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Correlation Analysis between Economic Growth and Environmental Quality

Baiqing Zhou[1], Na Li[1,*], Duan Lu[1] and Jinyue Xia[2]

[1]Huzhou Vocational & Technical College, Huzhou, 313000, China
[2]International Business Machines Corporation (IBM), New York, NY, USA
*Corresponding Author: Na Li. Email: linaxinxin11@163.com
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Abstract: With the rapid development of the economy, China's environment has been damaged severely, which has attracted much attention from scholars and the local government. The concept of green development has been an underlying trend since 2012, and it is of great significance to explore the relationship between economic growth and environmental quality. Huzhou is a prefecture-level city under the jurisdiction of Zhejiang Province, and it is one of the 27 cities in the central area of the Yangtze River Delta. In recent years, this city develops well not only in economic development but also in maintaining a green environment. In the paper, the back propagation neural network is used to evaluate the local environmental quality. Meanwhile, the panel model is exploited to analyze the relationship between economic growth and environmental quality. All the data presented in the paper range from the year 2008 to 2018. Theoretical analysis indicates that the evaluation value of environmental quality, the emissions of industrial SO_2, and waste water exhibit an inverted U-shaped relationship with economic growth. As for the regression results, the inflection point of income in the environmental Kuznets curve of the model which takes the evaluation value of the environmental quality as a dependent variable is higher than that of the model which takes the SO_2 emission as an independent variable. The research result would help the local government to take appropriate countermeasures to improve the environment and economy.

Keywords: Economic growth; environmental quality; BP neural network; environmental Kuznets curve

1 Introduction

With the rapid development of the economy, China's environment has been greatly damaged since its reform and opening to the world. Every autumn and winter, there are some fog and haze days in most areas in China. A harsh environment has affected people's lives. While they enjoy the dividend from the rapid development of the economy, they have to suffer a lot from environmental deterioration. The frequent environmental problems have attracted more and more attention from scholars and the local government.

How to keep the balance between the environment and the economy? President Xi Jinping, who is the general secretary of the Communist Party of China (CPC), said in the 19th CPC National Congress that China

should deal well with the relationship between economic growth and ecological environment protection, and the economy should never develop at the cost of destroying the environment. Huzhou, a prefecture-level city under the jurisdiction of Zhejiang Province and one of the 27 cities in the central area of the Yangtze River Delta, has turned lucid water and lush mountain into invaluable assets. Association analysis between economic growth and environmental quality will facilitate a more coordinated development, and help policymakers to make suitable policies and programs, as well as provide a reference for other cities to develop the green economy with high quality.

In this paper, the Back Propagation (BP) neural network is employed to evaluate the environmental quality in Huzhou City, and then the panel model is exploited to analyze the relationship between economic growth and environmental quality. Based on the empirical results, an Environmental Kuznets curve is drawn to explore the inflection point. The rest of this paper is organized as follows. Section 2 introduces the related work. Section 3 analyzes the association between economic growth and environmental quality. In Section 4, the panel model is used to show the association. Finally, the conclusion is given in Section 5.

2 Related Work

Scholars have been studying the relationship between economy and environment since the end of the last century. They find that an inverted U-shaped relationship exists between economy and environment, i.e., in the early stage of economic development, the environment becomes worse with the development in the economy; whereas, when the economy develops to a certain stage, the environment is improved with the development in economy. This inverted U-shaped relationship is called Environmental Kuznets curve by scholars.

Scholars around the world have made some attempts, such as input-output model [1–3], system dynamics model [4–6], Kuznets curve [7–11], ridge regression model [12–15], Vertical Auto-regression model [16–19], and computable general equilibrium assessment [20–25]. One of the most widely used methods is the Kuznets curve, which reflects the inverted U-shape between economy and environment. Li Zhou believed that the discharges of three wastes (i.e., waste gas, waste water, and industrial residue) in eastern and western China didn't reach the turning point [26–28]. Taking industrial emissions and discharged pollutants as environmental quality indicators, and based on the large amount of data collected from 1981 to 2004, Li Rui'e concluded that the pollutant like industrial SO_2 possessed an obvious characteristic of Environmental Kuznets Curve (EKC), and the income turning point was lower than that of the developed countries [29–32]. Li Bing studied the influence of the air pollution Kuznets curve by constructing a generalized matrix model and employing the panel data ranging from 2000 to 2011. He found that air pollution was featured with an inverted U-shaped Kuznets Curve. Other factors such as energy efficiency, industrial structure, urbanization, demographic structure, and the opening to the outside would also affect air pollution [33–35].

