Environmental Kuznets Curve in China: New evidence from dynamic panel analysis

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New Evidence from Dynamic Panel Analysis

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Abstract: This paper applies a panel of 28 provinces of China from 1996 to 2012 to study the impacts of economic development, energy consumption, trade openness, and urbanization on the carbon dioxide, waste water, and waste solid emissions. By estimating a dynamic panel model with the system Generalized Method of Moments (GMM) estimator and an autoregressive distributed lag (ARDL) model with alternative panel estimators, respectively, we find that the Environmental Kuznets Curve (EKC) hypothesis is well supported for all three major pollutant emissions in China across different models and estimation methods. Our estimation results also confirm the significantly positive effects of energy consumption on various pollutant emissions. In addition, there is some evidence that trade and urbanization may have harmful impacts on environmental quality in the long run, though perhaps not in the short run.

Keywords: Environmental Kuznets Curve; pollutant emissions; economic growth; energy consumption; Chinese panel data

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1. Introduction

China has experienced a period of extraordinary economic growth since the economic reform in 1978. When viewed in totality of both its magnitude and its duration, the average growth rate of around 9% in (real) per capita GDP from 1978 to 2012 is truly miraculous. Along with this remarkable economic growth process, China has also witnessed a considerable and rapid rise in pollution. China surpassed the U.S. as the largest carbon dioxide emitter in year 2008 and remained at the No. 1 spot ever since, reaching 9208.05 million tons of carbon dioxide emission in year 2012 (26.72% of the world's total).[1] The massive run up of pollution emission has brought about serious environmental problems in China, as well as heated debate on how economic growth affects environmental quality and whether China's high growth is sustainable once more environment-friendly policies are implemented. Of particular interest to this debate is the study of the Environmental Kuznets Curve (EKC), according to which environmental quality deteriorates with economic development at low levels of national income but improves with further economic development at high levels of income.

In the seminal work of the EKC literature, using a cross-country dataset at city level, Grossman and Krueger (1991) found that the air pollution measures (SO_2, dark matter, and suspended particles) increase with income at first but decreases once per-capita GDP reaches a certain threshold value. By examining additional indicators of air pollution and a dataset at country level, Selden and Song (1994) and Holtz-Eakin and Selden (1995) found a similar inverted-U relationship between per-capita income and air pollutant emissions. Grossman and Krueger (1995) further expanded their previous work by considering more comprehensive measures of environmental (both air and water) quality and confirmed the EKC hypothesis.

Subsequent studies on the environment-growth nexus often incorporated other factors (other than per-capita income) that may affect environmental quality in order to mitigate the omitted variables biases in the earlier EKC studies. This multivariate framework helps us understand both how these non-income factors contribute to environmental degradation individually and whether the EKC hypothesis still survives after controlling for these relevant variables. Some frequent variables that researchers

[1] See BP's Annual Statistical Review of World Energy, available from the website: http://www.bp.com/en/global/corporate/about-bp/energy-economics/statistical-review-of-world-energy-2013.html.

introduced into the EKC study include, among others, energy consumption, international trade, and urbanization (see, e.g., Torras and Boyce, 1998; Farzin and Bond, 2006; Jalil and Mahmud, 2009; Qu and Zhang, 2011; Wang et. al., 2011; and Jayanthakumaran et al., 2012).[2]

The inclusion of energy consumption in studying environmental conditions is an obvious choice, given its well-known, scientific impacts on generating pollution. It comes as no surprise that researchers have consistently found that the effects of energy consumption on a variety of environmental pollutants are significantly positive in previous EKC estimations (as in, for example, Ang, 2009; Baek and Gweisah, 2013; Liu, 2005 and Nasir and Rehman, 2011).

While openness to trade is also regarded as an important determinant of environmental quality, its impact is generally less clear. As articulated in Grossman and Krueger (1991), there are three major environmental effects associated with trade openness: a scale effect arising from the ensuing expansion of production; a composition effect due to the shifting of "dirty" industries to developing countries; and a technique effect because of the better abatement technology brought about through trade. From a developing country's perspective, the first two effects tend to bring environmental deterioration while the third effect tends to improve its environment quality. This ambiguity in environmental impact of trade is well reflected in the literature. Some studies found negative effects of trade on environmental quality (Ang, 2009; Jalil and Feridun, 2011; Nasir and Rehman, 2011); others reached the opposite conclusion (Birdsall and Wheeler, 1993; Ferrantino, 1997; Grether et al., 2007); while still others obtained insignificant long-run effects of trade from estimating ARDL models (Jalil and Mahmud, 2009; Jayanthakumaran et al., 2012).

Similarly, urbanization has been taken into account in previous EKC studies and shown to have mixed effects on environmental conditions. On the one hand, a higher level of urbanization tends to raise the per capita pollutant emissions due to industrial concentration and congestion in urban areas (Panayotou, 1997); on the other hand, urbanization can be beneficial for environment protection due to the economies of scale advantage in abatement technology in urban relative to rural areas (Torras and Boyce, 1998), and because it is more conducive in mobilizing people's effort in urban areas to influence environmental protection policies (Rivera-Batiz, 2002; Farzin and

[2] However, none of these previous studies included all of these three variables simultaneously in their estimations as in the current paper.

Bond, 2006). Meanwhile, the role of urbanization turned out to be insignificant in the study by Qu and Zhang (2011).

