted urban lakes, oceans, and other bodies of water, which has become a serious issue.

Finally, urban development has led to a continuous increase in industrial solid waste with a relatively slow garbage disposal capacity that lags behind the production of solid waste, resulting in a "garbage siege" phenomenon (Yuwen et al., 2015). Table 4 illustrates that when PSO_2, *PSOOT*, and *PIWG* are the dependent variables, 20, 21, and 25 provinces have proportions of secondary industry (*SIR*) that surpass the threshold, respectively. Therefore, most Chinese provinces still exhibit an incredibly high proportion of secondary industry (*SIR*); the top five are Inner Mongolia (0.505), Shaanxi (0.504), Jiangxi (0.503), Fujian (0.503), and Qinghai (0.499). Most of these provinces belong to China's central and western regions with relatively low levels of urbanization. As industrialization is the primary driver of urbanization and economic development, more pollution is generated during such development processes. Comparatively, the regions with relatively low proportions of secondary industry are Beijing (0.197), Hainan (0.237), Shanghai (0.318), and Heilongjiang (0.318), among others. These regions are mostly located in China's southeastern coastal areas or in the Beijing. Their urbanization levels are relatively high, with a relatively small proportion of traditional industries; therefore, they emit less pollution during their urbanization processes.

While urbanization has increased China's environmental pollution, this has decreased as the proportion of tertiary industry has increased. This is possibly due to the following reasons: First, with continued urbanization, improved technology, and the adjustment of industrial policies, the proportion of tertiary industry in the national economy has gradually increased. An improvement in the industrial structure can also reduce the dependence on resources and energy in enterprises' production processes to directly impact the ecological environment (Zhixin and Qiao, 2011).

Second, with the optimization and upgrading of industrial structure, the proportion of traditional industries with high energy consumption, pollution, and emissions has gradually decreased, and resources have shifted from industries with low utilization efficiency to industries with high efficiency and low pollution. Therefore, pollutant emissions have been successfully reduced and the ecological environment improved.

Third, developing the tertiary industry has led to constant improvements in urban education and science and technology, and residents' educational levels have improved; this will improve quality of life demands and require stricter environmental controls (Briggs et al., 2008). Additionally, improving science and technology can effectively control environmental pollution and enhance the quality of the urban environment. Table 4 reveals that when PSO_2, *PSOOT*, and *PIWG* are the dependent variables, 18, 18, and 21 provinces, respectively, have proportions of tertiary industry crossing the threshold, indicating that this proportion has crossed this threshold in most parts of China. Among these, the province with the highest proportion of tertiary industry is Beijing (0.797), and that with the lowest proportion is Guangxi (0.388); both are located in the central-eastern part of China. Simultaneously, the level of urbanization, proportion of tertiary industry (*TIR*), and energy efficiency and pollution controls in these areas are relatively high. However, the overall proportion of tertiary industry is not high enough, even though this proportion in most Chinese provinces has crossed the threshold. The tertiary industry accounts for more than 50% of only seven provinces, including Beijing (0.797), Shanghai (0.678), Hainan (0.533), Shanxi (0.532), Tianjin (0.522), Heilongjiang (0.507), and Guangdong (0.506). Given that 22 provinces still have a proportion of tertiary industry accounting for less than 50%, China's tertiary industry still has the potential to improve.

6. Conclusion and policy recommendations

This paper uses panel data from 29 provinces in China from 1998 to 2015 to construct a linear model with the GMM method to test the relationship between the level of urbanization and environmental pollution in China. The benchmark regression results indicate that urbanization has significantly increased environmental pollution in China, with the greatest promotion effect on PSO_2. Second, this paper combines the threshold model with the GMM method to develop a dynamic threshold panel model that helps to solve the endogeneity issues between variables. This dynamic threshold panel model is then used to verify the nonlinear relationship between urbanization and environmental pollution. The results reveal that urbanization has significantly increased environmental pollution in China, but this increase has also occurred in parallel with an increase in the proportion of secondary industry, and has decreased with an increase in the proportion of tertiary industry. Therefore, the following policy recommendations are proposed based on this work's primary estimation results:

First, China's rapid urbanization process has consumed substantial energy resources and created serious environmental problems; thus, China's existing energy consumption structure must be changed to alleviate the nation's air pollution problem and improve energy consumption efficiency (Salman et al., 2019a,b). This requires joint efforts by the government and enterprises. The government should formulate relevant policies to not only guide upgrades of the consumption structure in energy-intensive industries, but also encourage the entire nation to use clean energy. Simultaneously, regional differences must be considered when formulating environmental protection policies: the more developed eastern regions have entered a later stage of industrialization, with improved levels of urbanization and proportion of the service industry (Li et al., 2018a,b; Miao et al., 2019). Consequently, these regions can set higher entry barriers for businesses and higher environmental regulations.

As China's economically backward central and western regions are currently still in a stage of vigorous economic development, which will improve residents' living standards and accelerate the urbanization process, they should actively absorb the eastern regions' development experience and avoid post-contamination governance. Additionally, coal heating in northern China in the winter creates a substantial environmental burden; the government could respond by building a clean-energy-based heating infrastructure to reduce the region's proportion of traditional coal heating. Enterprises with high energy consumption and high emissions should actively promote and use clean coal technologies and increase their technology investments, as this would improve their utilization efficiency of coal resources and reduce emissions of SO_2 and soot.

