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An empirical test of the environmental Kuznets curve in China: A panel cointegration approach

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Abstract

This paper investigates the relationship between environmental pollution and economic growth in China based on the environmental Kuznets curve hypothesis, using Chinese provincial data over 1985–2005. Waste gas, waste water and solid wastes are used as environmental indicators and GDP is used as the economic indicator. It is found by panel cointegration test that there is a long-run cointegrating relationship between the per capita emission of three pollutants and the per capita GDP. According to comparisons with the dynamic OLS estimator and the Within OLS estimator, we find that panel cointegration estimation is preferable for all pollutants except for solid wastes. The results also show that all three pollutants are inverse U-shaped, and water pollution has been improved earlier than gas pollution and solid pollution.

JEL classification: C23; C52; O16; Q01; Q56
Keywords: Economic growth; Environmental pollution; Environmental Kuznets curve; Panel cointegration; China

1. Introduction

In the last few years, there have been growing studies on the relationship between economic growth and environmental pollution, e.g. Grossmann and Krueger (1991, 1993, 1995), Panayotou (1993), Selden and Song (1994).[1] The common finding is that there is an inverse U-shaped relationship between economic activity, usually measured in terms of per capita GDP, and the environmental impact indicator in per capita. That is to say, environmental degradation first increases with per capita national income during the early stages of economic growth, and then declines with per capita GDP after arriving at a threshold, called turning point. This has also been referred to as the environmental Kuznets curve (hereafter EKC) (Selden & Song, 1994; Stern, Common, & Barbier, 1996) which has become one of the “stylised facts” of environmental and resource economics (e.g., Stokey, 1998), because it follows a similar pattern to the income inequality, which was identified by Kuznets (1955).

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[1] The summary evidence can be seen in Panayotou (2000), and more recently, Galeotti (2003).

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The relationship depicted by this curve is that pollution is inevitable in the early stages of economic development, but that there will be alleviation as the economy reaches a certain turning point. If true, economic policies could allow extensive, although not necessarily absolute, use of the environment for growth purposes. But carrying out such policies involves inherent dangers. If developing countries decide to overlook environmental protection by reckoning on increasing incomes to abate environmental destruction, the consequences could be devastating. It is possible because the point of irreversible damage for a particular ecosystem may be reached before the turning point for environmental improvement. It can be illustrated in Fig. 1. EKC_1 represents the original inverse U-shaped relationship between environmental degradation and income per capita; EKC_2 is a divergent curve indicating that environmental degradation monotonously increases with the rise of income; EKC_3 which is lower than EKC_1 denotes our target with environmental protection, P is its peak. Once environment degradation exceeds the point of irreversible damage, it increases as the income increases, see EKC_2. On the contrary, if the peak value is controlled under the point of irreversible damage with environmental protection, the result would be improved and this follows the curve EKC_3. It is therefore meaningful for governments to take measures to reduce environment pollution.

The understanding of the EKC is actually positive for China. It is well known that China has been experiencing sustained and rapid industrialization starting in the late 1970s when economic reform was introduced. Since then, GDP per capita has been kept growing at close to 10% per year. Rapid economic growth enhances the living standard and the level of social welfare, while at the same time serious environmental problems come into being. Environmental quality deteriorates quickly as a consequence of a large number of natural resources are over-consumed. Although positive measures have been taken and some effects have been acquired, it is still a difficult and complicated task to realize sustainable development and coordinate the relationship between economic growth and environmental protection.

In this paper, we use Chinese provincial data from 1985 to 2005 to examine the existence of the EKC relationship between per capita income (with gross domestic product) and per capita pollution (with waste gas, waste water and solid wastes respectively) in China. According to the EKC hypothesis, the logarithm of the indicator is modeled as a quadratic or cubic function of the logarithm of income. However, because the EKC hypothesis posits a long-run relationship between per capita income and environmental quality, the analysis needs to be examined strictly and carefully in econometrics. Data for the EKC analysis are always time series, consideration of data properties is necessary because appropriate methods depend on whether data are stationary or nonstationary. That is, if there is no cointegration in a posited regression among nonstationary variables, the EKC regression could be a spurious regression, and interpreting the results in the classical way is invalid. Additionally, the economic indicator and the environmental degradation indicator are required to be integrated to satisfy the precondition for cointegration. To solute this problem, the panel unit root and panel cointegration tests which initially applied to the environmental Kuznets curve (EKC) in Perman and Stern (2003) are adopted in the present paper.

The EKC issues are carried out in the following three steps. First, unit roots properties of the panel dataset are properly examined by applying the tests for cross-sectionally independent panels. Second, the existence of a cointegrating relationship between pollutant emissions and per capita GDP is tested using the panel cointegration

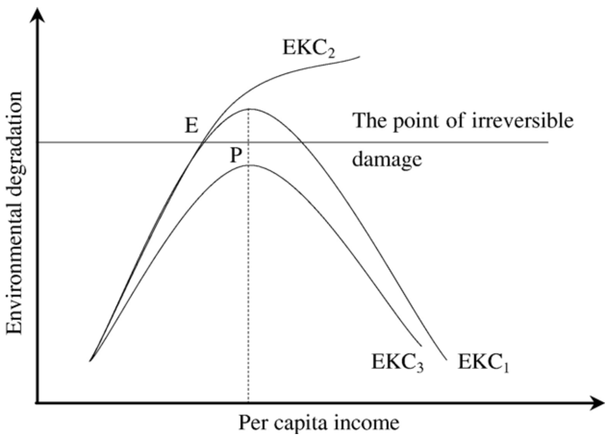

Fig. 1. The EKC relationship between environmental degradation and per capita income.

technology. Finally, a DOLS (dynamic ordinary least squares) estimator is used to evaluate the long-run relationship among the variables considered.

