Environmental quality, economic growth, and population changes: Examining Environmental Kuznets Curves for water and air quality in China

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ABSTRACT

Environmental quality has received extensive attention due to its close relationship with socioeconomic wellbeing and human health. The severity of environmental pollutions caused by productive and consumptive activities of human population may vary across different stages of economic development - worsening at the early stage of economic growth but improving after passing a threshold of income level, according to the widely accepted concept "Environmental Kuznets Curve (EKC)". Whether or not China has achieved better environmental conditions under the rapid economic and demographic transitions during the recent decades is the main research question this study aims to answer. Based on the monitoring data for water quality and air quality, the paper explores the relationship between per capita GDP and environmental qualities among the prefectural-level cities in China during 2003-2018, under the EKC framework. Three environmental indicators are used in the analysis, including potassium permanganate index (CODMn) and ammonium nitrogen (NH3-N) for measuring water quality and Air Pollution Index (API) for air quality. The OLS model, fixed effect model, and random effect model are applied to the analysis. This study also attempts to identify vital demographic, social and natural determinants of environmental quality. The results reveal an inverted-N relationship between API ad GDP, but a potentially U-shaped relationship between CODMn and NH3-N concentration and per capita GDP. Therefore, economic growth may help but does not necessarily lead to reducing environmental pollution; and, to achieve an improved environmental quality, the societies also need a strong political will, adequate socioeconomic and environmental policies, and broader public participations at both national and regional levels.

Keywords: Environmental Kuznets Curve; water quality; air quality; population changes

CONTENT

1 Introduction

The relationship between economic growth and environmental quality has always been a vital issue among academic scholars, policymakers, and the public. In the existing studies, Environmental Kuznets Curve (EKC), which refers to an inverted-U shaped curve, has been widely used as an important framework to examine the relationship it was proposed in the early 1990s (Grossman and Krueger 1991). The EKC concept states that at a low level of economic development, environmental degradation increases with income; after crossing a threshold, environmental degradation starts to decline as income rises (Grossman and Krueger 1991, Dinda 2004). The test of the EKC hypothesis has important policy implications. If the EKC exists for all the environmental indicators, it implies that environmental degradation is inevitable for a country at the early stage of economic growth, and pollutions would be eventually mitigated as the economic develops sufficiently in the long run. Hence, increasing economic growth would be the final and ultimate solution for improving environmental quality (Orubu and Omotor 2011). Therefore, many authors have engaged in examining the EKC hypothesis and reached mixed and inconclusive results. The existing empirical evidence shows that the EKC hypothesis does not hold for all aspects of environmental conditions (Hill and Magnani 2002, Dinda 2004, Sarkodie and Strezov 2019).

It is well known that China has experienced rapid economic growth after the reform and open up during the past five decades. The average annual gross domestic product (GDP) growth rate reaches near 10%, which is much higher than any other country in the world (Ma, Sun et al. 2020). At the same time, China is facing various and serious environmental challenges, particularly water pollution and air pollution (Kan 2009). In Chinese cities, outdoor air pollution is one of the biggest environmental challenges for public health. Water pollution has also caused serious damages to human health in China (Kan 2009, Khan and Chang 2018).

Over the past decades, China also experienced rapid demographic transition which may have also generated important effects on shaping the relationship between income and environment quality. Because growing population size may put pressure on the environment through increasing demand for consumption and production (Hill and Magnani 2002). On the other hand, rapid population growth can also reduce a nation’s capacity of investing in economic growth and improving income levels (Liu and Diamond 2005, Ma, Tian et al. 2020). Moreover, changes in population compositions by age and gender as well spatial distribution between rural and urban areas and across subregions can also affect not only the human capital and economy of scales as key components of economic growth but also the intensity of pollutants emissions and environmental degradations at local and global levels (Hill and Magnani 2002).