BP (Back Propagation) neural network, proposed by Rumelhart and McClelland in 1986, is a theory that imitates the biological processing model to realize intelligent processing of information. It is a multi-layer feed-forward neural network that is composed of layers of input, hidden, and output. Signals are transmitted forward while errors are propagated backward. The BP network does not require any mapped functions in advance. Expected output can be obtained by training with a large number of samples. Neuron activation values transmit from the input layer to the output layer through the middle hidden layers, and errors are computed and then propagated backward from the output layer to the input layer. The expected output is finally obtained by continuously modifying the weight and threshold in the network.

Since the 1980s, BP neural network has been widely applied to fields such as pattern recognition, intelligent robot, and automatic control [36,37]. In recent years, scholars in China have expanded the

application of BP neural networks to the economic field. Zhang Jingxin researched on prediction of stock price fluctuation by the financial index [38,39]. Xiao [40] investigated the performance evaluation of suppliers for telecommunication operating enterprises. Wang Jun explored the risk evaluation of the internet credit platform. Liu [41] researched financial risk evaluation of internet listed companies. Li et al. [42] investigated the impact of international competitiveness of China's Trade on producer services.

To sum up, scholars would draw different conclusions with different methods. But there is little corresponding research on one city by using BP neural network and panel model. The corresponding study in Huzhou city would provide a practical evaluation of the relationship between economic growth and environmental quality.

3 Association Analysis between Economic Growth and Environmental Quality Based on BP Neural Network

An area's economy is closely related to its eco-environment, which is a complex artificial ecosystem composed of society, economy, and environment. To conduct an overall and accurate quantitative analysis of the eco-environment in Huzhou city, the paper chooses the BP neural network and the data that relates to the local natural environment.

3.1 Construction of Evaluation Model

In this paper, the neurons in all layers are composed of quantifiable indexes. Those in the input layers are represented by a greening level which is measured by urban green coverage rate (%), green area *per capita* (sq.m.), and green coverage area (ha.), environmental governance which is measured by decontamination capacity of garbage (10000-ton), attainment rate of industrial waste water (%), the utilization rate of industrial solid waste (%), and environmental pollutants which is measured by discharges of industrial waste water (10000-ton), waste gas (million cu.m), and solid waste (10000-ton). The specific indexes in the input layer are listed in Tab. 1.

Table 1: Indexes in input layer in the environmental quality evaluation model

Overview indexes	Specific indexes	Unit
Greening level	Urban green coverage rate	%
	Green area *per capita*	sq. m.
	Green coverage area	ha.
Environmental governance	Decontamination capacity of garbage	10000-ton
	Attainment rate of the industrial waste water	%
	The utilization rate of industrial solid waste	%
Environmental pollutants	Discharge amount of industrial waste water	10000-ton
	Discharge amount of industrial waste gas	million cu.m
	Discharge Amount of industrial solid waste	10000-ton

The number of neurons in the hidden layer is initially determined by an empirical formula shown in Eq. (1). The training won't finish until an optimal fitting is obtained.

$$q = \sqrt{m + n} + \alpha \tag{1}$$

where q, m, and n represent the number of neurons in the hidden, input, and output layer respectively, and α can be any arbitrary integer ranging from 1 to 10.

The neurons in the output layer are represented by the evaluation value. The environmental quality evaluation model based on BP neural network is illustrated in Fig. 1.
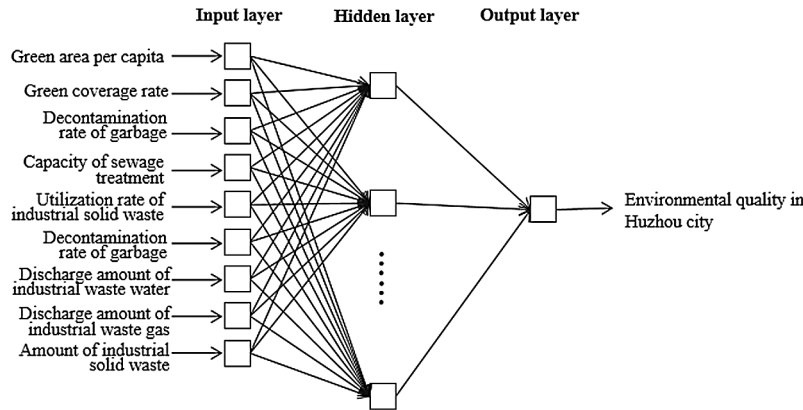

Figure 1: Model for evaluating the environmental quality

3.2 Empirical Analysis

3.2.1 Choosing and Processing Data

Based on the statistical yearbook of Huzhou, the indexes including greening level, environmental governance, and environmental pollutants ranging from 2008 to 2018 are selected as original samples. Since any difference in unit and dimension can cause problems such as a longer training time, a reduction in convergence and stability, and small numbers in the output being swallowed by big ones, standardized processing which is needed to transform the original samples into dimensionless values that range from 0 to 1. This process is shown in Eq. (2).

$$x_n^* = \frac{x_n}{x_{max}} \tag{2}$$

where x_n and x_{max} represent the index and the maximum one, respectively.