The fast economic growth in China, coupled with its enormous demand for energy consumption to fuel the economy and rapidly-rising environmental pollution, has made it an interesting subject of investigation in a number of recent EKC studies. By estimating autoregressive distributed lag (ARDL) models with time-series data and different control variables, Jalil and Mahmud (2009), Jalil and Feridun (2011), and Jayanthakumaran et al. (2012) supported the existence of long-run inverted-U relationship between carbon dioxide (CO_2) emissions and per-capita GDP in China. Using Chinese province-level panel data, but with a specification without other control variables, Song et al. (2008) confirmed the EKC hypothesis for waste gas, waste water, and solid wastes indicators in China. However, the estimation of a simultaneous equation model with Chinese panel data in Shen (2006) found evidence supporting EKC only for water pollutants but not for air pollutants; while the panel cointegration estimation by Wang et al. (2011) did not support the EKC hypothesis for CO_2 emissions in China.[3]

As Chinese economy continues to grow, soon replacing U.S. economy as the world's largest by most of estimates, and as China emerges as one of the largest energy consumers in the world, the investigation into how environmental conditions in China are affected by this process has important implications not only for China itself but, indeed, for the world as a whole. Given the inconclusive nature of the results from existing studies and the fast-changing environmental conditions in China, the current research aims at providing additional evidence regarding the EKC hypothesis for China by employing new estimation techniques and a more update dataset. Specifically, using a panel dataset at provincial level in China from 1996 to 2012 and a multivariate EKC framework that includes energy consumption, trade, and urbanization as auxiliary control variables, we estimate both the dynamic specification of the EKC equation by system GMM and the long-run EKC relationship by alternative estimators based on the ARDL model. Our empirical estimations yield robust results in supporting an invert U-shaped relationship between environmental

[3] Although evidences of EKC are found in many previous studies, there is by no means a unanimous consensus in the existing literature. In fact, a considerable amount of disparate conclusions has been reached in EKC studies, resulting from different data samples, different estimation methods, and across different pollution indicators (see, for example, Roca et al., 2001; Stern, 2004; and Brajer et al., 2011 for more details).

quality and economic development across the alternative indicators measuring air, water, solid pollutants in China. In addition, consistent with previous studies, our estimation reveals that energy consumption has a significantly positive effect on various pollutant emissions, while the effects of trade and urbanization on pollution are more mixed across different models and estimation methods.

The current paper makes contribution to the literature on EKC studies in terms of both methodology and scope. From the methodological perspective, applying system GMM to estimate a dynamic EKC specification with lagged dependent variable has been largely unexplored in the existing literature.[4] Much of previous EKC studies have focused on static specifications whereby environmental condition is assumed to be affected only by contemporaneous variables. However, environmental quality evolves cumulatively over time: the environmental quality of today is likely to be linked to that of yesterday, rendering it appropriate to consider a dynamic EKC specification that includes lagged dependent variable on the right hand side. Since the traditional pooled and fixed/random effects estimators, which are commonly used in previous panel estimations of EKC equations, would be inefficient and biased when applied to dynamic panel models, system GMM is the suitable approach in estimating a dynamic EKC specification as it can address the issues of endogeneity, heteroskedasticity, and autocorrelation within the involved variables.

Our second approach to studying the EKC hypothesis in China is to estimate the ARDL model by three different panel estimators, namely, the Mean Group (MG), the Pooled Mean Group (PMG) and the Dynamic Fixed Effects (DFE) estimators, to obtain the long-run relationships between various pollutant emissions and per-capita income. Although applying the ARDL approach to study the long-run EKCs is not entirely new, the current paper expands the scope of this limited strand of literature by estimating such a dynamic model with Chinese panel data. The previous studies using ARDL models are mostly restricted to time-series analysis (for example, Jalil and Mahmud, 2009; Jalil and Feridun, 2011; and Jayanthakumaran et al., 2012). One exception is perhaps the study by Martínez-Zarzoso and Bengochea-Morancho (2004), who applied the PMG estimator and confirmed the long-run EKC relationship for CO_2 emissions in a panel 22 OECD countries, but none of other control variables are

[4] We find only one study by Marrero (2010) that applies system GMM estimator to explore the EKC hypothesis. However, the results in this study based on a panel dataset of 24 European countries do not support the EKC hypothesis.

included in their EKC specification. In contrast with this group of papers using ARDL approach to study EKC, ours differs in that we apply panel estimators with Chinese data; we study EKC not only for CO_2 emissions but also for waste water emissions and solid waste emissions; and we include energy consumption, trade openness, and urbanization simultaneously in the EKC specification.

The reminder of this paper is organized as follows. Section 2 describes the dataset and the relevant variables we use for our estimations. Section 3 introduces the empirical models and estimation strategies. Section 4 presents results and Section 5 concludes.

2. The Data

For the purpose of our empirical estimation, we construct a panel of 28 provinces over the period of 1996-2012 in China from (1) China Statistical Yearbook (1996-2013); (2) China Compendium of Statistics 1949-2008; and (3) China Energy Statistical Yearbook (1997-2013).[5] The key variables in the current study are as follows. To measure environmental pollution, we adopt the popular indicators of carbon dioxide (CO_2), industrial waste water, and industrial waste solid emissions, alternatively. Specifically, we use $ln(c)$ to denote the natural logarithm of per-capita CO_2 emissions, $ln(water)$ the natural logarithm of per-capita industrial waste water emissions, and $ln(solid)$ the natural logarithm of per-capita industrial waste solid emissions. As is standard in the literature, we use the natural logarithm of per-capita real GDP (1980=100), $ln(y)$, to measure economic development. In addition, following control variables are included in our estimations: *energy* measures per-capita energy consumption; *open* is the total import and export share of GDP, representing for the degree of trade openness; and *urban* is calculated by the proportion of urban residents as a proxy for the level of urbanization. The summary statistics of the above variables are reported in Table 1.

