Economic growth and air pollution：

Examining the empirical basis of environmental Kuznets curves

in China

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Abstract

This paper is an empirical study on the relationship between economic growth and environmental emission (air pollution), using a dataset from the largest manufacturing country, China. Three air pollutants – NO_x emission, SO_2 emission, CO_2 emission-are considered. Some of the results support the existence of the standard environmental Kuznets curve (EKC). More specifically, with first difference estimations, I find an inverted "U" relationship between emissions and GDP, indicating that the environment deteriorates before improving with economic growth. But the alternative EKC model which, includes cubic term of log GDP per capita and a time trend shows us an inverted "N" shape curve, which means the environment first improves, then gradually deteriorates and finally improves with economic growth.

1. Introduction

Economic growth brings us many benefits, such as improved living standards, but it also has costs, sometimes in the form of environmental degradation. As a result, people are increasingly concerned about how to build a sustainable economy, especially in developing countries like China which is a giant manufacturing country. According to Ren and Wang (2000), China's economic growth has gone through an unprecedented 20 years from 1985 to 2004, when GDP's average annual growth rate was about 8.7 percent, a period often called the most glorious history of China. However, China has paid a high price for these achievements, particularly because of the high use of natural resources and extraordinary loss of environmental quality. Since 1980, energy efficiency has been China's national policy. Still, in the late 90s, the rate of increase in energy demand was 1.5 times that of economic growth per year, and China's energy consumption per dollar of GDP was more than three times that of the world average. Furthermore, Warburton and Horn (2007) suggest that China has bad prospects. The environmental crisis of China threatens future domestic growth. According to research by the World Bank, the State Environmental Protection Administration (SEPA) and a team of international experts, the combined economic costs and human health costs of outdoor air and water pollution for China's economy amount to around $US100 billion a year, or about 5.8 per cent of the country's GDP. Other estimates range from 3 to 20 per cent (World Bank, 2007). Even the former Chinese President, Hu Jintao, has recognized that China's economic growth imposed an excessively high cost on resources and the environment.

Recent empirical research suggests that certain types of emissions follow an inverted U-shape as income grows, which is a relationship referred to as an environmental Kuznets curve (EKC). But in different countries, the turning points for different pollutants are different. Grossman and Krueger (1995) found that in most cases, the turning point comes before a country reaches a per capita income of $8,000 US.

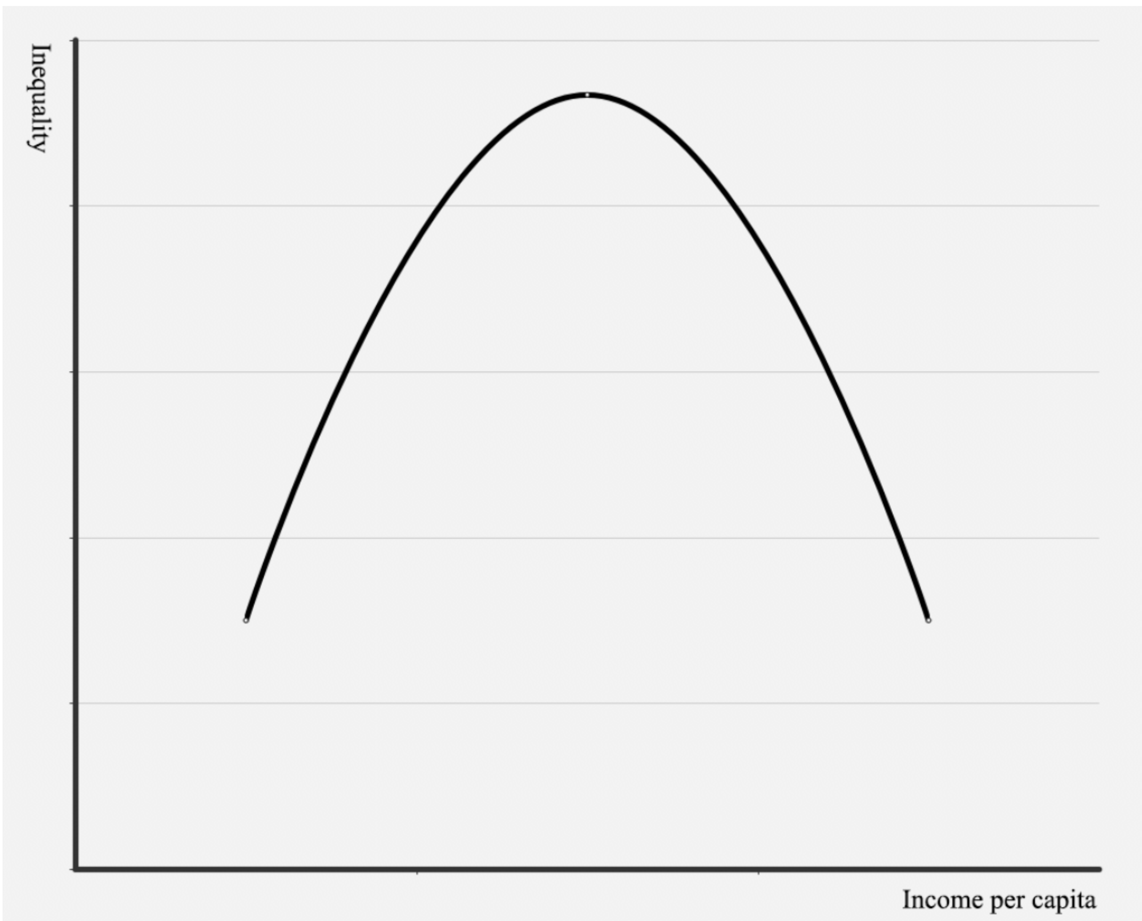
This paper is an empirical examination of environmental Kuznets curves in the largest manufacturing and developing country, China. Environmental variables are used as dependent variables and economic development variables (i.e., GDP per capita and its quadratic and cubic terms) are independent variables in this paper. We mainly use three types of emissions (CO_2, NO_x and SO_2) as environmental variables. CO_2 is a kind of greenhouse gas which changes the climate and weather on our planet, while NO_X gases react to form smog and acid rain as well as being central to the formation of fine particles (PM) and ground level ozone, both of which are associated with adverse health effects. Sulfur dioxide (SO_2) is a noticeable air pollutant which has significant impacts on human health.

This paper is organized as follows. In section 2, the environmental Kuznets curve is introduced. Section 3 presents a literature review on the EKC. Section 4 introduces the data. Section 5 presents an empirical analysis based on different EKC models and explains the findings. The conclusions and discussion are presented in section 6.

2. The Environmental Kuznets curve (EKC)

The original Kuznets curve graphs the hypothesis that economic inequality increases and then decreases as income per capita increases. That is, economic inequality exhibits an inverted U-shape when plotted against income per capita (Kuznets,1955), as shown in Figure 1.

Figure 1: Kuznets Curve



Source: Author’s graph.

Thirty-six years later, two American economists, Grossman and Krueger (1991) found an inverted U-shape relationship between a number of pollutants and GDP per capita by analyzing 42 countries’ cross section data. In the early stage of industrialization, pollutants will increase (environment quality will deteriorate) as GDP increases, as shown in Figure2.

Figure 2: Environmental Kuznets Curve

Source: Author’s graph.

After income attains a certain level (at the turning point), environmental degradation decreases as income increases. The turning points for different pollutants may vary, but in most cases they come before a country reaches a per capita income of $8,000 (Grossman and Krueger,1995).