Then, a linear interpolation is used to choose an interval between the maximum and the minimum samples. Based on this, the environmental quality in Huzhou city is divided into five levels, where level 1 indicates the highest level and level 5 indicates the lowest one. The training samples are shown in Tab. 2.

Table 2: Training samples in BP neural network

Output layer									Input layer
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	y_1
1	1	1	1	1	1	0	0	0	1
0.9785	0.8988	0.8930	0.8828	0.9905	0.9910	0.6920	0.5600	0.7070	2
0.9570	0.7975	0.7860	0.7655	0.9810	0.9820	0.7950	0.7070	0.8050	3
0.9355	0.6963	0.6790	0.6483	0.9715	0.9730	0.8970	0.8530	0.9020	4
0.9140	0.5950	0.5720	0.5310	0.9620	0.9640	1	1	1	5

3.2.2 Designing BP Network and Training

According to the above model, nine neurons are in the input layer and one in the output layer. After simulation training, a better result is obtained with four neurons in the hidden layer, which is shown in Fig. 2. It is a three-layer neural network with a dimension of $9 \times 4 \times 1$.
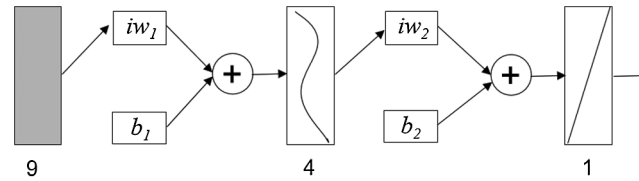

Figure 2: BP neural network ($9 \times 4 \times 1$)

The normalized samples are trained by BP neural network with the MATLAB software. Tansig (an S-type tangent function) and Purelin (a linear activation one) are selected as transfer functions in the hidden and output layers, respectively. The training parameters are set as follows. The learning rate is set to 0.05, and training time is set to 300. Besides, the target error is set to 0.00001. The training won't terminate until the error sum of squares reaches a minimum. Here, the training lasts thirty-three times.

The predictive and actual values of the nine groups of samples are shown in Fig. 3. We can draw a conclusion that they are overlapped completely, which indicates that the model achieves high accuracy and strong generalization ability.
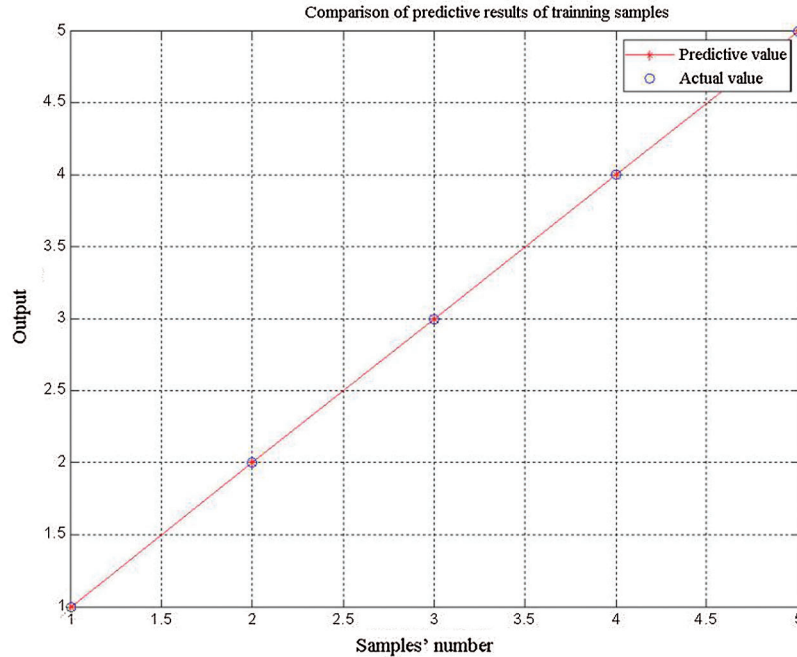

Figure 3: Actual and predictive values of environmental quality in Huzhou city

3.2.3 Analysis on Simulation of BP Network

To get the evaluation value of the environmental quality over the eleven years in Huzhou city which covers three counties (Anji, Deqing, and Changxing) and two districts (Wuxing and Nanxun), a

simulation experiment is conducted by using the trained BP network. When the standardized data is input into the trained BP network, a result can be obtained and it is listed in Tab. 3.