Apart from the introduction, the remainder of the paper is organized as follows. Section 2 is the review of the EKC literature. Section 3 is about data source and model specification. Section 4 presents empirical results. The last section draws some conclusions.

2. EKC literature review

The impact of economic growth on environment has attracted an increasing attention since the last few decades of the previous century. The EKC literature focused on this issue was initiated in the early 1990s by a paper of Grossmann and Krueger (1991, 1993) investigating the environmental impacts of the North American Free Trade Agreement. They postulated, estimated and ascertained an inverted U-shape relationship between measures of several pollutants and per capita GDP. Subsequently and almost contemporaneously, Shafik and Bandyopadhyay (1992) and Panayotou (1993) reported similar results.

From a theoretical point of view, the EKC does not only depend on levels of per capita GDP, but a series of changes behind economic growth. In general, economists analyze mechanisms behind the EKC by examining scale effect, structural effect and technique effect. A part of scholars believe that upgrading from the adjustment of economic structure gives birth to the EKC, e.g. Panayotou (1993). When economic development going through the stages of preliminary, rapid-development and high-grade, industrial structure first upgrades from agriculture to a high-pollution industry, finally turns to information concentrated industry, which leads to the improvement of the environmental quality. This is called the structural effect (Stern, 2004). Some scholars also consider that economic growth can break through one threshold when arriving at a certain stage of economic development. At a low income level, only the high-pollution technique can be used, but once leaping over the threshold of economic development, cleaner technologies can be adopted. This is called the technique effect (Stokey, 1998). In addition, some scholars attribute the demand factors to the EKC. This means that demands for a clean environment will be increased over the per capita income (Lopez, 1994). Andreoni and Levinson (2001) believe that the existence of scale effect is crucial for the EKC. In the static model of single department, the EKC can be derived technically, only if pollution control is increasing in scale. Suri and Chapman (1998) bring the contribution of industrial products of the import and export to industrial products of national production into the analytical framework of the EKC. That is to say, the low emission corresponds to the growth of industrial products of the import, while the high emission corresponds to that of the export. This result suggests that there is a strong relationship between trade and environmental quality, so the evolution of environmental quality can be predicted effectively.

It is, however, suggested that the EKC is an essentially empirical phenomenon, not a certain law, according to the EKC literature which shows mixed evidence. On the one hand, a large number of empirical literature provided strong evidence in support of the EKC relationship between income and emission, e.g. Panayotou (1993), Selden and Song (1994), and Giles and Mosk (2003). Panayotou (1993) finds the inverted U-shape relation between net deforestation and income per capita. Selden and Song (1994) also find an inverted U-shaped relationship for emissions of CO and NO_x. Giles and Mosk (2003) examine a very long-run relationship between income and emission of CH_4 in New Zealand over the period of 1895-1996. Based on traditional quadratic and cubic functional forms and nonparametric kernel regression, they found an inverted U-shape curve. On the other hand, some researchers argue that there is no evidence supporting the EKC hypothesis, e.g. Holtz-Eakin and Selden (1995), Hettige, Mani, and Wheeler, (1999), de Bruyn, van den Bergh, and Opschoor (1998), and Roca, Padilla, Farré, and Galletto (2001). Holtz-Eakin and Selden (1995) find that CO_2 emission does not show the EKC pattern, but instead monotonically increases with income. Hettige et al. (1999) explore the income-environmental quality relation for industrial water pollution and show that water pollution stabilizes with economic development, but have not detected an eventual decline. de Bruyn, et al. (1998) consider three pollutants (CO_2, NO_x, and SO_2) in four countries and find that emissions are positively correlated with income but it is possible to abate them because of technological progress and structural change. Roca et al. (2001) consider Spanish data for the emissions of six atmospheric pollutants—CO_2, SO_2, N_2O, CH_4, NO_x and non-methanic volatile organic compounds (NMVOC) for the period 1980-1996. With the exception of SO_2 they fail to find satisfactory econometric relationships to support EKCs for any of these pollutants.

As discussed in the Introduction, nonstationarity should be taken into account when investigating the relationship between pollutant emission and per capita income. This leads to a new area of empirical studies on the EKC. Perman and Stern (2003) perform both individual and panel unit root tests for SO_2 emissions and per capita GDP for 74 countries using 30 years of data and conclude that both these variables are integrated in the majority of countries, but evidence from panel cointegration tests show that the EKC does not exist. Galeotti, Manera and Lanza (2006) ask whether similar strong conclusions can be arrived at when carrying out tests of fractional panel integration and cointegration and the results show that more EKCs come back into life relative to traditional integration/cointegration tests, but the EKC remains a fragile concept. Further studies on important theoretical and econometric problems relating to unit root nonstationary regressors in panels when estimating the EKC are discussed in Wagner and Müller-Fürstenberger (2004) and Müller-Fürstenberger and Wagner (2007).[2]