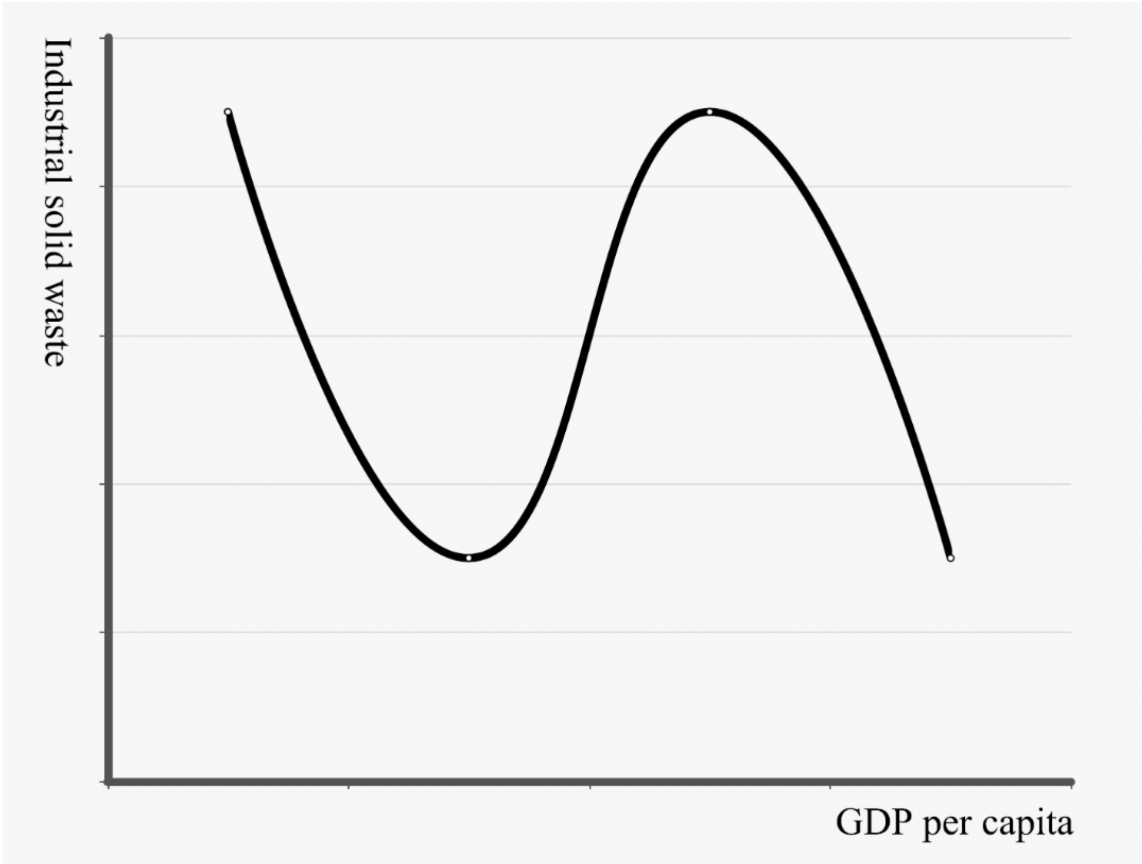
From then on, the environmental Kuznets curve attracted much attention from numerous scholars from all over the world.

3. Literature review

Numerous scholars have examined the EKC using different environmental indicators and different data sets, and have found that an EKC exists in some circumstances. Some papers support the standard environmental Kuznets curve. For example, Shafik and Bandyopadhyay (1992) studied 149 countries during the period 1961-1986 and concluded that emissions of sulfur dioxide (SO_2) and suspended particulate matter (SPM) originally increased and then decreased as income per capita rises. These two air pollutants conform to the EKC hypothesis with turning points at income levels between \$300 and \$4,000. Panayotou (1993) used cross-section data for 55 countries (SO_2 for late 1980s and SPM for 1987) and a translog specification, found similar results for these pollutants, with turning points at income levels ranging from \$3000 to \$5000. Panayotou (1995) then studied the relationship between CO_2 and income per capita for year 1988 and discovered that the relationship between carbon dioxide and income per capita was consistent with the inverse U-shape curve, with a turning point around \$800 per capita. Selden and Song (1994) used data averages for the periods 1973-1975, 1979-1981, and 1982-1984 for 30 countries and examined four air indexes, i.e, sulfur dioxide (SO_2), nitric oxide (NO_x), cobalt (CO) and suspended particulate matter (SPM), and confirmed the existence of the EKC with turning points at income levels ranging from \$800 to \$6000. Victor et al. (2011) found that an EKC relationship exists between sulfur dioxide and income per capita in some Chinese cities for the years 1984-2006 with a turning point around \$750 per capita, a result that robust in terms of overall pollution rather than to a specific pollutant. Wu and Dong (2002) discovered that the relationship between income per capita and sulfur dioxide in Beijing during the period 1980-2000 has an inverse U-shaped curve (EKC) with a turning point around $830 per capita. Grossman and Krueger (1995) examined the relationship between income per capita and four different kinds of environmental indicators, such as urban air pollution, the state of the oxygen regime in river basins, fecal contamination of river basins and contamination of river basins by heavy metals separately. A total of 42 countries are represented in their sample during the period 1979-1990. Their findings are consistent with the existence of an EKC. Moreover, they found that the turning point for different environmental indicators varies, but in most cases, the turning point occurs when income per capita reaches $8,000.

However, some other scholars' research implies other types of relationships between income per capita and pollution. For example, Kaufmann et al. (1998) found that the relationship between income per capita and sulfur dioxide (SO_2) during the period 1977-1996 was U-shaped in United State, rather than an inverted U shape. Aguayo (2010) argued that the inverted U relationship between income and emissions estimated from panel data need not hold for specific individual countries over time. Instead, the relationship was N-shaped. Fan et al. (2007) used three emissions indicators and GDP per capita in Yan Tai, Shandong province during the period 1980-2003, and found that the EKC was not the general rule. Ding and Lichtenberg (2011) used data from Guangxi province of China during the period 1976-2003 and concluded that the relation between environmental emissions and GDP per capita was a statistically significant N-shape rather than an inverted U-shape. Wu and Chen (2003) found that the EKC of Anhui province of China during the period 1976-2002 was "U-shape plus inverted U-shape", as depicted in Figure 3, differing from a traditional EKC.

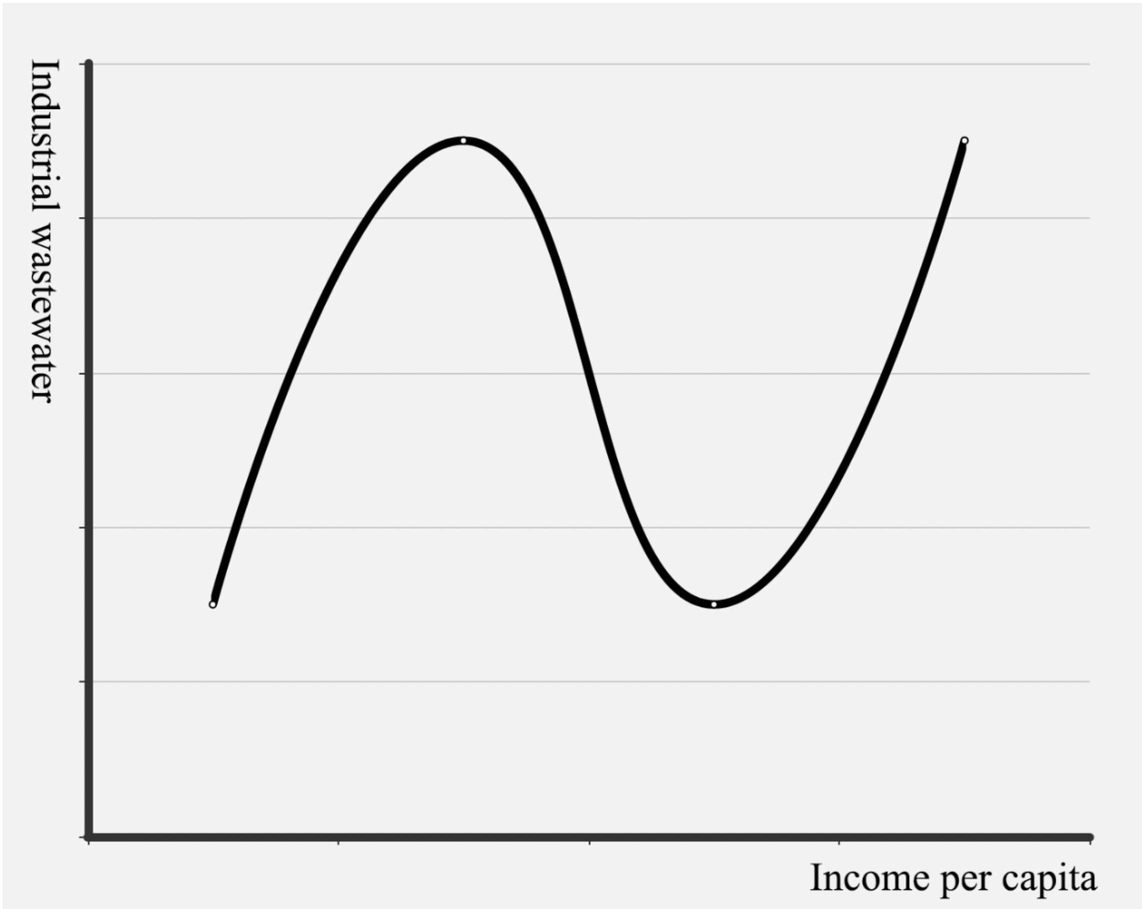
Figure 3: environmental Kuznets curve (U-shaped plus inverted U-shaped)



Source: Author's graph.