In recent years, the Chinese government has implemented a series of policies and set various targets to promote environmental governance, such as total emission control policies and developing clean technology (Liu, Feng et al. 2017, Khan and Chang 2018). In addition, many non-governmental organizations and citizens are increasingly aware of the severe damages of environmental pollution and engage in protecting environmental activities (Liu and Diamond 2005, Gleick 2009, Khan and Chang 2018). All these actions worked together and contributed to improved environmental conditions in China. Existing literature indicates that China's inland surface water quality and air quality have been improving in the last decade (Zhou, Ma et al. 2017, Zhang, Zheng et al. 2019, Ma, Zhao et al. 2020). However, others are still skeptical on whether Chinese cities achieved the win-win results for environmental protection and economic growth (Wang, Zhao et al. 2015).

Therefore, it is of great importance to study the performance of EKC in China. Some scholars have examined the existence of the EKC relationship in China by using various environmental indicators, such as carbon dioxide emission, sulfur dioxide emission, wastewater emission, and reached mixed conclusions (Tao, Zheng et al. 2008). It is noteworthy that most of the existing studies investigate the EKC relations by using pollutant emissions rather than environmental qualities (Stern and Zha 2016). Fewer existing studies considered both anthropogenic and natural factors when exploring the relationship between economic growth and environmental degradation, even though they both are important determinants of environmental quality (Liu, Fang et al. 2017, Liu, Wang et al. 2019).

The objective of this paper is to assess, under the framework of EKC, the relationships between environmental quality and economic growth, controlling for population dynamics and other social, economic, and institutional factors. We investigate environmental conditions in terms of water quality and air quality, using monitoring data from the prefecture-level cities during the period between 2003 and 2018. Taking advantage of the panel datasets, we are able to apply not only pooled OLS models but also the fixed effect model and random effect model to investigating the EKC across China cities. In addition, we control for variables as possible determinants of environmental pollution, including demographic characteristics, economic structure, trade openness, and weather conditions. We also report the threshold of income levels as turning points for pollutants reductions in estimating the EKC-type curves.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the EKC. Section 3 introduces the data and methodology used for the analysis. The results are reported in Section 4. Finally, Section 5 discusses the results, makes a conclusion, and presents policy references.

2 Literature Review

2.1 The EKC theory

The EKC hypothesis refers to an inverted-U relationship between economic performance and environmental degradation (Dinda 2004). In the early 1990s, EKC was put forward based on the initial work of Kuznets (1955) who revealed an inverted-U-shaped relationship between income per capita and income inequality. Grossman and Krueger (1991) found an inverted-U relationship between per capita GDP and air pollutants (sulfur dioxide and “smoke”) through a study of the environmental impacts of the North American Free Trade Agreement (NAFTA). Subsequently, similar results were found by Shafik and Bandyopadhyay (1992) and Panayotou (1993). Then, Panayotou termed this inverted U-shaped relationship as Environmental Kuznets Curve.

As shown in Fig.1, in a typical EKC curve, there’re three stages of economic development in an economy. At the pre-industrial stage, when primary production dominates, environmental degradation grows slowly because of limited consumption of natural resources and limited generation of wastes. During the second stage of economic development, environmental degradation grows rapidly along with rapid industrialization. At a higher level of development, structural changes towards service and information-intensive industries, coupled with advanced technology, enforcement of environmental policies, and increasing environmental awareness, result in a gradual decline of environmental degradation. The turning point refers to the level of income above which pollution started to decline (Dinda 2004, Stern 2004, Kaika and Zervas 2013, Sarkodie and Strezov 2019). Indicators of environmental degradation can be emissions or the concentration of a pollutant in a local area. The most commonly used pollution indicators in empirical EKC studies are air pollution, water pollution, and land or soil pollution. The independent variable is income or economic growth (GDP per capita) of the economy (Kaika and Zervas 2013).

The relationship between environmental quality and economic growth is not always U or inverted U-shaped type, but also in other shapes. Grossman and Krueger (1995) found evidence for ‘N’ shaped curve for some water pollutants which means that the curve has two turning points. The reason given for this is, at high income level, the scale of economic activity becomes so large that its negative impact on the environment could not be counterbalanced by the positive impact of the composition and technology effects (Mythili and Mukherjee 2011). Moreover, it might because as the economy develops, people cease to produce certain pollution-intensive goods, and begin instead to import these products from other countries (Grossman and Krueger 1995).