Although there is a large body of literature on the EKC phenomena for several countries and for several environmental quality indices, little is known about China. It is worth studying on the EKC of China—an important part of empirical evidence. Increasing studies have been taken in China, e.g. Shen and Hashimoto (2004), Liu, Heilig, Chen, and Heino (2007), Shen (2006). Shen and Hashimoto (2004) use the cross-province panel data of the seven pollutants of China to investigate whether the EKC hypothesis may even exist on a country level, and find out that the EKC hypothesis exists in five of these pollutants, while the other two show a N-shape relationship between pollutant emission and per capita income. Liu et al. (2007) utilize environmental monitoring data from Shenzhen on concentration of pollutants in ambient air, main rivers, and near-shore waters from 1989 to 2003. The results show that production-induced pollutants support EKC while consumption-induced pollutants do not support it. Shen (2006) uses Chinese provincial data from 1993 to 2002 to investigate the relationship between per capita income and per capita pollutant emission based on a simultaneous equation model. It is shown that an EKC relationship is found in COD, Arsenic and Cadmium emissions, but SO_2 shows a U-shaped curve and Dust Fall indicates no relationship. But also, none of the above studies take nonstationarity of the variables into account. Thus, this study on the EKC relationship in China is more valuable.

3. Data and model specification

3.1. Data source

In our empirical analysis, we use the data of 29 provinces[3] in mainland China from 1985 to 2005 to establish EKCs by using gross domestic product (GDP) as the economic indicator, and waste gas emission, solid wastes generated and waste water emission as environmental indicators. All provincial data are available in the China Statistical Yearbook and the China Environmental Yearbook. These data included here are as follows:

S	pollutant, e.g. waste gas emission (in 100 millions of metric cubic meters), waste water emission (in ten thousands of metric tons), and solid wastes generated (in ten thousands of metric tons).
GDP	gross domestic product (in 100 millions of RMB yuan).
P	population (in ten thousand).

Considering that the provincial GDPs data included in the China Statistical Yearbook are at current prices, they have to be converted into fixed prices. We adjusted every provincial GDP data by considering official provincial price index (Consumer Price Index, setting year 2000 = 100). Then it can be easy to obtain all the considered variables per capita, e.g. per capita GDP (in RMB yuan), per capita waste water (in kilogram), per capita solid wastes (in kilogram) and per capita waste gas (in cubic meter).

[2] The problems discussed in Wagner and Müller-Fürstenberger (2004) and Müller-Fürstenberger and Wagner (2007) are nonlinear transformations of integrated regressors in the EKC, the assumption of cross-sectional independence and the small sample properties of panel unit root and cointegration techniques, respectively.

[3] We selected 29 of the 31 provinces and municipalities directly under the administration of the central government in mainland China: Beijing, Tianjing, Hebei, Shanxi, Neimenggu, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Sichuang, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ninxia, Xinjiang. ChongQing and Tibet are excluded due to 1) Chongqing was a part of the Sichuan province. It was upgraded to a municipality (provincial level) in the late 1990s. Data in ChongQing is very recent and XiZhang (Tibet) data are not available in most years.

3.2. The model

A careful analysis of the EKC issue is a complicated task and the relationship between economic growth and environmental pollution can be very complicated, depending upon a host of factors. Among these are: the size of the economy, the industrial structure, population density, the vintage of the technology, the demand for environmental quality, the level of environmental protection expenditures and international trade. All these aspects are interrelated (Shen, 2006). In order to test the pure EKC relationship and simplify the analysis, these factors relative to the environmental pollution are ignored here. Of course, our analysis can be generalized to take these factors into account.

In this paper, a standard EKC model is expressed as a logarithmic quadratic or cubic function of the income to examine if the EKC relationship between environmental pollution and economic growth exists. Panel data model with fixed effects (including both individual specific and time specific effects) are adopted. Both dependent variable (per capita pollution) and independent variable (GDP per capita) are in natural logarithm. Then, the homogeneous EKC model is usually given by:

$$\ln\left(\frac{S}{P}\right)_{it} = \alpha_i + \theta_t + \beta_1 \ln\left(\frac{\mathrm{GDP}}{P}\right)_{it} + \beta_2\left[\ln\left(\frac{\mathrm{GDP}}{P}\right)_{it}\right]^2 + \beta_3\left[\ln\left(\frac{\mathrm{GDP}}{P}\right)_{it}\right]^3 + u_{it} \tag{1}$$

where the subscript i stands for a region index ($i=1,\ldots,N$), t is a time index ($t=1,\ldots,T$). α_i is the individual specific intercept, time dummy, θ_t, represents time (specific) effect, u is a stochastic error term which is in general allowed to be serially correlated.