He and Richard (2010) used the environmental Kuznets curve hypothesis to study the situation of Canada. They used time series data (1948 to 2004) and found a positive relationship between GDP per capita and CO_2 per capita. Li and Zhang (2011) examined the EKC hypothesis using industrial wastewater, industrial gas waste and industrial solid waste as measures of environmental pollution in China during the period 1980-2009. They found that industrial wastewater and Income per capita have an N-shape relationship, as represented in Figure 4, but industrial gas waste and industrial solid waste have a U-shaped relationship with GDP per capita.

Figure 4: environmental Kuznets curve (N-Shaped)



Source: Author’s graph.

Duan (2014) investigates the relationship between economic growth and environmental pollution in China’s municipalities. In this paper, industrial waste water, emission of industrial waste gas, emission of industrial sulfur dioxide and industrial solid waste are considered as typical environmental pollution indicators, and GDP per capita from 1997 to 2012 is chosen to be the economic development indicator. A cubic polynomial function model between GDP per capita and the four environmental pollution indicators is built. The empirical results show both N-shaped and inverted N-shaped relationships between economic growth and environmental pollution, which differs from the inverted U-shape of the typical EKC.

The previous studies show that the results vary with the country, the cities in one country as well as the pollutant. For China, some papers find EKC relationships between income per capita and environmental pollutants with different turning points, but some other researchers find different type of relationships.

4. Data

Environmental Kuznets curves are often estimated using panel data. However, the necessary data for many provinces are not available during the period 1970 to 2016 in China. Thus this paper chooses to use time series data.

The environmental Kuznets curve relates a measure of environmental quality or per capita emissions to per capita income. This paper examines the quadratic and cubic Kuznets relationships.

In order to carry out the analysis, I download a dataset from the website Knoema which includes 41 years of data (1970-2010). The names of the series are total nitrogen oxide emissions, total sulfur oxide emissions, and total carbon dioxide emissions in China. And another 6 years of data (2011-2016) of three emissions in China is downloaded from National Bureau of Statistic of China. I also download GDP per capita in constant local currency units and total population during the period (1970-2016) from the World Bank. Then I divided the three emissions variables by total population to get SO_2 per capita, CO_2 per capita and NO_x per capita. Per capita emissions are measured in kilograms and the unit of GDP per capita is constant local currency units (Yuan). The per capita data can be found in Appendix A. In some regressions, the logs of the per capita variables are used instead of the levels. Table 1 shows descriptive statistics of GDP per capita, SO_2 per capita, CO_2 per capita and NO_X per capita. In addition, the mean and standard deviation of the first differenced variables are much smaller, this suggests that the first differenced variables are more stationary.

Table 1: Descriptive statistics[1]

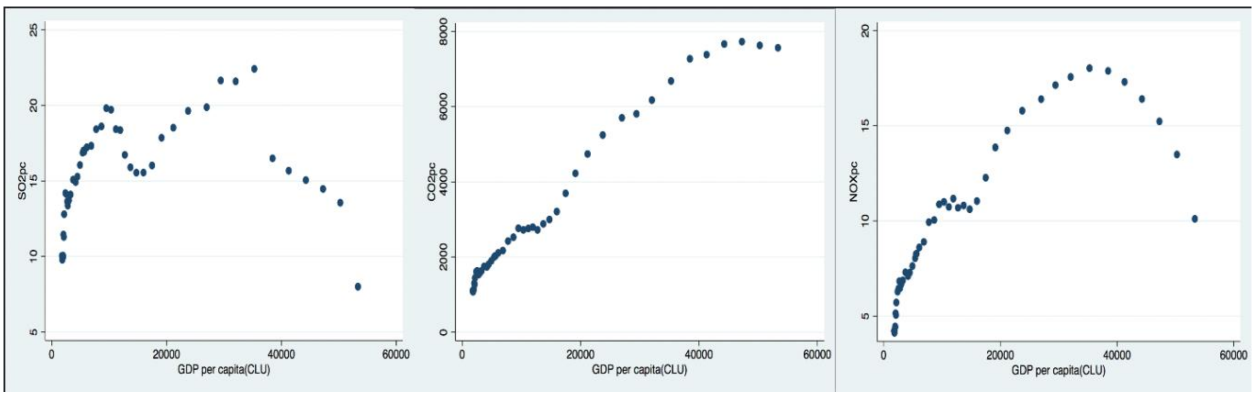
Variable	Obs	Mean	Std.Dev.	Min	Max
$GDPpc$	47	14376.25	14983.08	1766.025	53328.3
SO_2pc	47	15.5975	3.405839	7.999509	22.41832
CO_2pc	47	3233.546	2183.567	1077.928	7730.344
NO_xpc	47	10.03579	4.254762	4.125533	18.03355
$lnSO_2pc$	47	2.721424	0.2358022	2.07938	3.109879
$lnCO_2pc$	47	7.879389	0.6289364	6.982796	8.952909
$lnNO_xpc$	47	2.214469	0.4405943	1.417195	2.892234
$lnGDPpc$	47	9.016596	1.098781	7.476486	10.88422
$(lnGDPpc)^2$	47	82.48064	20.04026	55.89785	118.4663
$(lnGDPpc)^3$	47	765.2195	277.0045	417.9195	1289.413
ΔlnGDPpc	46	0.0740812	0.0325345	-0.031298	0.127850
$\Delta(lnGDPpc)^2$	46	1.360183	0.6195331	-0.47789	2.592155
$\Delta(lnGDPpc)^3$	46	18.94552	9.362929	-5.472626	39.42279
$\Delta lnSO_2pc$	46	-0.0049264	0.1039651	-0.52759	0.128134
$\Delta lnCO_2pc$	46	0.041854	0.0462712	-0.03657	0.140802
$\Delta lnNO_xpc$	46	0.018977	0.0692814	-0.28875	0.126824

Source: Author's calculations

[1] Data source:
(1): https://knoema.com/EDGARGEC2017/global-emissions-by-country?country=1000050&indicator=1000300&ipcc=1000590
(2): http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0C05&sj=2013
(3): https://data.worldbank.org/indicator/NY.GDP.MKTP.KN?locations=CN

As I said in the introduction, Grossman and Krueger (1995) found that the turning point comes before a country reaches a per capita income of $8,000 US in most cases. Before conducting the econometric analysis, it is useful to have a first look at the data by drawing three scatter plots for the three emissions indicators to see whether or not China seems to have reached the turning point for different types of emissions. (Note that we do not use logs of the per capita variables in these graphs, but GDP per capita, SO_2 per capita, CO_2 per capita and NO_x per capita instead.)

Figure 5: scatter plot for different emissions



Source: Author’s calculations

Consider the left panel of Figure 5. If I separate the figure in two parts (GDP per capita between 0 and 36000 Yuan and between 36000 Yuan and 53000 Yuan), I find that the left part shows a N-shape relationship as GDP per capita increases, but right part tends to be downward sloping. In contrast, CO_2 per capita is generally upward-sloping, as can be seen in the middle figure. However, if I focus on the last three dots in the middle figure, CO_2 per capita starts decreasing when GDP per capita reaches 48000 Yuan. Looking at the right panel of Figure 5, NO_x per capita increases at the beginning when GDP per capita is between 0 to 38000 Yuan, but then decreases after GDP per capita passes 38000 Yuan.