Table 3: Evaluation value of environmental quality from 2008 to 2018

County (or District) Year	Anji	Deqing	Changxing	Wuxing	Nanxun
2008	4.188	1.000	1.971	4.443	5.000
2009	4.168	5.000	2.053	3.225	4.337
2010	5.000	5.000	4.304	2.983	2.042
2011	2.981	5.000	5.000	3.053	3.205
2012	4.053	5.000	5.000	3.306	3.080
2013	3.016	5.000	5.000	3.024	3.066
2014	3.051	5.000	4.991	2.320	3.060
2015	5.000	3.935	5.000	1.000	3.167
2016	4.417	5.000	5.000	1.444	3.105
2017	3.919	4.030	4.108	1.498	2.884
2018	4.731	1.000	3.558	2.095	2.869

3.3 Analysis of Evaluation Result

According to Tab. 3, the average value of environmental quality is 3.631. This relatively high value doesn't indicate a good environment, because pollutants are mainly from the economic centers. Both the large emissions and the high concentration lead to a poor environment.

There is a significant difference in the environment of these three counties and two districts. In recent years, the change of the environmental evaluation becomes smaller and smaller in advanced districts like Wuxing and Nanxun. In other words, the local environment depends highly on its economy, the more advanced the economy, the better the environmental infrastructures.

Based on ArcGIS, a software used to analyze geographic information systems, the evaluation values in 2008, 2011, 2014, and 2018 are marked on the map, as shown in Fig. 4. It can be observed that the environments of Wuxing and Nanxun become better and better, while those in Deqing and Anji tend to be improved though they are below the average.

4 Panel Model Analysis

4.1 Choosing Indexes

There are two kinds of econometric models, one is based on time series data analysis, and the other is based on panel data analysis.

(1) The EKC model based on time series data analysis

The most representative relationship is a quadratic polynomial function shown in Eq. (3). It is a simplified measurement and commonly used.

$$E_t = \beta_0 + \beta_1 y_t + \beta_2 y_t^2 + u_t \tag{3}$$

where E_t is the environmental pressure at time t in some countries or regions, and is usually expressed with environmental index and pollutant discharge; β_0, β_1, and β_2 are related parameters; y_t is the economic output at time t, and is usually expressed with GDP or *per capita* GDP. If $\beta_2 < 0$ and $\beta_1 > 0$, then the curve will form an inverted U shape; if $\beta_2 > 0$ and $\beta_1 < 0$, then it will form a positive U shape. By deriving the first order of Eq. (3), the inflection point can be calculated by $y = \beta_1/2\beta_2$.

(2) The model based on panel data analysis

Proposed by Bandyopadhyay and Shafik in 1992, the model further expands the scope of discussion based on the combination of the quadratic and cubic functions and the influence factors beyond GDP. The primary expression is shown as follows:

$$\ln E_{it} = \beta_0 + \beta_1 \ln y_{it} + \beta_2 (\ln y_{it})^2 + \beta_3 (\ln y_{it})^3 + x_{it} + u_{it} \tag{4}$$