[Insert Table 1 here]

3. The Empirical Models

We build our empirical models from the benchmark specification of the Environmental Kuznets Curve as given by:

[5] Taiwan, Hong Kong and Macao are excluded. Hainan is merged with Guangdong and Chongqing is combined with Sichuan.

$$ln(pollutant)_{i,t} = \beta_0 + \beta_1 * ln(y_{i,t}) + \beta_2 * (ln(y_{i,t}))^2 + \gamma_i + \varepsilon_{i,t}, \quad (1)$$

where *pollutant* is the per-capita pollution indicator, represented alternatively by *c* (per-capita CO_2 emissions), *water* (per-capita industrial waste water emissions), and *solid* (per-capita industrial waste solid emissions); γ_i captures the provincial fixed effects; and $\varepsilon_{i,t}$ is the error term.

Since environmental quality changes cumulatively, pollution measures are likely to be correlated over time. In order to capture this dynamic nature of environmental quality, we then add the lagged term of the dependent variable into the specification in (1):

$$\begin{aligned} ln(pollutant)_{i,t} &= \beta_0 + \beta_1 * ln(y_{i,t}) + \beta_2 * (ln(y_{i,t}))^2 + \beta_3 * ln(pollutant)_{i,t-1} \\ &+ \gamma_i + \varepsilon_{i,t} \end{aligned} \quad (2)$$

Furthermore, as discussed in previous empirical studies, EKC is not only determined by national income but also other important variables. Therefore, we include some commonly used control variables into the model in order to mitigate the potential for misspecification and biased estimation:

$$\begin{aligned} ln(pollutant)_{i,t} &= \beta_0 + \beta_1 * ln(y_{i,t}) + \beta_2 * (ln(y_{i,t}))^2 + \beta_3 * ln(pollutant)_{i,t-1} \\ &+ \beta_4 * energy_{i,t} + \beta_5 * open_{i,t} + \beta_6 * urban_{i,t} + \gamma_i + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Under the dynamic specification in (3), the EKC hypothesis is supported if $\beta_1 > 0$ and $\beta_2 < 0$. Although Eq. (3) can be estimated by the conventional methods of pooled-OLS, fixed-effects, and random-effects regressions, these estimations would produce biased results in a small sample (T=17) because of the endogeneity caused by the lagged dependent variable ($ln(pollutant)_{i,t-1}$). For this reason, we employ the GMM approach, which is first put forth by Hansen (1982) and later refined into the difference GMM estimator by Arellano and Bond (1991). The basic idea of the difference GMM is using a group of lagged explanatory variables as instruments for the corresponding variables in the difference equation. Arellano and Bover (1995) and Blundell and Bond (1998) argued that the weak instrumental variable problem may be unavoidable for difference GMM and further proposed the system GMM estimator, which builds a system containing both the original level equation and the transformed difference equation.

In addition to estimating the dynamic EKC specification in (3), which captures the short-run contemporaneous effects of various variables on environmental quality, we also study another specification that allows us to estimate the long-run EKC relationship. To this end, we recast (3) into the general autoregressive distributed lag (ARDL) (p, q) model:

$$ln(pollutant)_{i,t} = \gamma_i + \sum_{j=1}^{p} \lambda_{i,j} ln(pollutant)_{i,t-j} + \sum_{j=0}^{q} \boldsymbol{\delta}_{i,j} \boldsymbol{X}_{i,t-j}{}' + \gamma_i + \varepsilon_{i,t} \tag{4}$$

Eq. (4) can then be transformed into the following error-correction model:

$$\begin{aligned}\Delta ln(pollutant)_{i,t} &= \phi_i (ln(pollutant)_{i,t-1} - \theta_{0,i} - \boldsymbol{\theta}_i \boldsymbol{X}_{i,t}{}') \\ &+ \sum_{j=1}^{p-1} \lambda^*_{i,j} \Delta \ln(pollutant)_{i,t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}^*_{i,j} \Delta \boldsymbol{X}_{i,t-j}{}' + \eta_i + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where

$$\boldsymbol{X}_{i,t} = (ln(y_{i,t}), (ln(y_{i,t}))^2, energy_{i,t}, open_{i,t}, urban_{i,t}),$$

$$\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{i,j}),$$

$$\boldsymbol{\theta}_i = -\frac{\sum_{j=0}^{q} \boldsymbol{\delta}_{i,j}}{\phi_i},$$

$$\lambda^*_{i,j} = -\sum_{m=j+1}^{p} \lambda_{i,m},$$

$$\boldsymbol{\delta}^*_{i,j} = -\sum_{m=j+1}^{q} \boldsymbol{\delta}_{i,m}.$$

In particular, the first term on the right hand side of Eq. (5) captures the long-run relationship between pollutant emission and its explanatory variables, with θ_i representing the vector of the corresponding long-run coefficients and ϕ_i the adjustment coefficient. We estimate Eq. (5) by employing three alternative methods: the Dynamic Fixed Effects (DFE) estimator, the Mean Group (MG) estimator, and the Pooled Mean Group (PMG) estimator. The DFE estimator assumes homogeneity of all parameters, except for the intercepts, across sections in the panel. If the underlying model fails to meet these requirements, the DFE estimator is likely to be inconsistent. On the other hand, the MG estimator (Pesaran and Smith, 1995) imposes no across-section homogeneity restrictions on any of the parameters. The PMG estimator proposed by Pesaran, et al. (1999) is an intermediate estimator between DFE and MG, as it constrains the long-run coefficients to be identical while allowing other parameters to differ across sections. When both the time dimension, T, and the width dimension, N, of the panel are large, the MG estimator is always consistent, whereas the PMG estimator is consistent and more efficient than the MG estimator if the homogeneity hypothesis is valid but inconsistent otherwise. In comparison, the MG estimator is sensitive to sample size and outlier when T is small (even if N is large) because of the lagged dependent variable bias. On the contrary, the PMG is quite robust to outliers and to the lag orders (Pesaran, et al., 1999). The difference among these estimators can be tested by the Hausman test.