Second, advanced industries must transform their development patterns to become green industries. China's industrialization has long been characterized as high input, low output, high consumption, and low efficiency. Despite decades of development, the proportion of the secondary industry in some parts of China is still high, close to 50% in regions such as Inner Mongolia (0.505), Shanxi (0.504), Jiangxi (0.503), Fujian (0.503), and Qinghai (0.499). Therefore, a significant path involves transforming the nation's traditional high-energy-consumption, high-input, and extensive-industrial-development mode to instead promote the development of green industry, which could initially involve optimizing inventory stocks and controlling increments. This purported "optimized" inventory will allow China to optimize existing enterprises' industrial production, continuously promote and use various new technologies and equipment, and gradually realize industrial enterprises' intensive, clean development.

Table 5
Dynamic threshold panel model regression results.

Variables	PSO_2		PSOOT		PIWG	
	SIR	TIR	SIR	TIR	SIR	TIR
$lnPollution_{it-1}$	0.110***	0.116***	0.158***	0.259***	0.018	0.187***
	(3.220)	(2.670)	(3.030)	(7.620)	(0.490)	(2.850)
lnPGDP	4.845***	4.820***	−7.941***	−13.073***	3.972***	1.969***
	(7.880)	(7.630)	(−4.250)	(−14.120)	(1.301)	(4.170)
$(lnPGDP)^2$	−0.262***	−0.253***	0.382***	0.635***	−0.147**	−0.051*
	(−8.260)	(−8.020)	(4.070)	(12.940)	(−2.190)	(−1.790)
lnIETVR	0.182***	0.214***	0.468***	0.329***	−0.051**	−0.076***
	(11.940)	(10.680)	(7.020)	(8.240)	(−2.180)	(−4.650)
lnEI	0.856***	0.759***	0.980***	1.063***	0.485***	0.726***
	(10.500)	(10.330)	(8.920)	(9.570)	(4.230)	(5.390)
lnPE	−0.122***	−0.061**	−0.278***	−0.212***	−0.098***	−0.238***
	(−3.830)	(−2.240)	(−5.390)	(−4.560)	(−4.810)	(−4.190)
$lnUR(SIR < C)$	1.272***		1.939***		0.244	
	(5.080)		(2.850)		(1.310)	
$lnUR(SIR \geq C)$	1.303***		2.075***		0.407**	
	(5.220)		(3.070)		(2.080)	
$lnUR(TIR < C)$		1.036***		3.690***		0.287***
		(3.750)		(5.240)		(6.590)
$lnUR(TIR \geq C)$		0.983***		3.619***		0.211***
		(3.560)		(5.140)		(5.690)
Curve Shape	Inverted U	Inverted U	U	U	Inverted U	Inverted U
AR(1)	−0.46	−1.21	−2.15	−0.15	−2.95	−3.16
	[0.648]	[0.226]	[0.031]	[0.885]	[0.003]	[0.002]
AR(2)	0.82	1.22	0.52	1.05	−1.34	−1.38
	[0.414]	[0.224]	[0.604]	[0.293]	[0.180]	[0.166]
Hasen Test	24.40	25.49	24.48	27.18	25.35	27.85
	[0.861]	[0.822]	[0.858]	[0.752]	[0.443]	[0.419]
Wald Test	2880.94***	3024.81***	2003.55***	2694.53***	35 027.91***	29 572.16***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
N	464	464	464	464	464	464

Note: The prefix "ln" before the explanatory variables denotes a logarithmic form. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses indicate the *z*-values of the coefficients and *p*-values of the corresponding test statistics.

Further, the 'control' increment is defined according to specific situations to establish a differentiated industry-entry mechanism. For coal, steel, cement, thermal power, chemical, and other high-pollution, high-energy, and high-emissions enterprises, the government can improve market access standards. For green, energy-related, and environmental protection industries, the government should increase technology and capital investments to encourage independent innovation by these enterprises (Hao et al., 2019). Simultaneously, the government could implement preferential fiscal and tax policies for these enterprises to promote the development of green and environmental protection technologies and cultivate green, energy-saving, and environmental protection industries.

Finally, the proportion of the tertiary industry should be increased and the industrial structure upgraded to reduce pressures from environmental pollution. Specifically, we should continue to optimize the proportion of labor-, capital-, and technology-intensive industries while eliminating those that are high polluting, energy intensive, and with high emissions. Financial investments and investments in research and development could be increased in the environmental protection industry to allow such businesses to introduce and absorb advanced foreign technologies. Advanced technology could then be used to upgrade traditional industries and eliminate low-end industries (Long et al., 2018a,b; Li et al., 2018a,b). Moreover, the application of science and technology in developing modern service-related, high-tech, and other low-carbon industries should be increased; this will promote the continuous development of emerging, energy-saving, and environmental-protection industries to gradually form a modern industrial system. Subsequently, this will reduce urbanization's impact on the environment.

Although this paper focuses on the neglected non-linear relationship between urbanization and environmental pollution to control endogeneity issues, the investigation can still be improved. First, while this study examines the non-linear relationship between energy consumption and urbanization from an empirical perspective, its driving mechanism has not been clearly explored. Therefore, subsequent studies can attempt to establish theoretical models to fully explain this study's empirical results. Second, this paper uses provincial-level data, and their availability is limited. However, substantial differences may exist in the economic and social development between different cities in a single province, and thus, the relationship between energy consumption and urbanization may be more accurate when using city-level data in the future.

Declaration of competing interest

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

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