where x_{it} is a control variable, a vector that affects the composition of the other variables of the environmental quality in country *i*. It usually consists of variables with a structural effect which is expressed by the ratio of the added value of the second or the third industries to GDP and technological progress represented by capital stock *per capita*. Besides, the dependence of export or FDI (Foreign Direct Investment) is added for further research on the influence of international trade and FDI on the environment.
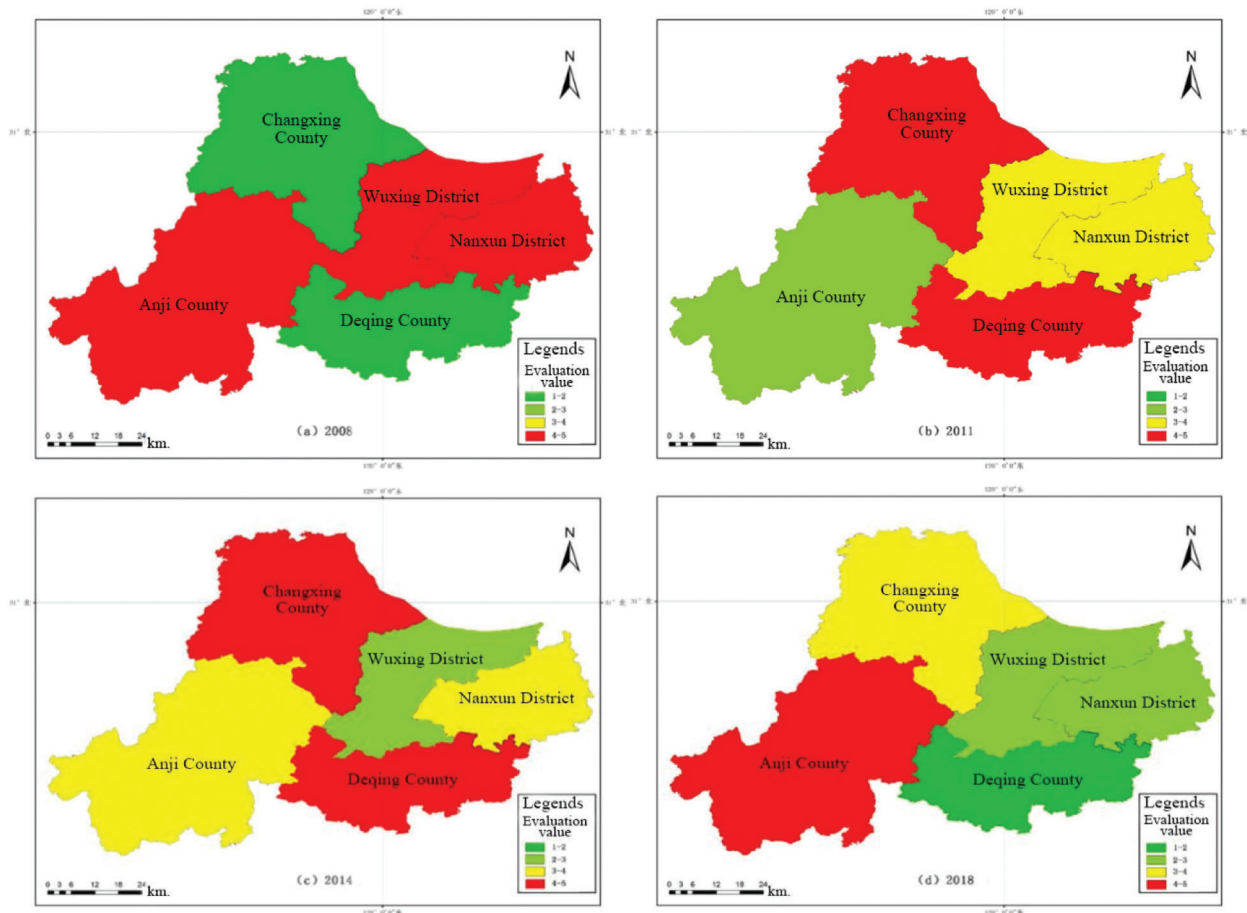

Figure 4: Evaluation value of the environments of the three counties and two districts in Huzhou City

4.2 Choosing Indexes and Data

According to the EKC model, the regression accuracy can be assured with environmental quality as a dependent variable, income *per capita* as an independent variable, and social development, industrial structure, and FDI as control variables.

Comprehensiveness, comparability, and availability are taken into account for choosing data, which is mainly obtained from the statistical yearbook of Huzhou and the statistical bulletin of each county and district. The specific indexes are listed in Tab. 4.

Table 4: Variables

Types	Overview variables	Specific variables	Identification
Dependent variable		Evaluation value of environmental quality	$Y1$
		Discharge of industrial SO_2	$Y2$
		Discharge of industrial waste water	$Y3$
Independent variable	Income *per capita*	*Per capita* GDP	GDP_{it}
Control variables	Social development	Population density	$Dens_{it}$
		Urbanization rate	$Urba_{it}$
	Industrial structure	The proportion of the second industry's in GDP	$Indu_{it}$
	FDI	FDI	FDI_{it}
	Technology progress	Sci-tech expenditure	$Tech_{it}$

4.3 Empirical Analysis

An empirical analysis is performed by using Stata, a software for statistics and data science. The stability of the variables has to be tested first to avoid pseudo regression because there is a space dimension covering five regions, a time dimension covering eleven years, and six variables composed of one independent variable and five control ones. Two variable intercept models (the random utility model and the fixed-effect model) are used for regression because the individual members affect each other. Meanwhile, the Housman test is exploited to determine which model is to be used. If the Housman test is passed, then the fixed-effect model is adopted; otherwise, the random utility model is used.

4.3.1 Stationary-Test and Housman-Test

All variables have to undergo a stationary test and pass it first. Then Housman test is conducted on these three models respectively. The testing results are listed in Tab. 5, which indicates that the random utility model is adopted in Panel 1 which represents the evaluation value of environmental quality, and the fixed-effect model is adopted in Panel 2 and 3 which represents the discharges of industrial SO_2 and waste water respectively.