In this model, homogeneity is assumed for the parameters β_1, β_2, and β_3, which depend neither on a specific region nor on the time period. It is suggested that all regions take on the same shape of the functional relation of income-pollution. More importantly, Eq. (1) allows for testing the various forms of environmental-economic relationships. (i) $\beta_1>0$, $\beta_2<0$ and $\beta_3>0$ reveals a cubic polynomial, representing a N-shaped curve (Fig. 2a); (ii) $\beta_1<0$, $\beta_2>0$ and $\beta_3<0$ reveals an inverse N-shaped relationship (Fig. 2b); (iii) $\beta_1<0$, $\beta_2>0$ and $\beta_3=0$ reveals a U-shaped relationship (Fig. 2c); (iv) $\beta_1>0$, $\beta_2<0$ and $\beta_3=0$ reveals an inverse U-shaped relationship, representing the EKC (Fig. 2d). The turning point of this curve is computed by $\hat{\tau}=\exp(-0.5\hat{\beta}_1/\hat{\beta}_2)$; (v) $\beta_1>0$ and $\beta_2=\beta_3=0$ reveals a monotonically increasing linear relationship (Fig. 2e); (vi) $\beta_1<0$ and $\beta_2=\beta_3=0$ reveals a monotonically decreasing linear relationship (Fig. 2f); (vii) $\beta_1=\beta_2=\beta_3=0$ reveals a level relationship (Fig. 2g).

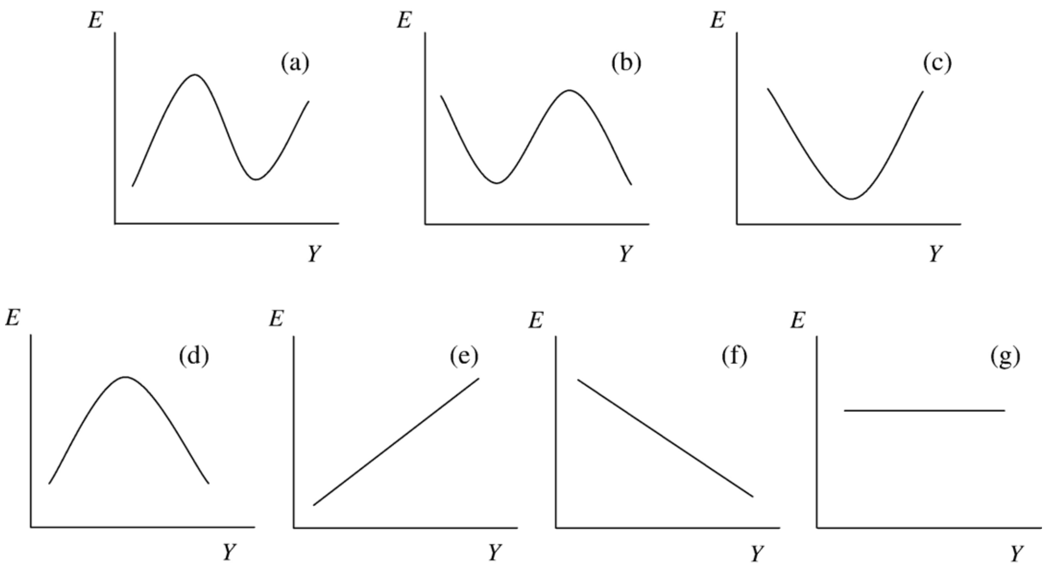

Fig. 2. Various relationships between environmental degradation and per capita income.

Table 1
F test for fixed effects

Null hypothesis of the *F* test	Waste gas		Waste water		Solid wastes	
	Quadric	Cubic	Quadric	Cubic	Quadric	Cubic
Ha: $\alpha_1 = \cdots = \alpha_{N-1} = 0$ and $\theta_1 = \cdots = \theta_{T-1} = 0$	78.518*	78.454*	84.866*	95.114*	79.513*	79.531*
Hb: $\alpha_1 = \cdots = \alpha_{N-1} = 0$ given $\theta_t \neq 0$ for $t=1,\ldots,T-1$	118.536*	118.282*	59.209*	66.367*	129.748*	129.242*
Hc: $\theta_1 = \cdots = \theta_{T-1} = 0$ given $a_i \neq 0$ for $i=1,\ldots,N-1$	12.659*	12.009*	12.881*	12.884*	6.351*	6.436*

Figures in this table are the resulting *F*-statistics. * denotes the rejection of the null hypothesis at 5% level of significance.

3.3. Model specification

The first task is to test if specific individual effects and time effects included in Eq. (1) are valid. To test for fixed effects, we carry out the resulting *F* test which can be found in classical textbooks, e.g. Baltagi (2002, p32–33). Table 1 reports the results of the *F* test for fixed effects. All the *F* statistics are significant at less the 5% level of significance, indicating that both specific individual effects and specific time effects exist.

Secondly, as shown in Fig. 2 there may be various functional forms for the EKC, the log–log model needs to be pre-specified. We first run the panel data within an OLS estimator for the quadratic and cubic specifications respectively, both considering individual effects and time effects. The corresponding results are reported in Table 2. For waste water, all parameter estimates are significant when using the quadratic and cubic functional forms. But for waste gas and solid wastes, only parameters estimated with the quadratic log–log model are significant at 5% level of significance. Therefore it is not easy for us to judge which model is preferred for waste water, though the quadric specification can be adequate for both waste gas and solid wastes.

Then, the Wald test is performed to choose the more appropriate one between the quadratic function and the cubic function, see also Table 2.[4] It is shown that the null can be rejected at 5% level of significance when using waste water as the environmental pollution indicator, while it cannot be rejected for both waste gas and solid wastes (which are the same as the results of parameter estimates).

Hence, to examine if these long-run (or cointegrated) relationships are valid in the next section, a cubic log–log model is pre-specified to describe the relationship between per capita emission and per capita GDP for waste water, while quadratic log–log models are pre-specified for waste gas and solid wastes. All the log–log models for three pollutants take specific individual effects and specific time effects into account.