4. The Estimation Results

4.1 The EKC for CO_2 emissions

Since polluting gas emissions have captured great attention in recent years along with China's rapid economy development, and since CO_2 is regarded as the main source of greenhouse gases, our study of EKC begins with the relationship between CO_2 emissions and economic development.

[Insert Table 2 here]

We first utilize the system GMM method to estimate the dynamic model of EKC in Eq. (3). Replacing $ln(pollutant)$ by $ln(c)$, our system GMM estimation results are presented in Table 2. In Columns (1) and (2) in Table 2, the lag range of (2-5) means that the 2nd through the 5th order lag terms of the endogenous variables are included as instruments in the transformed difference equation whereas the 1st order lag terms are included in the level equation in the system GMM estimation. While only the key variables $ln(c)$, $ln(y)$ and $(ln(y))^2$ are treated as endogenous and other control variables as exogenous in Column (1), all variables are treated as endogenous in Column (2).[6] In addition, since the problem of overfitting may arise in system GMM estimations due to the usage of large sets of instruments, we restrict alternatively the lag range to be (2-4) in Columns (3) and (4) to reduce the number of instruments.

In Table 2, we first note that the coefficient of $ln(y)$ is positive and the coefficient of $(ln(y))^2$ negative, both of which are highly significant, consistently across all

[6] Although the null hypothesis of no residual autocorrelation is accepted according to the second-order Arellano-Bond test (i.e., AR(2) test) in the estimation in Column (1), the null hypothesis regarding the orthogonality conditions is marginally rejected according to the Hansen's over-identification restriction test with a p-value of 0.0815. We then specify all the variables in Eq. (3) as endogenous and re-perform the system GMM estimation in Column (2), which passes both the Arellano-Bond test and the Hansen test.

estimations. These results thus lend robust support to the existence of an inverted U-shaped EKC for emissions in China, implying that the CO_2 emissions initially increase and then decrease after reaching with a turning point in economic development.[7] Secondly, the coefficients of the lagged dependent variable are positive and highly significant in all regressions, indicating that CO_2 emissions are positively serially correlated and hence justifying our study of a dynamic EKC specification. Furthermore, consistent with previous studies, the sign of per-capita energy consumption is positive and significant at 1% level, while the impacts of trade openness and urbanization are found to be ambiguous and insignificant.

We next examine the validity of long-run EKC in a panel ARDL model. Specifically, we apply PMG, MG and DFE estimators to estimate Eq. (5) in order to deduce the long-run relationship among CO_2 emissions, per-capita output, energy consumption, trade openness, and urbanization. The estimation results of Eq. (5) are reported in Table 3.

[Insert Table 3 here]

Following the literature that applies ARDL models to study a variety of issues, we estimate Eq. (5) with p=1 and q=1 in Columns (1) to (3).[8] The estimated adjustment coefficient, ϕ_i, is negative and highly significant in all regressions, indicating that the economic dynamics converge to a long-run equilibrium relationship between CO_2 emissions and its determinants. Moving from MG to PMG to DFE reduces this speed of adjustment estimate due to the downward bias in dynamic heterogeneous panels. Furthermore, the pair-wise Hausman tests reveal that both the PMG and the DFE estimators are more efficient than, hence superior and preferred to, the MG estimator. This suggests that, in spite of their obvious differences in many aspects, Chinese provinces tend to share the same long-run pollution-growth nexus and the same speed with which this long-run equilibrium is approached.

According to the results from the preferred PMG and DFE estimators in Columns (1) and (3) in Table 3, there exists a long-run, inverted U-shaped EKC, as the long-run coefficient of $ln(y)$ is significantly positive whereas the long-run coefficient of $(ln(y))^2$

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[7] The pooled-OLS, fixed-effects, and random-effects estimation results of Eq. (3) also confirm the existence of EKC in China. We did not report them here because these estimations are biased as discussed in the preceding section.

[8] The specification of $p = q = 1$ is widely used and most concerned in the existing studies that apply ARDL models to examine a variety of economic issues, for example, Martínez-Zarzoso and Bengochea-Morancho (2004), Frank (2009), and Xing (2012) .

is significantly negative.[9] Meanwhile, the energy consumption is found to contribute positively to CO_2 emissions in the long run, although its coefficient is not significant in the DFE estimation in Column (3). Different from the short-run effects in the GMM estimations in Table 2, the impacts of both trade openness and urbanization on CO_2 emissions turn out to be positive and significant in the long run (except for the impact of trade in the DFE estimation Column (3)). In the context of the three separate mechanisms by which trade affects the level of pollution as articulated in Grossman (1991), our result regarding the effect of trade openness implies that the sum of negative "scale effect" and "composition effect" outweighs the positive "technique effect" for China in the long run. The positive and significant estimates of the coefficient of urbanization in Table 3 suggest that, in the long run, the adverse impact on air pollutant emissions due to higher resource consumption and environmental degradation accompanied by urbanization process tends to outweigh its potential benefit to environmental quality via the economies-of-scale effect and the preference effect, as argued by some previous studies.