Table 5: The results of the test

Variables	F-Test	Housman Test	Model
Panel 1	1.07	4.26	Random Utility Model
Panel 2	44.85***	37.91***	Fixed Effect Model
Panel 3	5.59***	16.08***	Fixed Effect Model

where ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively. All the data and special symbols listed in Tab. 5 and Tab. 6 are derived from the automatic analysis of Stata.

4.3.2 Panel Regression Analysis

The regression results are obtained by making empirical analysis on the three panels, as shown in Tab. 6.

(1) Evaluation value of environmental quality and *per capita* GDP

The regression of Panel Model 1 is calculated through Eq. (5).

$$Y1_{it} = 64.3695 \ln GDP_{it} - 2.9131 \ln GDP_{it}^2 - 1.3482 \ln Dens_{it} - 1.4052 Urba_{it} + 6.7185 Indu_{it}$$
$$- 0.2907 \ln FDI_{it} - 0.4078 \ln Tech_{it} - 347.3748 \tag{5}$$

Table 6: The estimation results of panel models

Variables	Panel Model 1	Panel Model 2	Panel Model 3
$\ln GDP_{it}$	64.3695**	29.7744***	41.8059***
	(2.05)	(2.94)	(2.95)
$\ln GDP_{it}^2$	–2.9131**	–1.3844***	–1.8672***
	(–2.03)	(–2.94)	(–2.83)
$\ln Dens_{it}$	–1.3482**	–0.3574	3.9617
	(–2.14)	(–0.04)	(0.34)
$Urba_{it}$	–1.4052***	–0.6171	0.7873
	(–0.51)	(–0.65)	(0.60)
$Indu_{it}$	6.7185*	0.4509*	0.4749*
	(1.90)	(0.31)	(0.23)
$\ln FDI_{it}$	–0.2907***	–0.1172	–0.1248
	(–0.60)	(–0.81)	(–0.61)
$\ln Tech_{it}$	–0.4078***	–0.1595	–0.2821
	(–0.81)	(–0.69)	(–0.87)
Constant	–347.3748***	–148.9527*	–246.6514**
	(–2.00)	(–1.72)	(–2.04)
R^2	0.1442	0.1731	0.1011
Relationship characteristics	Inverted U-shape	Inverted U-shape	Inverted U-shape

where, ***, **, and * represent the significance level of 1%, 5%, and 10%, respectively. T-statistic is shown in the brackets.

According to the regression result, a conclusion can be drawn that there is an inverted U-shaped relationship between the evaluation value of environmental quality and *per capita* GDP. The calculation of the result's coefficient indicates that the inflection point is CNY 62943.95. When the income *per capita* exceeds the coefficient, the environment becomes better with the rising in income. The peak income (CNY 63719) appeared in 2012.

There are four groups of negative relationships between the evaluation value and: (1) the population density. The larger the population, the better the environment. It is mainly because of the enhanced awareness of environmental protection, and people prefer to residence in a better environment. (2) the urbanization rate. The higher the rate, the smaller the evaluation value, and the better the environment. In recent years, the idea of "Lucid water and lush mountains are invaluable assets" has prevailed in Huzhou, and the environment of this city becomes better and better with the continuous improvement in

infrastructure, living conditions, and urban environment. (3) FDI. The higher the FDI, the better the environment. In the past years, the city has mainly focused on the third industry that produces no pollutants. The development of tourism can improve the environment. (4) the progress in technology. The more the expenditure on science and technology, the better the environment. The progress can not only reduce energy consumption and pollutants but also improve the energy efficiency and the control level of pollution.

However, there is a positive relationship between the evaluation value and the industrial structure. The proportion of the second industry in GDP has a negative effect on the environment because heavy industry with high pollution belongs to the second industry. The higher the proportion of the second industry, the more environmental pollution.

(2) Emission of industrial SO_2 and *per capita* GDP

The regression of Panel Model 2 is calculated by Eq. (6).

$$\ln Y2_{it} = 29.7744 \ln GDP_{it} - 1.38441 \ln GDP^2_{it} - 0.35741 \ln Dens_{it} - 0.6171 Urba_{it} + 0.4509 Indu_{it}$$
$$- 0.1172 \ln FDI_{it} - 0.1595 \ln Tech_{it} - 148.9527 \tag{6}$$

According to the regression result, a conclusion can be drawn that most variables in Panel Model 2 are not as significant as those in Panel Model 1, and there is an inverted U-shaped relationship between the industrial SO_2 emission and the rise of income *per capita*. CNY 46770.13 is the inflection point of the industrial SO_2 emission, which is smaller than that of the evaluation value. When the income *per capita* exceeds the inflection point, the emission of industrial SO_2 decreases with the rising income. The income *per capita* in Huzhou was CNY 42547 in 2009, and CNY 50146 in 2010. The peak emission emerged between the years 2009 and 2010.