4. Econometric methods and empirical findings

In this section, the methods used in this article and the resulting empirical findings will be introduced. Panel unit root tests of Levin and Lin (1992) (hereafter, LL) test and Im, Pesaran, and Shin (1997) (hereafter, IPS) are first applied to test if there are unit roots in panel data sets. In the second step, Pedroni's (1999) panel cointegration test is used to examine the cointegrating relationship. Afterward, we proceed to estimate the EKC with the DOLS (dynamic OLS) estimator.

In what follows, the econometric procedures and the resulting findings are to be described in the steps of the present exercise.

4.1. Panel unit root tests

One familiar panel unit root test is the Levin and Lin (1992) test. The LL test is an extension of the standard Dickey–Fuller test to the panel framework. The null of a unit root is investigated against the alternative of a stationary process for all cross-sectional regions. That is, they test the null hypothesis of $\rho_i = \rho = 0$ for all i, against the alternative of

[4] The Wald statistic is to test the parameter restriction on $\beta_3 = 0$, i.e. the null of the quadratic specification when $\beta_3 = 0$ against the alternative of the cubic specification when $\beta_3 \neq 0$.

Table 2
Estimation of the alternative model and the resulting Wald test

Variables	Waste gas		Waste water		Solid wastes	
	Quadric	Cubic	Quadric	Cubic	Quadric	Cubic
ln(GDP)	3.0716** (9.282)	0.6331 (0.202)	2.0075** (7.556)	−16.4287** (−6.878)	1.2662** (3.997)	5.0073^{+} (1.672)
[ln(GDP)]^2	−0.1184** (−7.416)	0.1581 (0.446)	−0.0658** (−4.902)	2.0626** (7.514)	−0.0611** (−3.815)	−0.4930 (−1.433)
[ln(GDP)]^3		−0.0104 (−0.781)		−0.0817** (−7.762)		0.0166 (1.257)
Adjusted R^2	0.7766	0.7764	0.5294	0.5746	0.4318	0.4324
Turning point	430 441	—	4 190 985	31564 [a]	31 668	—
Wald test	H_0: the quadratic curve, H_1: the cubic curve					
Wald statistic	0.6100		60.2475**		1.5790	

Figures in parentheses are t statistics for regression coefficients. "**", "*" and "+" denote that the parameter estimate is significant at 1%, 5% and 10% level of significance, respectively. "a" denotes the larger value which is calculated by solving the root of the first-order derivative of the cubic inverse N-shaped curve, and "—" denotes no existence of the turning point.

$\rho_1 = \rho_2 = \cdots = \rho<0$ for all i, with the test statistics $t_{\hat{\rho}}=\hat{\rho}/\text{s.e.}(\hat{\rho})$, where $\hat{\rho}$ is estimated from the autoregressive model as follows:

$$\Delta y_{it} = \mu_i + \rho y_{it-1} + \sum_{k=1}^{p} \phi_{ik}\Delta y_{it-k} + \varepsilon_{it} \tag{2}$$

for (i=1,…,N) and (t=1,…,T). This panel-based ADF test restricts the coefficients ρ_i by keeping them homogenous across all units of the panel. The limitation of the LL test is the assumption of homogeneity and independent error terms across cross-sectional units.

The second test presented here is the well known Im et al. (1997) test which relaxes the assumption of the identical first order autoregressive coefficients of the LL test and allows varying across regions under the alternative hypothesis. IPS test the null hypothesis of $\rho_i=0$ for all i, against the alternate of $\rho_i<0$ for all i. Thus, instead of pooling the data, IPS uses separate unit root tests for the N cross-section units. Their test is based on the (augmented) Dickey–Fuller statistics averaged across groups. Then the average of the $t_{\rho i}$ statistics can be used to perform the following $Z_{t-\text{bar}}$ statistic:

$$Z_{t-\text{bar}} = \sqrt{N}(\overline{t} - E(\overline{t}))/\sqrt{\text{Var}(\overline{t})} \tag{3}$$

where $\overline{t} = (1/N)\sum_{i=1}^{N} t_{\rho_i}$, the terms $E(\tilde{t})$ and $\text{Var}(\tilde{t})$ are, respectively, the mean and variance of individual specific t-statistic ($t_{\rho i}$). Based on the Monte Carlo experiment results, IPS demonstrates that their test has more favorable finite sample properties than the LL test. Both test statistics of LL and IPS are asymptotically distributed as standard normal with left-sided rejection area.

Table 3 reports the results of panel unit root tests. At the 5% significance level, the null hypothesis of nonstationarity can be only rejected for per capital solid wastes with and without time trend using LL test, and the IPS test statistics show that all series are nonstationary in level. The results show that these panels have heterogeneous unit roots, or are integrated of order one (i.e. they are symbolically I(1)). It should be noted that the integrated orders of the square and cubic terms of per capita GDP are the same as that of per capita GDP, in support of the finding of Granger and Hallman that if per capita GDP is I(1), its square is also I(1).[5] [6]

4.2. Panel cointegration test

This section proceeds to test per capita GDP and per capita pollution for cointegration to determine if there is a long-run relationship in the econometric specification.