We also estimate the alternative ARDL (1, 0) model and report the corresponding results in Columns (4) to (6) in Table 3. These estimation results are quite similar to the corresponding results obtained from estimating the ARDL (1, 1) model in Columns (1) to (3). Although the ARDL (1, 1) model is most commonly employed in the literature, and it is deemed as more appropriate according to the Akaike information criterion (AIC) as well as the Bayesian information criterion (BIC), we consider the estimation of this alternative model of ARDL (1, 0) as a useful robustness check.

4.2 The EKCs for industrial waste water and industrial waste solid emissions

[Insert Tables 4 here]

In this subsection, we explore the EKCs for industrial waste water emissions and industrial waste solid emissions, respectively. Table 4 displays the system GMM estimates of the dynamic EKC equation in (3) with *ln*(*pollutant*) replaced alternatively by *ln*(*water*) and *ln*(*solid*). For the key interest of our current study, similar to the case of CO_2 emissions, the EKC is confirmed in Table (4) under various lag ranges when

[9] Similar to Pesaran, Shin and Smith (1999), the estimation results from the MG estimator in Table 3 are different from those from the PMG and DFE estimators. Such differences are likely due to the MG estimator's property of being sensitive to outliers.

these alternative pollutant emissions are applied as the indicators of environmental quality. The regressions in all columns are proved to be valid as both the second-order Arellano-Bond test and Hansen's over-identifying restrictions test are passed. In addition, the current levels of industrial waste water/solid emissions are positively correlated with their levels in the preceding period. Energy consumption is again found to be positively correlated with both waste water and waste solid emissions, although the correlation is significant only with the latter but not the former. The potential reason for this varied finding is that fossil fuel burning mainly generates polluting gases and waste residues, while its pollution to the water environment is less serious. Also similar to the case of CO_2 emissions in Table 2, the roles of trade openness and urbanization in environmental degradation remain largely insignificant, except for one difference: while openness fails to be a significant explanatory variable for the waste water emissions in Columns (1) and (2), its coefficient is significantly negative in the estimation of waste solid emissions in Columns (3) and (4).

[Insert Table 5 here]

Correspondingly, the estimation results of the long-run EKCs for industrial waste water emissions are presented in Table 5. The existence of, and convergence to, a long-run relationship between waste water emissions and its determinants is confirmed in all estimations, as the adjustment coefficients are negative and significant in all columns. The PMG and DFE estimators are again preferred to the MG estimator, based on the Hausman tests, in both model specifications of ARDL (1, 1) and ARDL (1, 0), though the ARDL (1, 1) specification appears to fit the panel data better according to AIC and BIC. Focusing on the results from the preferred PMG and DFE estimators in Table 5 (Columns 1 and 3 and Columns 4 and 6), an inverted U-shaped long-run EKC for industrial waste water emissions is strongly supported, as the estimated coefficients of $ln(y)$ and $(ln(y))^2$ are highly significant with the correct signs. Differing from the short-run contemporaneous effect estimated by system GMM, the long-run effect of energy consumption on waste water emissions is still positive and (mostly) significant. The long-run coefficient of trade openness is largely insignificant; whereas urbanization has a significantly positive long-run impact on water pollution, similar to its long-run impact on the CO_2 emissions shown in Table 3.

[Insert Table 6 here]

Finally, Table 6 presents the estimation results of the long-run EKC for industrial waste solid emissions. The Hausman-test, as well as the AIC and BIC, statistics again indicate that the PMG or DFE results are superior to the MG results and the ARDL (1, 1) specification is preferred to the ARDL (1, 0) specification. Importantly, the long-run EKC relationship is also supported across PMG and DFE estimations. Among the remaining results in Table 6, energy consumption predictably generates a significantly positive effect on industrial waste solid emissions; the long-run coefficient of trade is mostly insignificant as in Table 5; and the harmful effect of urbanization on industrial waste solid emissions appears to be less robust, comparing to its effects on waste gas and waste water emissions.

5. Conclusions

Using a panel of 28 Chinese provinces over the period 1996-2012, the current paper empirically estimated the dynamic relationship between pollutant emissions and economic development, while controlling for the impacts of energy consumption, openness, and urbanization. Specifically, we used air, water, and solid pollutant emissions as alternative indicators of environmental quality, and applied various econometric methods to study the validity of EKC in China. Of particular interest, our results from estimating a dynamic panel model by the system GMM estimator, as well as from estimating the ARDL model by the PMG, MG and DFE estimators, have all supported EKC hypothesis for the three major pollutants in China. While the estimated contemporaneous relationship between pollutant emissions and income levels in Eq. (3) confirms the EKC in the short run, the estimation results of the ARDL specification in Eq. (5) confirms it in the long run. Additionally, energy consumption is found to be positively and significantly correlated with all of the three pollutant emissions across different estimations and models (with perhaps only one exception in the case of waste water pollution under system GMM estimation). This set of results shows that energy consumption had a direct impact on the environment deterioration in China, both in the short run and in the long run. Meanwhile, though trade and urbanization had insignificant short-run impacts on the pollutant emissions in most of the cases (as shown by the system GMM estimations in Tables 2 and 4), they appeared to exert some positive impacts in the long run (especially for CO_2 emissions, as revealed by the significantly positive long-run coefficients in some of the estimations in Tables 3, 5, and 6). These results suggest that, unlike energy consumption, it takes time for trade openness and urbanization to manifest their adverse impacts on environmental quality.