Overall, the figures seem to show that emissions increase relatively rapidly at low levels of GDP per capita, and that the turning point is different for different types of emissions in China. For SO_2 per capita, the turning point happens when GDP per capita is around 36000 Yuan; for CO_2 per capita, it seems that the turning point emerges at 48000 Yuan; as for NO_x, the curve is the one most similar to the standard environment Kuznets curve, and the turning point for NO_x per capita happens when GDP per capita reaches around 38000 Yuan. However, this situation is fine, because other researches have also found that different pollution emissions vary in different datasets. (Stern and Zha 2016). In addition, Stern and Common (2001), using a sample of 73 countries, including several developing countries, found an EKC with a turning point much higher than that found by Selden and Song (1994) with a similar sample containing only 22 OECD countries.

Besides, from the left panel of Figure 5, I find that per capita Sulphur dioxide and per capita nitrogen dioxide drop sharply after 2010. Lewis (2011) explained some details of China's 12th five-year plan (the period 2011-2015) for environmental protection that may have contributed to this reduction: "Any new coal-fueled generating unit in power industry simultaneously installed sulfur and nitrogen removal facilities. Any existing coal-fueled generating units without desulphurization facilities were phased out or installed desulphurization facilities. The smoke desulphurization facilities eliminated flue gas bypass according to requirements. Low-nitrogen combustion technical reform of coal-fueled generating units and installation of smoke denitrification facilities were accelerated. All coal fueled generating units with capacity at and over 300,000 kW installed denitrification facilities. The government strengthened supervision on the operation of sulfur and nitrogen removing facilities. Any generating unit failing to steadily meet emission standard has made corrections within a given period of time". In addition, Lyons (2018) said that China "EPA" phased out and shut down tens of thousands of businesses which didn't meet the requirement of environmental regulations contained in the 12th five-year plan during 2014 to 2016. As a result, there is an even sharper drop in 2016.

5. Method and empirical analysis

We begin our analysis by considering parametric model that is quite standard in the EKC literature and take the following form:

$$lnEpc_t = \beta_0 + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \varepsilon_t \quad (1)$$

where Epc is a measure of emissions.

In addition, I will use model (2) shown below, which is used in the study of Duan (2014) and Bruyn (1998). These scholars add the cubic term of the log of GDP per capita in model (1), since cubic polynomial functions have the advantages of high goodness of fit and high precision of F tests.

$$lnEpc_t = \beta_0 + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \beta_3 (lnGDPpc_t)^3 + \varepsilon_t \quad (2)$$

The analysis will compare results from models (1) and (2).

Depending on the signs of the coefficients on the RHS of the above equation, as proposed by Duan (2014) and Bruyn (1998), there are seven different polygonal forms related to the environment–economic development relationship that might arise. By the way, note that model (2) becomes model (1) when $\beta_3 = 0$. The seven different models are the following:

1) When $\beta_1 = \beta_2 = \beta_3 = 0$, the equation becomes a vertical line, i.e., economic growth has no impact on the environment.
2) When $\beta_1 > 0$, $\beta_2 = \beta_3 = 0$, the equation exhibits a linear monotonically increasing function; i.e., as economic growth occurs, the environment deteriorates.
3) When $\beta_1 < 0$, $\beta_2 = \beta_3 = 0$, the equation exhibits a linear monotonically decreasing function; i.e., as economic growth occurs, the environment improves.
4) When $\beta_1 > 0$, $\beta_2 < 0, \beta_3 = 0$, the equation exhibits an inverted "U" shape curve; i.e., the typical environmental Kuznets curve applies that the environment deteriorates before improving with economic growth.
5) When $\beta_1 < 0$, $\beta_2 > 0, \beta_3 = 0$, the equation exhibits a U-shape curve; i.e., the environment improves before deteriorating with economic growth.
6) When $\beta_1 < 0$, $\beta_2 > 0, \beta_3 < 0$, the equation may exhibit an inverted "N" shape curve, i.e. the environment first improves, and gradually deteriorates and then improves with economic growth. Sometimes it produces a monotonically decreasing function. It depends on the magnitudes of coefficients.
7) When $\beta_1 > 0$, $\beta_2 < 0, \beta_3 > 0$, or $\beta_1 > 0$, $\beta_2 > 0, \beta_3 > 0$ or $\beta_1 < 0$, $\beta_2 > 0, \beta_3 > 0$, the equation may exhibit an N-shape figure, i.e. the environment first deteriorates, and gradually improves later and then deteriorates with economic growth, and sometimes it produces monotonically increasing function. It depends on the magnitudes of coefficients.

Nonstationarity of the variables of the model is a potential problem. In previous researches, He and Richard (2010) adds a linear time trend into a standard EKC model to deal with this issue; Lantz and Feng (2006) include a non-linear time trend to address the nonstationarity problem; and Stern and Common (2001) estimate a model in first-differences to deal with nonstationarity.

To address the potential nonstationarity problem, we apply these three different methods to models (1) and (2). All equations are estimated using OLS.[2]

[2] All estimation and testing was carried out using Stata.

The Breusch-Pagan-Godfrey Test is used to test the heteroscedasticity of errors in the following regressions. The null hypothesis is that there is homoscedasticity and the alternative hypothesis is that there exists heteroscedasticity. The Breusch-Godfrey LM Test is used to test for autocorrelation. The null hypothesis is that there is no autocorrelation and the alternative hypothesis is that there exists autocorrelation. If the model does not have heteroscedasticity or autocorrelation, we can confirm that the model is a good specification. And t-test is used to see whether or not there is a relationship between independent variable and dependent variable, the null hypothesis is that there is no relationship between one independent variable and the dependent variable controlling for the other independent variables.

5.1 Adding a linear time trend

If we add a linear time trend to model (1) and model (2), we obtain

$$lnEpc_t = \beta_0 + \alpha_1 t + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \varepsilon_t \quad (3)$$

$$lnEpc_t = \beta_0 + \alpha_1 t + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \beta_3 (lnGDPpc_t)^3 + \varepsilon_t \quad (4)$$

In this process, I assume that the data are trend stationary, and include the year as my linear time trend in estimating equations. I also need to carry out tests for heteroscedasticity and autocorrelation to verify whether this is a good specification or not.

In Table 2 below, the column (1), column (2) and column (3) show the coefficient estimates and testing results of model (3) for three pollutants. The p-value of the Breusch-Pagan-Godfrey Statistic is 0.7676 in column (1) which is greater than 0.1. Thus I cannot reject the null hypothesis of homoscedasticity at the 5 % significance level, which means that model (3) does not have a heteroscedasticity problem for $\mathrm{lnSO_2pc}$. However, the corresponding p-values of the Breusch-Pagan-Godfrey Statistic for $\mathrm{lnCO_2pc}$ and $\mathrm{lnNO_xpc}$ in column (2) and column (3) are 0.0217 and 0.0005, which means I can reject the null hypothesis at the 5 % significant level and there exists heteroscedasticity. The use of heteroscedasticity-consistent standard errors will ease the heteroscedasticity problem. In addition, for the Breusch-Godfrey LM Test, the p-values are equal to 0.0000 at lag (1) in columns (1), (2) and (3), so I can reject null hypothesis of no autocorrelation at lag (1).

There are several sources of autocorrelation. The yearly emission per capita maybe influenced by the per capita emissions of the preceding year. Another source of autocorrelation is the effect of omitted variables. In regression modeling, it is not possible to include all possible variables in the model. Then Newey-West robust standard errors are computed to fix autocorrelation. p is the number of lags which is determined by the equation: p=$47^{\frac{1}{4}}$. In order to check whether Newey-West standard errors are sensitive to truncation parameter, so I increase the number of lags to 6. As I expected, the Newey-West standard errors at lag (3) are very close to the OLS standard errors and the robust standard errors at lag (6). The p-values of F-test for the regressions with Newey-West standard errors at lag (3) are also very close to the p-values at lag (6). The corresponding p-values of t-test for lnGDPpc and $(\mathrm{lnGDPpc})^2$ are close to 0.000, which reject the null hypothesis at the 5% significance level, so lnGDPpc and its quadratic term have an effect on $\mathrm{lnSO_2pc}$, $\mathrm{lnCO_2pc}$ and $\mathrm{lnNO_xpc}$. The equation of $\mathrm{lnSO_2pc}$ and $\mathrm{lnNO_xpc}$ shows an inverted “U” shape curve in Model (3), but the equation of $\mathrm{lnCO_2pc}$ shows a U-shape curve.