[5] Granger and Hallman (1988, 1991) first discussed these possible problems with the transformed I(1) time series data. They used nine kinds of function forms to investigate whether the transformed I(1) series still keep the nonstationary properties. They found whether the integrated process keep its nonstationary characteristic after transformed will depend on functional forms.

[6] Park and Phillips (1999) extended the existing limit theory for integrated processes to nonlinear models. They use the concept of local time to derive asymptotically results for nonlinear regression models.

Table 3
Panel unit root tests

	LL		IPS	
	No time trend	Time trend	No time trend	Time trend
ln(GDP/*P*)	0.3139	0.4622	11.0772	−0.4768
[ln(GDP/*P*)]^2	2.2778	1.6090	13.8928	1.9091
[ln(GDP/*P*)]^3	4.2852	2.8297	16.1631	4.7773
ln(Gas/*P*)	−0.9102	−0.6658	12.4552	4.3950
ln(Water/*P*)	−2.8046*	−2.5655*	2.8033	4.5350
ln(Solid/*P*)	−2.3383*	−2.2198*	9.0688	4.2762
Δ ln(GDP/*P*)	−12.2789*	−12.0457*	−5.5714*	−5.0312*
Δ [ln(GDP/*P*)]^2	−10.5018*	−9.8312*	−3.0931*	−4.4503*
Δ [ln(GDP/*P*)]^3	−8.2560*	−7.2673*	−0.3662	−3.8021*
Δ ln(Gas/*P*)	−20.7974*	−19.8315*	−5.9766*	−5.6255*
Δ ln(Water/*P*)	−20.2863*	−20.2578*	−8.2834*	−7.7191*
Δ ln(Solid/*P*)	−31.9514*	−31.7601*	−9.6164*	−10.1413*

A * denotes the rejection of the null of nonstationary at the 5% level of significance.

A panel cointegration test proposed by Pedroni (1999) who developed to test for no cointegration in dynamic panel allowing for heterogeneity among the individual regions is adopted. In line with the two-step strategy proposed by Engle and Granger (1987), Pedroni extends it to panels and uses the ADF and PP principles. The procedures make use of the residuals from the long-run regression of the following form:

$$y_{it} = \alpha_i + \delta_i t + \theta_t + \beta_{1i}x_{1it} + \cdots + \beta_{Mi}x_{Mit} + \varepsilon_{it} \tag{4}$$

where (i=1,..,N) and (t=1,…,T) are the number of cross-section units and time observations respectively, and M is the number of regressors. This can be seen as a fixed effects model where α_i, $\lambda_i t$ and θ_t represent individual specific effect, individual specific linear trend, and common time effect, respectively. The coefficients β_{Mi} are allowed to be heterogeneous.

Two types of seven tests are suggested by Pedroni to examine whether the error process of the estimated equation is stationary. The first four statistics are based on within-dimension approach, including panel v-statistic, panel ρ-statistic, panel PP-statistic, and panel ADF-statistic. These statistics restrict autoregressive parameter to be the same across all cross sections on the estimated residuals. The next three statistics are based on between-dimension approach, including group ρ-statistic, group PP-statistic and group ADF-statistic. These statistics allow autoregressive parameter to vary over the cross section, based on estimators that simply average the individually estimated coefficients for each member. All seven tests are distributed as being asymptotically standard normal. The panel v-statistics is a right-sided test where large positive values reject the null of no cointegration. The remaining statistics diverge to negative infinitely, which means that large negative values reject the null.

To test the long-run relationships among variables, the LSDV estimator is first run on the model (Eq. (1)), and then the Pedroni procedures are carried out.[7] Table 4 presents the results of panel cointegration tests. The first system includes per capita waste gas as the dependent variable, and the second and third systems include per capita waste water and per capita solid wastes, respectively. The results show that all statistics are well significant at 5% critical values, so the null hypotheses of no cointegration in panels are very strongly rejected for three pollutants.

Consequently, the panel cointegration tests strongly support the existence of a long-run equilibrium relationship between per capita GDP and per capita emission for three pollutants.

4.3. Panel cointegration estimation

Given the evidence of panel cointegration, the long-run pollution income relations can be further estimated by several methods for panel cointegration estimation, e.g. the bias-corrected OLS (BCOLS) estimator, the fully modified

[7] The panel unit root and cointegration analysis was carried out with the NPT1.3 package developed by Chiang, and Kao (2002) in addition to some routines kindly provided by Peter Pedroni.

Table 4
Panel cointegration test

Statistics	Waste gas	Waste water	Solid wastes
Panel v-statistic	13.57*	15.37*	26.15*
Panel ρ statistic	−18.17*	−21.64*	−35.97*
Panel PP-statistic	−6.50*	−6.67*	−11.83*
Panel ADF-statistic	−96.82*	−87.24*	−129.57*
Group ρ statistic	−30.12*	−27.42*	−46.86*
Group PP-statistic	−9.24*	−7.96*	−13.27*
Group ADF-statistic	−9.47*	−7.39*	−15.83*

Note: The Pedroni statistics are described in detail in Pedroni (1999). NPT 1.3 is used in the estimation as Chiang and Kao (2002) developed it. The variance ratio test is right-sided, while the other Pedroni tests are left-sided. A * indicates the rejection of the null hypothesis of no cointegration (Pedroni) at least on the 5% significance level.