The above findings of our study proffer a mixed prospect for China's environmental quality and some potential policy implications. On the one hand, the validity of an inverse U-shaped EKC confirmed by our analysis is comforting, as it suggests that, with its development deepening, China has successfully deviated from the "pollution first, treatment later" development strategy that had been practiced in the early part of the economic reform. However, several aspects of the Chinese economy, such as rising energy consumption, increasing globalization through trade liberalization, and the process of urbanization, continue to pose serious threats to its environmental degradation in the long run, if not in the short run.

Indeed, environmental concerns have registered higher and higher on the minds of average Chinese and policymakers alike, and government regulations on industrial pollutant emissions have been tightened considerably in the recent years. The admission to a "new normal" of growth by the current Chinese government also reflects its mindset of seeking a more sustainable path of development from both economic and environmental viewpoints. It's worth mentioning that in the communique of the 3rd Plenary Session of 18th CPC Central Committee in 2013, the Chinese government has put forth a plan of establishing a compensation system for the use of natural resources and the subsequent impact on the ecosystem. Such an initiative will force firms and local governments to internalize the environmental costs when they make decisions in technology adoption, sourcing of energy, and FDI/trade strategies. For instance, it will encourage the adoption of more energy efficient technology, cleaner energy as a replacement of the traditional energy, and trade policies with large technique effect relative to their scale and composition effects. Another recent Chinese government initiative that pertains to our current study is its policy toward urbanization. Since integrating urban and rural development has been identified as a main potential source of future growth, the "National Plan on New Urbanization (2014 - 2020)" issued by Chinese State Council in 2014 aims to increase the proportion of permanent urban residents and the proportion of urban residents with a household registration to 60% and 45%, respectively. Such an urbanization policy, however, is likely to exert a detrimental impact on environmental quality according to our estimation, at least in the long run. Clearly, a careful evaluation of these Chinese government initiatives needs to balance between the environmental concerns and the growth implications, and our current study provides a useful basis on which such an evaluation can be made.

To summarize, the current study revealed two robust findings regarding the pollutant emissions in China: the EKC relationship and the positive correlation with energy consumption, both in the short-run and in the long-run, are consistently supported in the data. However, the positive effects of trade openness and urbanization on environmental degradation are significant perhaps only in the long run, and may vary in severity across different pollutant emissions. These findings can shed new lights on some current policy issues and debates regarding the environment-growth nexus in China.

Appendix A: Calculation of Carbon Dioxide Emissions

Based on the data in Table A1, the emission coefficient of carbon dioxide for different types of energy can be calculated as follow:

$$\ln dex\_CO_{2j} = Qnet_j * 10^{-9} * C\_per_j * ratio\_C_j * 10^3 * 3.6667 \quad \text{(A.1)}$$

where $Qnet_j$ is the average net calorific value of energy *j*, C_per_j is the carbon content per calorific value of energy *j* and $ratio\_C_j$ is the carbon oxidation rate of energy *j*. And note that the ratio of the relative molecular mass of carbon dioxide to the relative molecular mass of carbon equals to 3.66667.

Table A1: Referential indexes for carbon emissions of various energies

Type of energy	Average net calorific value	The carbon content per calorific value	The carbon oxidation rate	emission coefficient of carbon dioxide
Coal	20908 kJ/kg	26.37	0.94	1.9003 kg-CO_2/kg
Coke	28435 kJ/kg	29.5	0.93	2.8604 kg-CO_2/kg
Crude oil	41816 kJ/kg	20.1	0.98	3.0202 kg-CO_2/kg
Gasoline	43070 kJ/kg	18.9	0.98	2.9251 kg-CO_2/kg
Kerosene	43070 kJ/kg	19.5	0.98	3.0179 kg-CO_2/kg
Diesel oil	42652 kJ/kg	20.2	0.98	3.0959 kg-CO_2/kg
Fuel oil	41816 kJ/kg	21.1	0.98	3.1705 kg-CO_2/kg
Natural gas	38931 kJ/m^3	15.3	0.99	2.1622 kg-CO_2/m^3

Note:

1. The data of the average net calorific value comes from the General principles for calculation of the comprehensive energy consumption (GB/T 2589-2008) which is forwarded by the National Development and Reform Commission (NDRC) and the Standardization Administration of China (SAC) in 2008.
2. The data of the carbon content per calorific value and the carbon oxidation rate are taken from the Guidelines for the preparation of provincial greenhouse gas inventory which is proposed by the National Development and Reform Commission (NDRC) in 2011.
3. The National Bureau of Statistics of China contributes anthracite, bituminous coal and lignite as coal.

In the present study, only the carbon dioxide emissions from the burning of fossil fuels, which is the major source of carbon dioxide emissions, are considered. With the emission coefficient of carbon dioxide listed in Table A1, we can calculate the carbon dioxide emissions from the burning of fossil fuels through Eq. (A2) as:

$$CO_{2i,t} = \sum_{j}^{8} \ln dex\_CO_{2j} * Q_{i,j,t} \quad \text{(A.2)}$$

where $CO_{2i,t}$ is the carbon dioxide emissions for province *i* in year *t*. $Q_{i,j,t}$ is the consumption of energy *j* for province *i* in year *t*.