In all, the equation for the Environmental Kuznets curve could be specified as equation (1), which allows for testing the various forms of environmental-economic relationships.

$$ED_{it} = \beta_0 + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \epsilon_{it} \qquad (1)$$

Where i and t represent state and year; ED environmental degradation; Y economic development. The possible shapes of the curves are illustrated as following and depicted in Figure 1.

1) $\beta1 > 0$, $\beta2 = \beta3 = 0$; represents a monotonically increasing relationship.

2) $\beta1 < 0$, $\beta2 = \beta3 = 0$; represents a monotonically decreasing relationship.
3) $\beta1 > 0$, $\beta2 < 0$, $\beta3 = 0$; represents a quadratic relationship (i.e. EKC).
4) $\beta1 < 0$, $\beta2 < 0$, $\beta3 = 0$; represents a quadratic relationship (i.e. U-shaped).
5) $\beta1 > 0$, $\beta2 < 0$, $\beta3 > 0$; represents a cubic relationship (i.e. N-shaped).
6) $\beta1 < 0$, $\beta2 > 0$, $\beta3 < 0$; represents a cubic relationship (i.e. inverted-N-shaped).

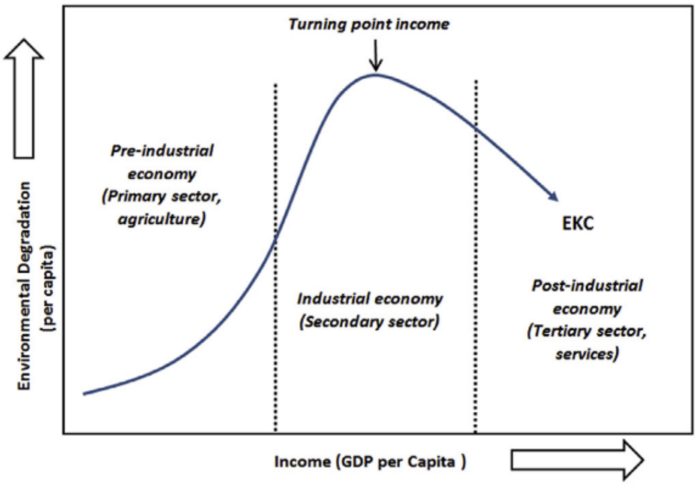

Figure 1. A typical Environmental Kuznets Curve, adopted from Kaika and Zervas (2013).

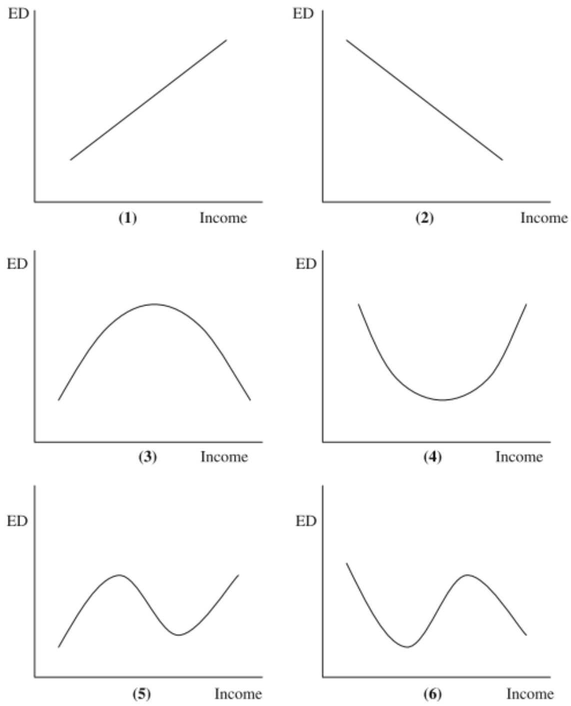

Figure 2. Various relationships between environmental degradation (ED) and per capita income, adopted from Mythili and Mukherjee (2011)