Adjusted R-square instead of R-square is listed in Table 2 as well as Table 3, because I am using it to draw comparisons across equations with different numbers of explanatory variables. Comparing with model (3), the adjusted R-square becomes smaller after adding one explanatory variable $(lnGDPpc)^3$ in column (4) and (5). This means $(lnGDPpc)^3$ does not greatly increase the explanatory power of model (3). After adding $(lnGDPpc)^3$, all p-values of the coefficient of independent variables in column (4), (5) and (6) are greater than 0.05, meaning I can reject the null hypothesis at 5% significant level. This implies that no independent variables have a significant effect on emissions.

Table 2: Regression models including a linear time trend

	model (3) $\ln SO_2 pc$ (1)	model (3) $\ln CO_2 pc$ (2)	model (3) $\ln NO_x pc$ (3)	model (4) $\ln SO_2 pc$ (4)	model (4) $\ln CO_2 pc$ (5)	model (4) $\ln NO_x pc$ (6)
C	12.18201 (0.759)	-53.33169 (0.001)	-27.1326 (0.438)	6.32641 (0.876)	-52.98826 (0.025)	-39.40223 (0.000)
t	-0.01282 (0.557)	0.03300 (0.000)	0.01051 (0.584)	0.0002108 (0.994)	0.035218 (0.032)	0.03787 (0.000)
lnGDPpc	3.31836 (0.000)	-1.4999 (0.001)	1.61958 (0.004)	-2.971155 (0.716)	-2.201727 (0.641)	-11.56813 (0.101)
$(lnGDPpc)^2$	-0.16749 (0.000)	.090306 (0.000)	-0.07519 (0.002)	0.4971123 (0.564)	0.1644675 (0.741)	1.318202 (0.077)
$(lnGDPpc)^3$				-0.023823 (0.442)	-0.0026574 (0.881)	-0.0499661 (0.062)
Adj R-squared	0.6698	0.9847	0.9269	0.6667	0.9844	0.9372
F-test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BPG test (p-value)	0.7676	0.0217	0.0005	0.9670	0.0251	0.0008
B-G LM test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Turning point	8×10^9	2×10^8	5.8×10^{10}	22181 3.7×10^9	2.5×10^8 7.1×10^{32}	2.4×10^8 1.5×10^9

Source: Author's calculations.
Notes: P-value of each coefficient is in the parenthesis; There are 47 observations in our regression. The p-value of B-G LM test result is listed at lag (1). The turning points are showing the value of GDP per capita.

5.2 Adding a nonlinear time trend

If we add a nonlinear time trend to model (3) and model (4), we obtain

$$lnEpc_t = \beta_0 + \alpha_1 t + \alpha_2 t^2 + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \varepsilon_t \quad (5)$$

$$lnEpc_t = \beta_0 + \alpha_1 t + \alpha_2 t^2 + \beta_1 lnGDPpc_t + \beta_2 (lnGDPpc_t)^2 + \beta_3 (lnGDPpc_t)^3 + \varepsilon_t \quad (6)$$

For model (5), BPG test tells us that we cannot reject the null hypothesis at the 5% significance level, which means that there is no heteroscedasticity for the three pollutants. But the B-G LM test still shows that there exists an autocorrelation problem at lag (1) (see BPG test result and B-G LM test result for model (5) in Table 3). Thus Newey-West robust standard errors are computed again to deal with autocorrelation. As I expected, the Newey-West robust standard errors at lag (3) are very close to the OLS standard errors and the robust standard errors at lag (6). In previous table, we find that in model (3), p-value of time trend for SO_2 per capita and NO_x per capita are not statistically significant at 10 % significant level (see column (1) and (3) in table 2), however, they become statistically significant after we added a quadratic trend term into model (3) (see column (1) and (3) in table 3). This suggests that a nonlinear time trend has more powerful explanatory powers as a deterministic time trend than a linear time trend and that nonlinear time trend has an effect on dependent variable. In addition, compared to adding a linear time trend, the results show that the p-value of the coefficient of GDP per capita and the quadratic terms of GDP per capita are exactly 0.000, which means the nonlinear time trend makes the coefficients of our independent variables more statistically significant. The signs of the coefficients for model (5) suggest a U-shaped curve, i.e., the environment improves before deteriorating with economic growth.

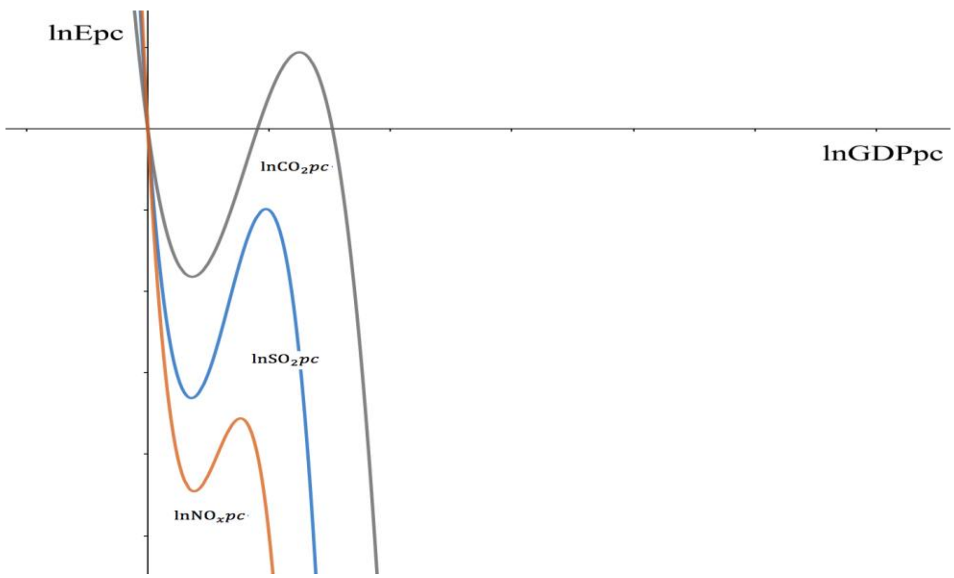
For model (6), the p-value of the BPG test is greater than 0.05, so we cannot reject the null hypothesis and there is no heteroscedasticity problem. For the Breusch-Godfrey LM Test for autocorrelation, all p-values are also greater than 0.05, which means that model (6) does not have autocorrelation for any of the three pollutants (BPG test results and B-G LM test results for model (6) are shown in Table 3). The adjusted R-squares for model (6) are greater than the adjusted R-squares for model (5) since we add a cubic term of GDP per capita and it is statistically significant at the 5% significance level.

Similar to model (5), model (6) shows that all p-values of t-tests for each coefficient of independent variables are statistically significant at 5% significant level, and the overall F-test for testing that all of the slopes are simultaneously 0 is significant (p-values are smaller than 0.05), as shown in Table 3. Furthermore, it is obvious that the coefficient of GDP per capita is negative (β_1<0), the quadratic term for the coefficient of GDP per capita is positive ($\beta_2 > 0$) and the cubic term for the coefficient of GDP per capita is negative ($\beta_3 < 0$). That implies that model (6) follows case 6. Since the magnitudes of the coefficients matter a lot, I use the GeoGebra math application to graph the shapes of three different pollutants. Because I just want to know the shape of them, the constants of the cubic equations are set to zero, resulting in figure 6. The relationships between emissions and GDP exhibits an inverted "N" shaped curve which means the environment firstly improves, then gradually deteriorates and then improves again with economic growth.

The results of the diagnostic tests provide some clues as to which model is best, but a comparison of these models might help me in favoring one of the four models.

Akaike's information criterion and the Bayesian information criterion are used to check which model is the best one. A large difference in either the AIC or BIC indicates stronger evidence for one model over the other (the lower the better) and the results are shown in Table 4. For $\ln SO_2pc$, $\ln CO_2pc$ and $\ln NO_xpc$, the lowest value of AIC and BIC is that of model (6). So these criteria suggest that model (6) may be the best model.