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Table 1: Summary Statistics of the total sample

	Provinces	years	Observations	mean	Std. Dev.	Min	Max
$ln(c)$	28	17	476	1.658867	0.684708	0.0960852	3.449955
ln(water)	28	17	476	2.703558	0.535611	1.126004	4.470932
ln(solid)	28	17	476	-0.0246444	0.7468087	-1.75626	3.066563
$ln(y)$	28	17	476	8.250787	0.7577362	6.570799	10.30083
$(ln(y))^2$	28	17	476	68.64844	12.711	43.1754	106.1071
energy	28	17	476	2.298689	1.448019	0.4839664	7.946185
open	28	17	476	0.3189519	0.4053436	0.032074	1.80001
urban	28	17	476	41.65924	15.95517	16.9	89.3

Table 2: The system GMM estimates of dynamic EKC equations for per capita CO_2 emissions (*ln(c)*)

	Lag (2-5)		Lag (2-4)	
	(1)	(2)	(3)	(4)
ln(y)	0.850***	0.739***	0.692***	0.643***
	(7.96)	(5.82)	(6.44)	(4.59)
ln(y))^2	-0.0518***	-0.0448***	-0.0419***	-0.0392***
	(-7.78)	(-5.96)	(-6.25)	(-4.77)
ln(c)$_{t-1}$	0.932***	0.923***	0.971***	0.959***
	(30.01)	(31.94)	(45.89)	(36.51)
energy	0.0388***	0.0377***	0.0232***	0.0265***
	(3.65)	(4.16)	(2.97)	(3.47)
open	0.00171	0.00390	0.00325	0.00960
	(0.09)	(0.15)	(0.19)	(0.37)
urban	0.000169	0.000167	-0.000278	-0.000106
	(0.26)	(0.19)	(-0.45)	(-0.11)
Constant	-3.385***	-2.936***	-2.763***	-2.550***
	(-7.78)	(-5.50)	(-6.28)	(-4.31)
N	476	476	476	476
AR(1) test	-3.56	-3.56	-3.48	-3.49
	[0.000370]	[0.000366]	[0.000505]	[0.000477]
AR(2) test	0.31	0.35	0.30	0.32
	[0.754]	[0.730]	[0.763]	[0.745]
Hansen test	20.59	25.74	19.61	25.98
(Chi2)	[0.0815]	[0.422]	[0.0332]	[0.131]

Note: The dependent variable is *ln(c)* in each column. In Columns (1) and (3), only the key variables (*ln(c)*, *ln(y)*, and *(ln(y))^2* are treated as endogenous variables while in Columns (2) and (4), all variables are treated as endogenous variables. Lag (a-b) specifies the lags a through b of endogenous variables as instruments for the transformed equation and lag a-1 as for the level equation. The regressions are done in the collapsed form and in the orthogonal deviation transformation, adjusted for small sample, and based on the robust one-step estimations. The *p*-value of the serial correlation tests in Arellano and Bond (1991) and the p-value of the Hansen tests of overidentification are reported in square brackets. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The PMG, MG, and FDE estimates of ARDL EKC equations for per capita CO_2 emissions (*ln(c)*)

	ARDL (p=1, q=1)			ARDL (p=1, q=0)		
	(1) PMG	(2) MG	(3) DFE	(4) PMG	(5) MG	(6) DFE
Adjustment coefficient (ϕ_i)						
	-0.418***	-0.921***	-0.164***	-0.208***	-0.783***	-0.205***
	(-6.38)	(-11.10)	(-7.03)	(-8.84)	(-14.23)	(-8.16)
Long-run coefficients (θ_i)						
ln(y)	1.409***	0.564	3.737***	6.837***	2.756	6.216***
	(3.82)	(0.22)	(5.33)	(11.07)	(1.39)	(8.49)
$(ln(y))^2$	-0.075***	-0.0462	-0.190***	-0.411***	-0.167	-0.348***
	(-3.24)	(-0.23)	(-4.51)	(-10.09)	(-1.16)	(-7.81)
energy	0.219***	0.254	0.0466	0.485***	0.584***	0.189***
	(11.73)	(0.94)	(1.09)	(8.61)	(3.84)	(5.88)
open	0.251***	3.240	0.157	1.130***	1.431**	0.445**
	(7.15)	(1.88)	(0.97)	(7.10)	(2.98)	(2.94)
urban	0.0039***	0.0165	0.0085***	0.00271	0.0156	0.00822***
	(4.93)	(1.03)	(2.68)	(1.28)	(1.34)	(2.94)
Number of observation	476	476	476	476	476	476
Number of provinces	28	28	28	28	28	28
AIC	-1956.75	-2568.77	NA	-1420.67	-2036.09	NA
BIC	-1906.77	-2518.79	NA	-1391.51	-2006.93	NA
Hausman test	(2) vs (1)	(2) vs (3)		(5) vs (4)	(5) vs (6)	
Chi2	0.80	0.00		7.27	0.02	
Prob>chi2	0.9768	1.0000		0.2015	1.0000	

Note: The dependent variable is $\Delta ln(c)$ in each column. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The estimates of dynamic EKC equations for per capita industrial waste water emissions (*ln(water)*) and per capita industrial waste residue emissions (*ln(solid)*)