OLS (FMOLS) estimator proposed by Phillips and Moon (1999) and Pedroni (1995), and the dynamic OLS (DOLS) estimator proposed by Kao and Chiang (2000). The choice of the preferred methods has been discussed in McCoskey and Kao (1998) and Kao and Chiang (2000). They pointed out that the latter two estimators have a nonnegligible bias in small samples. On that account the FMOLS and DOLS are preferable, with the DOLS exhibiting the least bias in small samples using Monte Carlo simulations. Moreover, time effects can be included in the panel dynamic regression without affecting the sequential asymptotic variance of the estimator (Mark & Sul, 2003). Therefore, we base our following inferences mainly on the DOLS estimators with time effects.

The DOLS estimator is fully parametric and offers a computationally convenient alternative to the FMOLS estimator proposed. Consider a cointegrated regression for homogeneous panels as follows:

$$\begin{aligned} y_{it} &= \alpha_i + \lambda_i t + \theta_t + \beta' \boldsymbol{x}_{it} + u_{it} \\ \boldsymbol{x}_{it} &= \boldsymbol{x}_{it-1} + v_{it} \end{aligned} \tag{5}$$

for (i=1,…,N) and (t=1,…,T). $\boldsymbol{x}_{it}$ is a $k\times 1$ vector composed of the regressors. α_i, $\lambda_i t$ and θ_t represent individual specific effect, individual specific linear trend, and common time effect, respectively. The second equation in (5) states that the independent variables are an integrated process of order one for all i so that their first differences are stationary. The estimator is based on the error decomposition

$$u_{it} = \sum_{j=-p}^{q} \gamma'_j \Delta \boldsymbol{x}_{it-j} + \varepsilon_{it} \tag{6}$$

where p and q are respectively the number of lead and lag, and ε_{it} is orthogonal to all leads and lags of the first difference of the variables $\boldsymbol{x}_{it}$. Inserting Eq. (6) in the regression Eq. (5) yields

$$y_{it} = \alpha_i + \lambda_i t + \theta_t + \beta' \boldsymbol{x}_{it} + \sum_{j=-p}^{q} \gamma'_j \Delta \boldsymbol{x}_{it-j} + \varepsilon_{it} \tag{7}$$

The OLS estimator for β in Eq. (7) is known as a panel dynamic OLS estimator. The DOLS estimator is straightforward to compute, and relevant test statistics have standard asymptotic distributions (Mark & Sul, 2003).

Table 5 reports the results of the DOLS estimator for three pollutants. The values of the DOLS estimator are determined under the assumption of one lead and one lag of the change of the regressors.[8] The parameters are quite significant at a 1% level of significance when using waste gas, waste water and solid wastes as dependent variables. From the sign of the parameter, the results show that there are inverse U-shaped relationships between per capita pollution and per capita GDP for waste gas and solid wastes, while there is an inverse N-shaped relation for waste water. Moreover, the turning points calculated with the parameters are 29,017 yuan, 9,705 yuan and 28,296 yuan respectively. Compared with Table 2, the turning point for waste gas from the DOLS estimator is much smaller and hence more promising than that (430,441 yuan) from the Within OLS estimator. All adjusted R^2 statistics from the

[8] Often the DOLS estimator has the drawback that its results are sensitive to the choice of number of lags and leads. But for or our sample we find that most coefficient estimates vary only little when the leads and lags are changed.

Table 5
Panel cointegration estimation

Variables	Waste gas	Waste water	Solid wastes
ln(GDP)	1.9834** (4.046)	−20.5696** (−5.191)	1.4266** (2.965)
$[\ln(\mathrm{GDP})]^2$	−0.0965** (−3.405)	2.8226** (6.121)	−0.0696** (−2.463)
$[\ln(\mathrm{GDP})]^3$		−0.1236** (−6.945)	
Adjusted R^2	0.7893	0.6501	0.4255
Turning point	29,017	9,705 [a]	28,296

Note: Figures in parentheses are t statistics for regression coefficients. TP denotes turning point of quadratic curve. "**" denotes the estimator of a parameter is significant at 1% level of significance.
[a] denotes the larger value which is calculated by solving the root of the first-order derivative of the cubic inverse N-shaped curve.

DOLS estimator are markedly larger than those calculated by the OLS estimator except for solid wastes, indicating that the DOLS estimator may have higher performance of model fitting. Thus, it is suggested that the panel cointegration approach for the EKC panel data models be preferable for all pollutants except for solid wastes.

4.4. The EKC relationships in China

The EKC curves for three pollutants can be easily obtained by calculating the quadric function or the cubic function. The fitted values are calculated by $\hat{\alpha}+\hat{\beta}_1\ \ln(\mathrm{GDP/P})+\hat{\beta}_2\ (\ln(\mathrm{GDP/P}))^2$ for waste gas and solid wastes, and added by the term $\hat{\beta}_3(\ln(\mathrm{GDP/P}))^3$ for waste water, where $\hat{\alpha}$ is computed by averaging across all observations, $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ are from the Within OLS estimator or the DOLS estimator. All fitted curves are reported in Fig. 3. The scales in the y-axis stand for fitted values of per capita emission in logarithm and those in the x-axis denote per capita GDP in logarithm.