There are also four groups of negative relationships between the SO_2 emission and: (1) the population density. Generally, the greater the population density, the larger the SO_2 emission. However, this convention does not hold for in Huzhou. On the contrary, the regions with higher population density have a better environment, and the SO_2 emission is lowered because of the protection performed by the local government. (2) the urbanization rate. The larger the rate, the less the SO_2 emission. Under the guidance of "Lucid water and lush mountains are invaluable assets", the environment becomes better and better, and more support is provided by the local government. (3) FDI. The higher the FDI, the less the emission. Because FDI focuses mainly on the third industry, most of which is the service industry without emitting SO_2 into the atmosphere. (4) the progress in technology. Effective protection works better with the support of advanced technology and equipment. The progress in technology can greatly reduce the emission of SO_2.

However, there is also a positive relationship between the SO_2 emission and the industrial structure. The proportion of the second industry in GDP adversely affects the environment of Huzhou. It is consistent with the traditional experience, which indicates that the emission increases with the second industry with heavy pollution.

(3) Discharge of industrial waste water and *per capita* GDP

The regression of Panel Model 3 is calculated through Eq. (7).

$$\ln Y3_{it} = 41.8059 \ln GDP_{it} - 1.86721 \ln GDP^2_{it} + 3.9617 \ln Dens_{it} + 0.7873 Urba_{it} + 0.4749 Indu_{it}$$
$$- 0.1248 \ln FDI_{it} - 0.2821 \ln Tech_{it} - 246.6514 \tag{7}$$

According to the regression result, a conclusion can be drawn that there is an inverted U-shaped relationship between the income *per capita* and the discharge of waste water. CNY 72692.97 is the inflection point. When the income *per capita* exceeds the inflection point, the discharge decreases with

the rising income. The GDP *per capita* in Huzhou reached CNY 69213 in 2013, and CNY 74334 in 2014. The peak emission appeared between the years 2013 and 2014.

There are three groups of positive relationships between the discharge of waste water and: (1) the population density. The greater the population density, the larger the discharge. It is consistent with the traditional experience, which indicates that pollution becomes more serious with the increasing demand in consumption and the promoted production. (2) the urbanization rate. An increased urbanization rate results in a rise in industrial enterprises, and thus more industrial water and waste water. (3) the industrial structure. The proportion of the second industry in GDP has a negative influence on the environment. It is consistent with the traditional experience, which indicates that the discharge increases with the proportion of the second industry.

However, there are two groups of negative relationships between the discharge of waste water and: (1) FDI. The discharge is reduced with the increase of FDI. It is consistent with the traditional experience, which indicates that the emission increases with the proportion of the second industry. (2) the progress in technology. Effective protection can works better with the support of advanced technology and equipment.