	ln(water)		*ln(solid)*	
	(1) Lag (2-5)	(2) Lag (2-4)	(3) Lag (2-5)	(4) Lag (2-4)
ln(y)	0.609^{**}	0.606^{**}	1.314^{***}	1.290^{***}
	(2.54)	(2.52)	(4.42)	(4.46)
$(ln(y))^2$	-0.0361^{**}	-0.0359^{**}	-0.0792^{***}	-0.0778^{***}
	(-2.44)	(-2.42)	(-4.41)	(-4.45)
$ln(water)_{t-1}$	0.955^{***}	0.957^{***}		
	(54.16)	(54.46)		
$ln(solid)_{t-1}$			0.925^{***}	0.923^{***}
			(21.40)	(21.25)
energy	0.00629	0.00753	0.0499^{**}	0.0509^{**}
	(0.76)	(0.86)	(2.07)	(2.14)
open	0.0439	0.0556	-0.178^{**}	-0.182^{**}
	(0.80)	(1.00)	(-2.54)	(-2.55)
urban	-0.00114	-0.00156	0.00244	0.00247
	(-0.92)	(-1.13)	(1.56)	(1.60)
constant	-2.414^{**}	-2.399^{**}	-5.487^{***}	-5.393^{***}
	(-2.48)	(-2.45)	(-4.33)	(-4.39)
N	476	476	476	476
AR(1) test	-3.69	-3.69	-3.36	-3.35
	[0.000223]	[0.000222]	[0.000776]	[0.000820]
AR(2) test	0.73	0.75	-1.48	-1.48
	[0.465]	[0.454]	[0.140]	[0.140]
Hansen test (Chi2)	22.55	17.72	20.44	22.41
	[0.604]	[0.541]	[0.723]	[0.264]

Note: In each columns, all variables are treated as endogenous variables. Lag (a-b) specifies the lags a through b of endogenous variables as instruments for the transformed equation and lag a-1 as for the level equation. The regressions are done in the collapsed form and in the orthogonal deviation transformation, adjusted for small sample, and based on the robust one-step estimations. The p-value of the serial correlation tests in Arellano and Bond (1991) and the *p*-value of the Hansen tests of over-identification are reported in square brackets.
t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The PMG, MG, and FDE estimates of ARDL EKC equations for per capita industrial waste water emissions (*ln(water)*)

	ARDL (p=1, q=1)			ARDL (p=1, q=0)		
	(1)	(2)	(3)	(4)	(5)	(6)
	PMG	MG	DFE	PMG	MG	DFE
Adjustment coefficient (ϕ_i)						
	-0.564***	-1.065***	-0.192***	-0.353***	-0.872***	-0.182***
	(-7.12)	(-12.31)	(-7.40)	(-7.34)	(-13.56)	(-7.45)
Long-run coefficients (θ_i)						
ln(y)	2.831***	-1356.1	4.624***	2.947***	-1.740	5.921***
	(4.35)	(-1.00)	(3.96)	(9.52)	(-0.48)	(5.32)
$(ln(y))^2$	-0.199***	90.30	-0.307***	-0.187***	0.0803	-0.375***
	(-4.99)	(1.00)	(-4.35)	(-9.66)	(0.36)	(-5.50)
energy	0.0621**	-67.88	0.0661	0.121***	0.422*	0.146**
	(2.15)	(-1.00)	(1.00)	(5.83)	(1.95)	(2.33)
open	0.105	139.5	0.117	0.247***	0.321	0.161
	(1.31)	(1.02)	(0.43)	(3.35)	(0.50)	(0.59)
urban	0.0131***	-18.80	0.0139***	0.0131***	-0.0353	0.0154***
	(11.04)	(-1.00)	(2.64)	(9.02)	(-1.47)	(2.84)
Number of observation	476	476	476	476	476	476
Number of provinces	28	28	28	28	28	28
AIC	-1178.82	-1721.71	NA	-894.378	-1249.55	NA
BIC	-1128.83	-1671.72	NA	-865.220	-1220.39	NA
Hausman test	(2) vs (1)	(2) vs (3)		(5) vs (4)	(5) vs (6)	
Chi2	1.30	0.00		2.69	0.02	
Prob>chi2	0.7299	1.0000		0.7477	1.0000	

Note: The dependent variable is Δ*ln(water)* in each column. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: The PMG, MG, and FDE estimates of ARDL EKC equations for per capita waste solid emissions (*ln(solid)*)

	ARDL (p=1, q=1)			ARDL (p=1, q=0)		
	(1)	(2)	(3)	(4)	(5)	(6)
	PMG	MG	DFE	PMG	MG	DFE
Adjustment coefficient (ϕ_i)						
	-0.682***	-1.146***	-0.259***	-0.396***	-1.095***	-0.284***
	(-9.51)	(-13.22)	(-7.33)	(-7.04)	(-19.78)	(-8.07)
Long-run coefficients (θ_i)						
ln(y)	1.180**	-1.035	4.417***	2.629***	-1.240	5.651***
	(2.42)	(-0.37)	(4.30)	(10.75)	(-0.79)	(6.38)
$(ln(y))^2$	-0.0579*	0.124	-0.254***	-0.124***	0.116	-0.322***
	(-1.87)	(0.63)	(-3.99)	(-7.06)	(1.15)	(-5.80)
energy	0.283***	0.225	0.330***	0.250***	0.134	0.421***
	(7.72)	(1.56)	(5.46)	(5.58)	(1.50)	(7.43)
open	0.0402	1.366	-0.0874	0.165**	-0.273	0.00591
	(0.62)	(1.54)	(-0.36)	(2.03)	(-0.43)	(0.03)
urban	0.0052***	-0.0247	0.00262	-0.00043	-0.00126	0.00490
	(3.43)	(-0.63)	(0.54)	(-0.31)	(-0.09)	(1.10)
Number of observation	476	476	476	476	476	476
Number of provinces	28	28	28	28	28	28
AIC	-1163.35	-1737.62	NA	-802.275	-1246.99	NA
BIC	-1113.36	-1687.63	NA	-773.118	-1217.83	NA
Hausman test	(2) vs (1)	(2) vs (3)		(5) vs (4)	(5) vs (6)	
Chi2	0.30	0.00		2.95	0.07	
Prob>chi2	0.9976	1.0000		0.7074	0.9999	

Note: The dependent variable is Δ*ln(solid)* in each column. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.