Note that for three pollutants the differences caused by the two estimators are visible. According to Fig. 3a and b, the fitted curves from the DOLS estimator are lower than those from the Within OLS estimator, and the Gas-GDP relation becomes an inverse U-shaped if the panel cointegration approach is considered, while the Water-GDP relation has a lower turning point. It seems more convergent for the DOLS estimator since panel cointegration estimation takes more long-run error-corrected information into account, see Eqs. (6) and (7). In contrast, the fitted results for the Solid-GDP relation seem to have little improvement when using the DOLS estimator, i.e. two curves from different methods are very close each other as well as these turning points. All these results for three pollutants are also consistent with the previous analysis about parameter estimation and method evaluation.

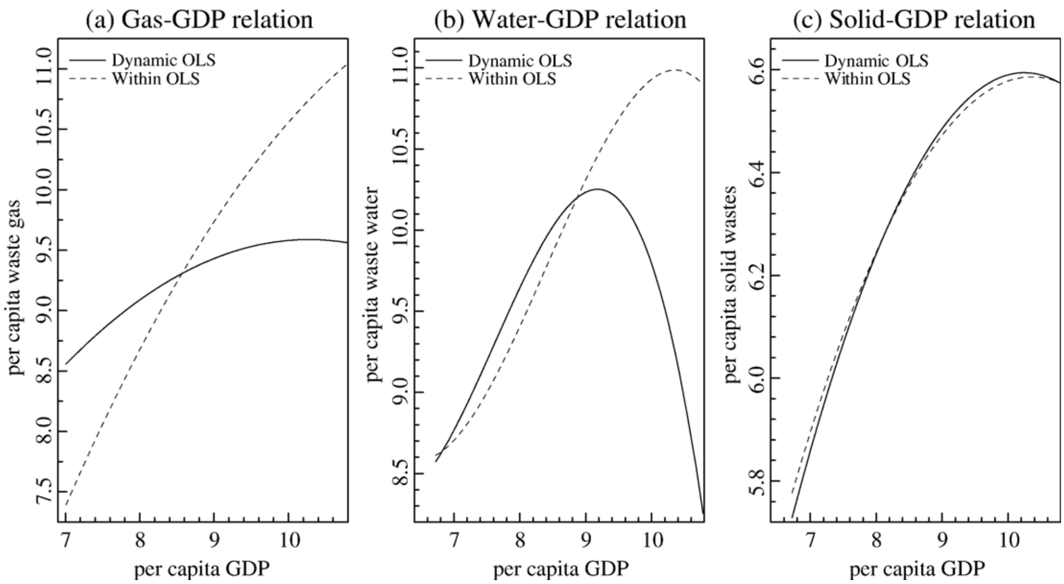

Fig. 3. The pollution-income relationships for three pollutants from the DOLS and Within OLS estimators.

Based on the panel cointegration estimation, we now discuss the underlying relationships for three pollutants. Three curves are all inverse U-shaped, indicating that with the rise of economic growth, waste gas, waste water and solid wastes first increase, and then decline after arriving at the turning points. The Water-GDP relation seems an inverse U-shaped (see Fig. 3b), though the estimates for waste water denote that there is an inverse N-shaped relation. This is because the left part which has another solution (=421 yuan) of the first-order derivative is too low. However, positions of these turning points for three pollutants are quite different. The curves of waste gas and solid wastes seem similar (see Fig. 3a and c), having two close turning points, while for waste water the turning point is lower than the former two. It is shown that water pollution has decreased much earlier than gas pollution and solid pollution. More provinces may have reached the stage of environmental improvement. For waste gas and solid wastes, only few developed provinces like Beijing, Shanghai could have reached the peaks of the EKCs, while some of other provinces are possibly being in structural change, and others are being on the rise.

5. Conclusions

This paper investigates the relationship between economic growth and environmental pollution in China based on the EKC hypothesis. The discussions are exemplified for three EKCs, relating per capita GDP to three pollutants including per capita waste gas, per capita waste water, and per capita solid wastes, on a panel comprising 29 provinces over 1985–2005.

Before the panel cointegration analysis, some model specification tests are carried out. According to the F test results, the log–log models for three pollutants should be taken specific individual effects and specific time effects into account. Then the Wald test results further specify the functional forms of these models and show that a cubic log–log model should be pre-specified for waste water, while quadratic log–log models for waste gas and solid wastes.

In providing estimates for the EKC, unit root properties of the panel dataset are firstly tested and shown that both the economic variable and the environmental variables are first order integrated. Afterwards, the panel cointegration test results indicate that there are the cointegrating relationships between per capita emission and GDP per capita for all pollutants. As a result of the existence of long-run cointegration, normal estimation methods for panel data model should be bias-corrected in econometrics and thus the DOLS estimator is adopted. According to comparison with the DOLS estimator and the Within OLS estimator, we find that panel cointegration estimation is preferable for all pollutants except for solid wastes. The results also show that all three pollutants are inverse U-shaped, although there is an inverse N-shaped relationship for waste water in terms of coefficient estimates. In addition, the turning points show that water pollution has improved earlier than gas pollution and solid pollution.

This study reveals that with the rise of economic growth, the problems of environmental pollution are increasingly severe. Only few high-income regions have reached the stage of environmental improvement, especially for waste gas and solid wastes, while environmental degradation of most provinces have being still worse. As mentioned in the Introduction, if environmental pollution exceeds the point of irreversible damage, it would be destructive to the environment. Thus, it is essential for China's government to take positive measures to lower the peak of the EKCs and implement effective policies of environmental protection consistently.

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