In the past decades, numerous pieces of literature have discussed the nexus between economic development and environmental quality EKC hypothesis. Generally, it has both advantages and limitations. On the one hand, many scholars stressed the relevance of the EKC hypothesis as a policy tool, since environmental degradation per unit of output, implied by EKC, can be regarded as an efficiency factor, which is amenable to policy manipulation (Dinda 2004, Stern 2004, Carson 2010, Pasten 2012). However, even though the EKC exists, it doesn't mean the environment would get better naturally as the economic development, the other factors, and the influence system is important as well (Hill and Magnani 2002). The majority of later studies critiqued the reduced form of the initial inverted-U curve and tried to test the EKC incorporating population, structural, and spatial effects (Kijima, Nishide et al. 2010). In addition, the EKC hypothesis cannot be generalized to all types of pollutants, it was found that pollutants that have local and short-term healthy and environmental costs are more likely to support the hypothesis (Dinda 2004, Farzanegan and Markwardt 2012).

2.2 Related empirical studies of EKC

Since the EKC hypothesis was proposed, plenty of empirical studies provided evidence supporting the inverted-U relationship for per capita GDP and pollution level (Grossman and Krueger 1991, Ramakrishna 2020). However, some empirical studies illustrated that not only inverted-U relationship, but also U, N, and linear relationships between economic and pollution (Hill and Magnani 2002, Stern 2004). Furthermore, many scholars indicated that the empirical EKC findings are sensitive to the choice of pollutant, development stages of countries or regions, time period, as well as the definition of economic growth, which usually leads to inconsistent results (Dinda, 2004; Orubu & Omotor, 2011). Using SO2 as the proxy for environmental quality, Grossman and Krueger (1991) found an inverted-U-shaped relationship for 42 countries. Harbaugh et al. (2002) could not confirm the EKC hypothesis for cities internationally. Stern and Common (2001) using the same environmental indicator also did not find enough evidence for the EKC in 74 countries globally from 1960 to 1990. Balsalobre-Lorente and Alvarez-Herranz (2016) find N-shaped pattern. Kaneko, Managi et al. (2009) didn’t find significant EKC relationships for industrial water pollution, air pollution, and solid waste in China during 1992-2003, only slightly support the EKC curve for solid waste. while, some studies found inverted-U and inverted-N-shaped relationships for the industry "three waste" (Li, Wang et al. 2016).

Firstly, as far as the sample scale is concerned, many empirical EKC studies have estimated global EKC relationships by analyzing multi-country panel data (Wong and Lewis 2013). These studies found developed countries are often associated with lower emission reductions but in developing countries, the environmental pressure increases over time (Dinda 2004). Developing countries have not yet reached income levers high enough to be able to derive their turning points. However, some scholars critiqued that the relationships and coefficients in such kinds of studies may vary depending on the study sample(Dinda 2004, Carson 2010). The results of panel countries and that of individual or sub-sample countries vary widely because of regional differences. For example, Harbaugh, Levinson et al. (2002) reexamined the EKC study initially conducted by Grossman and Krueger (1995) on ambient air pollution. However, the former test the sensitivity of the findings in the latter study by changing the functional forms of the models specified, adding recent observations to the dataset, including country-level fixed effects, correcting data errors by removing outliers and introducing new explanatory variables. These changes result in substantial differences in the regression results obtained, in terms of coefficient signs as well as their statistical significance. Therefore, it is important to consider the specific individual effects.

Secondly, with respect to environmental indicators, the majority of studies focused on water indicators and air indicators. Besides, solid waste indicators, land indicators, ocean and biodiversity indicators have also been used to test the EKC hypothesis. (Dinda 2004, Sarkodie and Strezov 2019, Cheng, Shi et al. 2020). Moreover, it is important to make a distinction between emissions (flows) and concentrations (stocks) of environmental indicators in EKC studies. (Jiang, Lin et al. 2011). For instance, Guohua and Zhixian (2011) found the total wastewater emission was increasing after 1995 in Qingdao, but the river quality around Qingdao was gradually improving. Thus, the total wastewater emission fitted to the left-part of inverted-U shaped curve, while CODMn concentration fitted to cubic specification EKC and was declining.