Figure 6: Shapes of Model (6) for each pollutants



Source: Author's calculations

Table 3: Regression model including nonlinear time trend

	model (5) $\ln SO_2 pc$ (1)	model (5) $\ln CO_2 pc$ (2)	model (5) $\ln NO_x pc$ (3)	model (6) $\ln SO_2 pc$ (4)	model (6) $\ln CO_2$pc (5)	model (6) $\ln NO_x pc$ (6)
C	-18640.2 (0.000)	-9820.85 (0.000)	-16087.26 (0.000)	-20030.75 (0.000)	-10293.14 (0.000)	-3973.054 (0.000)
t	18.8978 (0.000)	9.936471 (0.000)	16.29295 (0.000)	20.32405 (0.000)	10.42102 (0.000)	18.785933 (0.000)
t^2	'-0.00478 (0.000)	-0.002504 (0.000)	-0.004118 (0.000)	-0.005136 (0.000)	-0.002624 (0.000)	-0.0046574 (0.000)
lnGDPpc	-6.564203 (0.000)	-6.674992 (0.000)	-6.891165 (0.000)	-21.96098 (0.000)	-11.90583 (0.000)	-28.65509 (0.000)
$(lnGDPpc)^2$	0.484467 (0.000)	0.4317121 (0.000)	0.4861955 (0.000)	2.082473 (0.000)	0.9746119 (0.000)	2.746621 (0.000)
$(lnGDPpc)^3$				-0.055579 (0.000)	-0.018882 (0.000)	-0.0789613 (0.000)
Adj R-squared	0.8496	0.9916	0.9651	0.8716	0.9918	0.9789
F-test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BPG test (p-value)	0.2722	0.8917	0.3354	0.4737	0.6449	0.2131
B-G LM test (p-value)	0.0001	0.0000	0.0000	0.1764	0.3645	0.2533
Turning point	8×10^6	5.38×10^7	1.53×10^7	3.7×10^7 2.6×10^{17}	8.7×10^7 2.9×10^{26}	8.4×10^7 1.8×10^{15}

Source: Author's calculations.

Notes: P-value of each coefficient is in the parenthesis; There are 47 observations in our regression. The p-value of B-G LM test result is listed at lag (1). The turning points are showing the value of GDP per capita.

Table 4: Akaike's information criterion and Bayesian information criterion

Akaike's information criterion and Bayesian information criterion for $lnSO_2pc$						
model	0bs	ll(null)	ll(model)	df	AIC	BIC
3	47	1.719097	29.34004	4	-50.68008	-43.27949
4	47	1.719097	29.67538	5	-49.35076	-40.10002
5	47	1.719097	48.38162	4	-88.76324	-81.36265
6	47	1.719097	52.66012	5	-95.32023	-86.06949
Akaike's information criterion and Bayesian information criterion for $lnCO_2pc$						
model	0bs	ll(null)	ll(model)	df	AIC	BIC
3	47	-44.38963	55.47887	4	-102.9577	-95.55716
4	47	-44.38963	55.49149	5	-100.983	-91.73224
5	47	-44.38963	70.09382	4	-132.1876	-124.7871
6	47	-44.38963	71.25962	5	-132.5192	-123.2685
Akaike's information criterion and Bayesian information criterion for lnNOxpc						
model	0bs	ll(null)	ll(model)	df	AIC	BIC
3	47	-27.66207	35.41013	4	-62.82026	-55.41967
4	47	-27.66207	37.38567	5	-64.77134	-55.52061
5	47	-27.66207	53.30243	4	-98.60485	-91.20426
6	47	-27.66207	65.67925	5	-121.2585	-112.1078

Source: Author’s calculations.

The results in Tables 2 and 3 indicate that models (3), (5) and (6) all imply a significant relationship between the log of real GDP per capita and the log of emissions per capita. Remember that Figure 5 is just a first look of data; it shows the relationship between the real GDP per capita and emissions per capita, but logs of variables are estimated in all regression models, thus the magnitudes of turning points in Figure 5 are much larger than the magnitudes of turning points in regression models. The turning points of regression models are shown in Table 2 and 3. I find that almost all calculating turning points are beyond the sample interval, which is somewhat unexpected, the reasons may be considered in future studies.

Then model (1) and (2) are estimated to see how the predicted turning points from those models compare to the data and to the predicted turning points of the models that include deterministic trends. The estimating results are shown in Table 5. BPG test tells us that there is no heteroscedasticity at the 5% significant level. And B-G LM test shows that there is no autocorrelation at lag (1). For model (1), The real GDP per capita at the turning points for NO_X per capita and SO_2 per capita are fairly high, compared with CO_2 per capita (40041 Yuan per capita). For model (2), SO_2 per capita has one much lower real GDP per capita (20439 Yuan per capita) at the turning point, compared with NO_X per capita (209829 Yuan per capita). I cannot calculate the real GDP per capita for CO_2 per capita at the turning point since they are imaginary numbers. Predictive margins tell us that the estimations are statistical significant at the 5% significant level.

Comparing with the models including time trends, model (2) which includes the cubic term of GDP per capita has lower real GDP per capita at the turning point.

Table 5: Regression model without time trend

	model (1) $lnSO_2pc$ (1)	model (1) $lnCO_2pc$ (2)	model (1) $lnNO_xpc$ (3)	model (2) $lnSO_2pc$ (4)	model (2) $lnCO_2pc$ (5)	model (2) $lnNO_xpc$ (6)
C	-11.088 (0.000)	7.912 (0.000)	-8.056 (0.000)	6.602 (0.716)	-7.99 (0.471)	10.026 (0.528)
lnGDPpc	2.968 (0.000)	-0.577 (0.014)	1.905 (0.000)	-2.929 (0.627)	4.73 (0.202)	-4.123 (0.436)
$(lnGDPpc)^2$	-0.157 (0.000)	0.06 (0.000)	-0.084 (0.000)	0.493 (0.459)	-0.522 (0.203)	0.581 (0.320)
$(lnGDPpc)^3$				-0.024 (0.330)	0.021 (0.153)	-0.024 (0.256)
Adj R-squared	0.6746	0.9825	0.9281	0.674	0.983	0.9286
F-test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
BPG test (p-value)	0.7480	0.1682	0.1269	0.7492	0.2794	0.1902
B-G LM test (p-value)	0.1690	0.1374	0.2142	0.2435	0.2453	0.3566
Predictive Margins (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Turning point	2.8×10^9	40041	2.2×10^{11}	20439 3.7×10^9	Imaginary numbers	209829 4.6×10^{10}

Source: Author's calculations.

Notes: P-value of each coefficient is in the parenthesis; There are 47 observations in our regression. The p-value of B-G LM test result is listed at lag (1). The turning points are showing the value of GDP per capita.

5.3 Estimating model in first differences

Following Stern and Common (2001), I estimate the model in first differences. In this case, the regression equations are:

$$\Delta lnEpc_t = \beta_0 + \beta_1 \Delta lnGDPpc_t + \beta_2 \Delta[(lnGDPpc_t)^2] + \varepsilon_t \quad (7)$$

$$\Delta lnEpc_t = \beta_0 + \beta_1 \Delta lnGDPpc_t + \beta_2 \Delta[(lnGDPpc_t)^2] + \beta_3 \Delta[(lnGDPpc_t)^3] + \varepsilon_t \quad (8)$$

Prior to the regression for the relationship between environmental pollution and economic growth, we conduct Augmented Dickey Fuller unit root tests for the stationarity of the time series variables. The results are presented in Table 6.

Table 6: Results for Unit Root Tests

Variables	ADF test data	Test type (c, t, p)	10% critical value	p-value for Z(t)	Conclusions
$\ln SO_2pc$	-0.791	c, t, 0	-2.605	0.8216	nonstationary
$\Delta\ln SO_2pc$	-3.846	c, t, 1	-2.606	0.0216	stationary
$\ln NO_xpc$	-1.967	c, t, 0	-2.605	0.3012	nonstationary
$\Delta\ln NO_xpc$	-6.345	c, t, 1	-2.606	0.0002	stationary
$\ln CO_2pc$	-0.666	c, t, 1	-2.606	0.9891	nonstationary
$\Delta\ln CO_2pc$	-5.373	c, t, 2	-2.607	0.0009	stationary
lnGDPpc	-1.034	c, t, 0	-2.605	0.9987	nonstationary
ΔlnGDPpc	-6.245	c, t, 0	-2.605	0.0000	stationary

Source: Author’s calculations.