4.3.3 Comprehensive Analysis on Panel Regression

Based on the regressions calculated above, Fig. 5 shows the fitting curves between *per capita* GDP and the evaluation value of environmental quality, the SO_2 emission, and the waste water, respectively. The inflection points of the three inverted U-shaped curves are CNY 62943.95, CNY 46770.13, and CNY 72692.97, respectively. The curves show obviously that the environment in Huzhou is improved when the income *per capita* exceeds the inflection points.
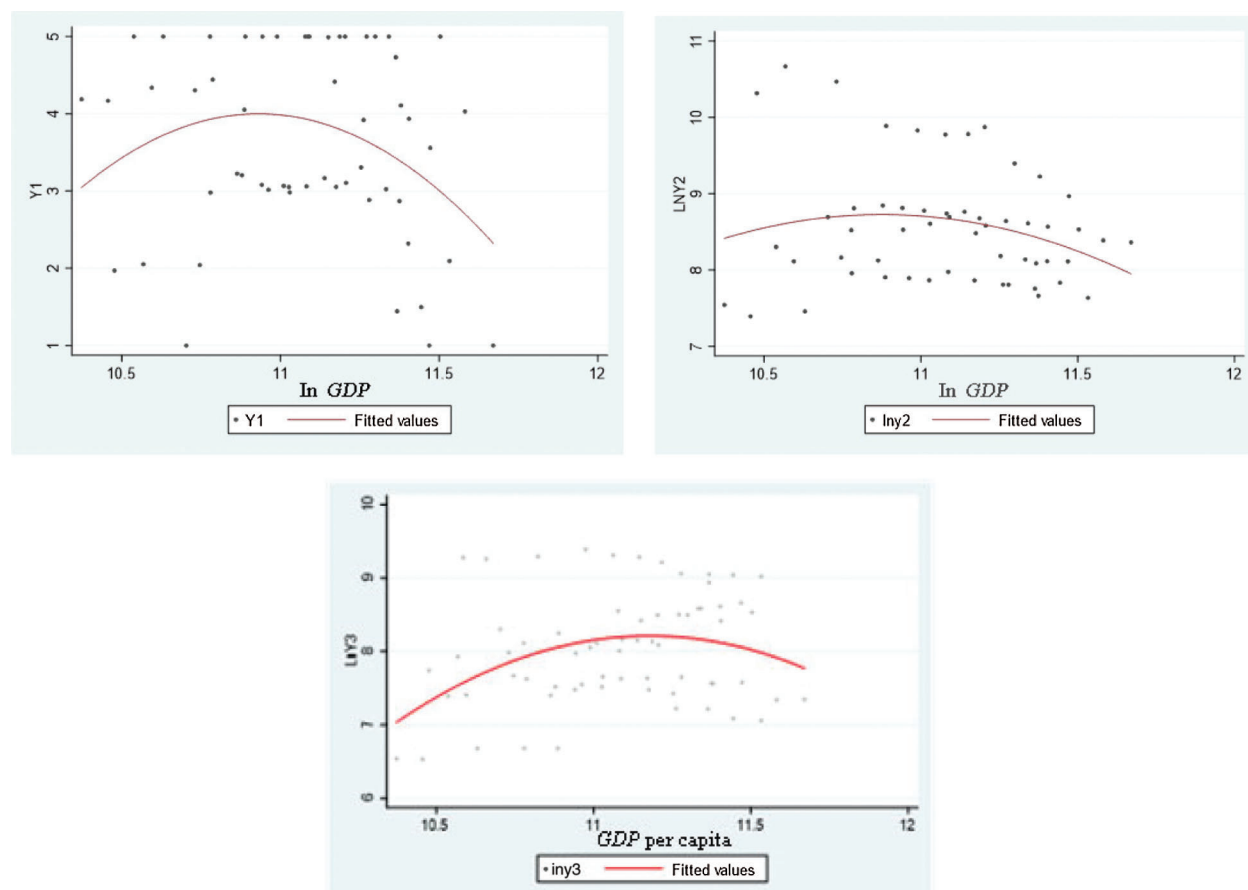

Figure 5: The relationships between environmental quality and economic growth

There is a significant and positive relationship between the proportion of the second industry and the environmental indexes. The pollution is mainly caused by the second industry, such as mining, manufacturing, power supply, gas, water supply, and construction. In this industry, a large amount of energy is consumed, and lots of waste gas, waste water, and solid waste are produced.

There are two groups of negative relationships between the environmental indexes and: (1) the progress in technology. The progress in science and technology can solve the current and potential problems in the environment, which helps to improve the environment greatly in the long term. (2) FDI. In the era of the new normal, Huzhou's industrial structure is upgraded constantly. FDI focuses mainly on the third industry or high-end manufacturing with high technology and low pollution, which contributes to an enhanced environment.

The urbanization rate correlates positively to the SO_2 emission but negatively to the discharge of waste water. It is because of people's cognitive differences in pollutants. SO_2 has been considered harmful and controlled effectively for a long time, while the waste water hasn't received much attention from the local government until rich nutrition emerges in it.

5 Conclusion

There is a significant difference in space and time dimensions of environmental quality. In the space dimension, the environmental quality relates closely to the economic growth; in the time dimension, the average value of environmental quality was 3.32 in 2008 and fluctuated from 3.7 to 3.8 in the year between 2010 and 2012, and even decreased steadily in the next few years. Meanwhile, an inverted U-shaped relationship exists between economic growth and evaluation value, SO_2 emission, and discharge of industrial waste water. The inflection point of income in the environmental Kuznets curve in the model which takes the evaluation value of the environmental quality as a dependent variable (CNY 62943.95) is higher than that of the model which takes SO_2 emission as an independent variable (CNY 46770.13). The empirical results indicate that the pollutants are mainly caused by the second industry. For every percentage increase of the proportion of the second industry in GDP, the SO_2 emission will increase by 0.451% and the waste water by 0.475%.

Future improvements of this study lies in the accurate data. Also, more samples are needed because the limitation of choosing samples can lead to a subjective bias in the empirical results.

Conflicts of Interest: We declare that we have no conflicts of interest to report regarding the present study.

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