Notes: c means intercept, t means trend term, p is the number of lags which is determined by the modified AIC, Δ means first difference.

For the levels of each series, we cannot reject the null hypothesis that the series is difference stationary, i.e., none of them are difference stationary. As a result, we take first differences. According to Table 6, the null hypothesis is rejected at the 10 percent significant level for all variables in first differences, which means they are integrated of order 1, or I (1).

The estimation results for the models in first difference are reported in Table 7. The adjusted R^2 statistics for these models are, as expected, far lower than for the levels models. For model (7), The Breusch-Pagan-Godfrey test for heteroscedasticity shows that the regressions for $\Delta \ln SO_2 pc$ and $\Delta \ln NO_x pc$ have heteroscedasticity at the 5% significance level. However, there is no heteroscedasticity for $\Delta \ln CO_2 pc$. In addition, the Breusch-Godfrey LM test shows that we can reject the null hypothesis at 5% significant and therefore there is autocorrelation. Therefore, Newey-West robust standard errors are computed The p-values of coefficients show that ΔlnGDPPC and its quadratic term are statistically significant for $\Delta \ln SO_2 pc$ and $\Delta \ln NO_x pc$ at 5% significant, but not for $\Delta \ln CO_2 pc$. Considering the coefficients of ΔlnGDPPC and its quadratic, model (7) shows an inverted "U" shape curve.

With respect to heteroscedasticity and autocorrelation, model (8) for each variable has the same results as model (7). These results are shown in columns (4), (5) and (6). The p-values of the coefficients show that the coefficients of ΔlnGDPPC, its quadratic term and 1 cubic term are not statistically significant at the 5% significance level for all emissions. This might be a sign of multicollinearity.

Then I try to take first differences of model (3). The results are shown in Table 8. The Breusch-Pagan-Godfrey test for heteroscedasticity shows that the regressions for $\Delta \ln SO_2 pc$ and $\Delta \ln NO_x pc$ have heteroscedasticity at the 5% significance level. However, there is no heteroscedasticity for $\Delta \ln CO_2 pc$. Comparing with model (7) which including the deterministic time trend, the Breusch-Godfrey LM test for first differenced model (3) shows that we cannot reject the null hypothesis at 5% significant and therefore there is no autocorrelation. I find that the coefficients of ΔlnGDPpc and $\Delta(lnGDPpc)^2$ have the inversed sign for $\Delta\mathrm{lnSO}_2pc$, $\Delta\mathrm{lnCO}_2pc$ and $\Delta\mathrm{lnNO}_xpc$. The first differenced model (3) shows a U-shape curve. In addition, comparing with model (3), the first differenced model (3) doesn't have autocorrelation at 5% significant level.

Table 7: Estimating model in first differences

	model (7) $\Delta\mathrm{lnSO}_2pc$ (1)	model (7) $\Delta\mathrm{lnCO}_2pc$ (2)	model (7) $\Delta\mathrm{lnNO}_xpc$ (3)	model (8) $\Delta\mathrm{lnSO}_2pc$ (4)	model (8) $\Delta\mathrm{lnCO}_2pc$ (5)	model (8) $\Delta\mathrm{lnNO}_xpc$ (6)
c	-0.04314 (0.235)	-0.00731 (0.637)	-0.02176 (0.359)	-0.02993 (0.413)	‘-0.00651 (0.687)	‘-0.01078 (0.646)
ΔlnGDPPC	5.30758 (0.005)	0.20387 (0.792)	3.60104 (0.004)	-23.97285 (0.211)	-1.57174 (0.852)	-20.71086 (0.096)
$\Delta(lnGDPpc)^2$	-0.26097 (0.008)	-0.02505 (0.538)	-0.16618 (0.000)	2.94372 (0.160)	0.21938 (0.811)	2.49471 (0.067)
$\Delta(lnGDPpc)^3$				-0.11628 (0.127)	-0.00705 (0.832)	-0.09655 (0.051)
Adj R-squared	0.1342	0.1901	0.1619	0.1620	0.1718	0.2170
F-test (p-value)	0.0000	0.0000	0.0000	0.0128	0.0000	0.0000
BPG test (p-value)	0.0000	0.9121	0.0034	0.0000	0.9684	0.0024
B-G LM test (p-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's calculations.

Notes: P-value of each coefficient is in the parenthesis; There are 46 observations in our regression. The p-value of B-G LM test result is listed at lag (1).

Table 8: Regression results for first differences of Model (3)

	$\Delta\ln SO_2pc$ (1)	$\Delta\ln CO_2pc$ (2)	$\Delta\ln NO_xpc$ (3)
C	15.96865 (0.007)	5.760272 (0.026)	13.60537 (0.000)
t	-0.008078 (0.007)	0.0012583 (0.026)	-0.0068754 (0.000)
ΔlnGDPPC	-4.460666 (0.249)	-3.314737 (0.056)	-4.712403 (0.050)
$\Delta(lnGDPpc)^2$	0.3393198 (0.145)	0.2412766 (0.022)	0.3447091 (0.018)
Adj R-squared	0.2566	0.2645	0.3752
F-test (p-value)	0.0014	0.0011	0.0000
BPG test (p-value)	0.0000	0.4120	0.0044
B-G LM test (p-value)	0.7694	0.0704	0.1116

Source: Author's calculations.

Notes: P-value of each coefficient is in the parenthesis; There are 46 observations in our regression. The p-value of B-G LM test result is listed at lag (1).

5.4. Comparisons with the results of previous studies

He and Richard (2010) used a standard EKC model during the period 1948 to 2004 in Canada, including a linear time trend, and found evidence that the relationship between CO_2 per capita and GDP per capita has a U-shape with a peak around 22 615$ per capita GDP, which is consistent with the results in model (3). Lantz and Feng

(2006) used a five-region panel data with a non-linear time trend in Canada during the period 1970 to 2000 and found that GDP per capita is unrelated to CO_2 per capita which is inconsistent with the results in model (5) and model (6). Stern and Common (2001) estimate a model in first-differences for the world which include some OECD and non-OECD countries. They found that the EKC has an inverted “U” shape for the world as a whole, which is consistent with the result in model (7).

6: Conclusion and discussion

This paper studies the relationship between three air pollutants and GDP per capita in China from 1970 to 2016. Based on EKC model, we try to find how environmental pollutants changes with economic growth. We had a first look at the data by drawing three scatter plots for each emission indicator and found that China seems to have passed the turning point for these three emission indicators, but the turning point is different for different pollutant.

A contribution of this paper is that we used three sets of methods to address nonstationarity issue and proceeded with presenting these three sets of estimation results for one standard EKC model and an alternative EKC model. The results of estimating the model including nonlinear time trend and a cubic term of GDP show an inverted “N” shape curve which means the environment first improves, then gradually deteriorates and finally improves with economic growth. The first difference model exhibits an inverted “U” shape curve, which is a typical environmental Kuznets curve. It means that the environment deteriorates before improving with economic growth. However, the first differenced model (3) and the model including nonlinear time trend show a U-shaped relationship between emissions and GDP, the environment first improves, then gradually deteriorates.

Air quality in China is an important problem that has attracted government's attention in recent years. Various new policies in order to improve the environment have been implemented. National Public Radio (2017) said that China "EPA" phased out and shut down tens of thousands of business activities during 2014 to 2016. These businesses are technology-backward, causing heavy pollution and relying heavily on resources and energy. Despite some policy efforts, air pollution remains a significant problem. Understanding better the relationship between economic growth and pollution is an important step in addressing this problem, and this paper contributes to improving knowledge on this issue.

Nevertheless, there are still some limitations to this study area. The emission indicators we used in this paper are three main air pollutants. However, there are many other air pollutants that could also be studied, but it is, in some cases, hard to collect data. If it is possible, they could be added in future research.

REFERENCES

Aguayo, F. (2010). Stuck in the jam? CO_2 emissions and energy intensity in Mexico. *IDEAS Working Paper Series from RePEc*, IDEAS Working Paper Series from RePEc, 2010.

Bruyn, S. M., Bergh, J. C., & Opschoor, J. B. (1998). Economic growth and emissions: reconsidering the empirical basis of environmental Kuznets curves. *Ecological Economics*, *25*(2), 161-175.

Ding, C., & Lichtenberg, E. (2011). Land and urban economic growth in China. *Journal of Regional Science, 51*(2), 299-317.

Duan, Y. (2014). The Empirical Study Between Economic Growth and Environmental Pollution in China's Municipalities. *International Business and Management*, *9*(1), 44-61.

Fan, Y., Liu, L. C., Wu, G., Tsai, H.Y., & Wei, Y. M. (2007). Changes in carbon intensity in China: empirical findings from 1980–2003. *Ecological Economics*, *62*(3-4), 683-691.

Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American free trade agreement* (No. w3914). National Bureau of Economic Research.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics*, *110*(2), 353-377.

He, J., & Richard, P. (2010). Environmental Kuznets curve for CO2 in Canada. *Ecological Economics*, *69*(5), 1083-1093.

Kaufmann et al. (1998). The impact of climate change on US agriculture: a response to Mendelssohn et al. (1994). *Ecological Economics*, *2*(26), 113-119.

Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Eeview*, *45*(1), 1-28.

Lantz, V., & Feng, Q. (2006). Assessing income, population, and technology impacts on CO2 emissions in Canada: where's the EKC? *Ecological Economics*, *57*(2), 229-238.

Lewis, J. (2011). Energy and climate goals of China's 12th five-year plan. *Center for Climate and Energy Solutions*, 1.

Li, L., & Zhang, C. (2011). A disaggregated analysis of the environmental Kuznets curve for industrial emissions in China. *Applied Energy*, *190*, 172-180.

Lyons, P. (2018). *Red Skies: The Impact of Environmental Protests in the People's Republic of China, 2004-2016*(Doctoral dissertation, Wright State University).

National Public Radio. (2017, October 23). China shuts down tens of thousands of factories in unprecedented pollution crackdown. Retrieved from https://www.npr.org/sections/parallels/2017/10/23/559009961/china-shuts-down-tens-of-thousands-of-factories-in-unprecedented-pollution-crack

Panayotou, T. (1993). *Empirical tests and policy analysis of environmental degradation at different stages of economic development* (No. 992927783402676). International Labour Organization.

Panayotou, T. (1995). Environmental degradation at different stages of economic development. *Beyond Rio: The environmental crisis and sustainable livelihoods in the third world*, 13-36.

Ren, H.P., &Wang S.Q. (2000). It is necessary to develop the ecological economy of achieve the sustainable development in China. *Environmental and Development Economics,* 8 (4), 581-601.

Selden, T. M., & Song, D. (1994). Environmental quality and development: is there a Kuznets curve for air pollution emissions? *Journal of Environmental Economics and Management*, *27*(2), 147-162.

Shafik, N., & Bandyopadhyay, S. (1992). *Economic growth and environmental quality: time-series and cross-country evidence* (Vol. 904). World Bank Publications.

Stern, D. I., & Common, M. S. (2001). Is There an Environmental Kuznets Curve for Sulfur? *Journal of Environmental Economics and Management*, Elsevier, vol. 41(2), pages 162-178, March.

Stern et al. (2017). Modeling the emissions–income relationship using long-run growth rates. *Environment and Development Economics*, *22*(6), 699-724.

Stern, D. I., & Zha, D. (2016). Economic growth and particulate pollution concentrations in China. *Environmental Economics and Policy Studies*, *18*(3), 327-338.

Victor et al. (2011). Searching for an Environmental Kuznets Curve in China's air pollution. *China Economic Review*, *22*(3), 383-397.

Wagner, M. (2008). The carbon Kuznets curve: a cloudy picture emitted by bad econometrics. *Resource and Energy Economics*, *30*(3), 388-408.

Warburton, J., & Horn, L. (2007). China's Environmental Crisis: What does it mean for development? *Development*, *50*(3), 48-56.

World Bank. (2007, July 11). Statement from World Bank China Country Director on 'Cost of Pollution in China' Report. Retrieved from http://www.worldbank.org/en/news/press-release/2007/07/11/statement-world-bank-china-country-director-cost-pollution-china-report.

Wu, K. Y., & Chen, X. J. (2003). Study on the relationship between economic growth and environmental degradation of Anhui province. *Chongqing Environmental Science*, *25*, 9-11.

Wu, Y. P., & Dong, S. C. (2002). Evaluating environmental policy of Beijing. *Urban Environment & Urban Ecology*, *15*(2), 4-6.

Appendix A

Data Sources

Year	GDP per capita(Yuan)	SO_2pc(kg)	CO_2pc(kg)	NO_xpc(kg)
1970	1766.024687	10.03413863	1103.570385	4.224539119
1971	1839.476766	9.770349429	1077.927845	4.125532514
1972	1863.207965	10.02290107	1121.585908	4.271399569
1973	1962.466513	10.05089293	1142.449486	4.414223334
1974	1966.744801	9.931401924	1137.00883	4.461790406
1975	2100.80679	11.28908401	1273.775719	5.065105554
1976	2036.074169	11.44511931	1301.377802	5.153264455
1977	2160.559778	12.79622729	1439.762151	5.720801259
1978	2380.554337	14.19504834	1608.835818	6.291596885
1979	2527.535096	14.12619044	1628.942059	6.441210039
1980	2690.889721	13.63750654	1570.432465	6.828942924
1981	2794.052974	13.3638127	1531.712522	6.477291197
1982	2999.190425	13.71951366	1575.820965	6.679179754
1983	3276.472069	14.09954139	1630.511575	6.871634189
1984	3723.328279	15.08199062	1748.541364	7.301728828
1985	4166.74348	14.92633502	1736.108997	7.099978626
1986	4472.221279	15.28799288	1804.70983	7.2858407
1987	4915.515282	16.05730354	1894.531634	7.629586325
1988	5380.419859	16.87622429	1994.761127	8.03714736
1989	5520.348659	17.00875616	2022.28445	8.257908524
1990	5652.484412	16.92999552	2030.880165	8.282260159
1991	6094.110633	17.21860136	2108.171588	8.608807712
1992	6875.676999	17.32427893	2170.128072	8.899568016
1993	7739.676496	18.41533466	2421.716167	9.938921943

1994	8651.531799	18.60562218	2524.994735	10.05298731
1995	9495.080287	19.81237407	2764.780077	10.87577596
1996	10328.95579	19.71090625	2721.971582	11.00647167
1997	11167.51704	18.42112512	2758.932016	10.73930444
1998	11927.77997	18.3575609	2794.311458	11.17790607
1999	12731.62527	16.73075789	2721.105421	10.69413752
2000	13704.32165	15.90693077	2881.771203	10.81704925
2001	14739.79302	15.54829617	2998.237607	10.61833907
2002	15978.21791	15.55414869	3209.770853	11.05006236
2003	17472.55905	16.02744152	3695.079478	12.28047202
2004	19125.31899	17.84808907	4227.962502	13.86558661
2005	21179.86639	18.51787923	4743.73907	14.75001463
2006	23740.90116	19.6328554	5242.577001	15.79288532
2007	26978.29231	19.8749989	5701.552108	16.40103988
2008	29431.66371	21.64692207	5807.326436	17.14112058
2009	32038.43494	21.59062397	6173.649024	17.56881964
2010	35275.31029	22.41831895	6682.069664	18.03355137
2011	38454.62252	16.50069687	7273.45718	17.88721693
2012	41274.12736	15.68081617	7383.867564	17.30784316
2013	44256.98231	15.05768466	7666.819903	16.40924977
2014	47246.88597	14.47220858	7730.344433	15.2316003
2015	50251.02411	13.55799945	7629.513864	13.49910438
2016	53328.29824	7.999508974	7567.285309	10.11348587

Notes: Data is from

1: https://knoema.com/EDGARGEC2017/global-emissions-by-country?country=1000050&indicator=1000300&ipcc=1000590

2: http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0C05&sj=2013

3: https://data.worldbank.org/indicator/NY.GDP.MKTP.KN?locations=CN