Water indicators encompass wastewater emission, fecal coliform concentration, biological oxygen demand in water body (BOD), and wastewater treatment. Numerous studies have tried to estimate the EKC towards the water environment in other countries. Wong and Lewis (2013) conducted an EKC test of water quality in the Lower Mekong Basin(LMB), they do not find consistent evidence of EKC for any of the 4 pollutants (TOTP, DO, NH4, and NO2) in their study, but found the results are entirely dependent on models and error specification as well as a pollutant. Choi, Hearne et al. (2015) conducted a case study to test the relationship between water pollution (COD and BOD) and economic growth using the EKC hypothesis in South Korea. The results provided statistically significant support for the EKC hypothesis in South Korea at the national level, while the results were heterogeneous for the four major river basins when modeled individually. They addressed that it is necessary to disaggregate the analysis across the four principal river basins in South Korea. Orubu and Omotor (2011) investigated the relationship between per capita income and organic water pollutants under OLS and fixed effect model in Africa under OLS and fixed effect model, the evidence weighs more in favor of rising pollution as per capita income increases.

The majority of air pollutants include an ambient concentration of particulate matter (PM10, PM2.5, suspended particular matter (SPM), sulfur dioxide, nitrogen dioxide, and so on. Orubu and Omotor (2011) also investigated the relationship between per capita income and suspended particulate matter in Africa, and the results generally suggest the existence of an environmental Kuznets curve for suspended particulate matter. Al-Rawashdeh, Jaradat et al. (2014) tested the EKC hypothesis in 22 Middle East and North Africa (MENA) countries for SO2 emission and CO2 emission, the results indicated that the MENA region as a whole does not show EKC for SO2 emissions and CO2 emissions, but SO2- and CO2- EKC existed for some specific countries.

Thirdly, the turning points show the level of income above which pollution declines, and it is after this point that higher growth will accompany lower environmental degradation. The estimated turning points are associated with the kind of pollutant studied (Dinda 2004). While a higher turning point may indicate that more environmental degradation has happened in the past, Orubu and Omotor (2011) reported that a low turning point could appear earlier if human activities are environmentally friendly and sustainable. Also, low turning points may indicate that countries do not need to wait long for a high threshold per capita income to appreciate a cleaner environment. Several studies found that turning points for wastewater occurring at a lower income level than waste gas(Jiang, Lin et al. 2011). While some scholars found opposite results, Grossman and

Krueger (1995) found the turning points for these water quality indicators come somewhat later than those for urban air quality. In addition, several scholars argued that the EKC relationship is less likely to be detected for transboundary pollution where the costs of pollution or the benefits of abatement are less likely to be experienced by those residing proximate to the source of pollution(Wong and Lewis 2013). Grossman and Krueger (1995) indicated that the turning points for the different pollutants vary, but in most cases, they occur before a country reaches a per capita income of $8000.

Fourthly, there are a lot of factors, including both socioeconomic and natural factors, that mitigate the relationship between economic growth and environmental quality except for income or economic growth (Liu, Wang et al. 2019). It is critical to explore the influence mechanism by incorporating the other factors (Kaika and Zervas 2013). And these factors might affect the shape of the EKC and the threshold level (Dogan and Inglesi-Lotz 2020). It is well known that population growth and industrial activities are the main drivers of environmental quality changes. Water quality was found to be in the poorest in North and Northeast China where there is greater coverage of higher GDP and higher population density (Ma, Zhao et al. 2020). Trade openness has a potential role to impact environmental pollution in two ways. As Grossman and Krueger (1991) indicated, trade openness would increase industrial activities to increase pollution. It would also possible that the foreign investment would introduce cleaner technology to mitigate the pollution (Balaguer and Cantavella 2018, Jiang, Zhou et al. 2018). In terms of the role of government, implementation of environmental policies, establishment of institutions, and investment of environmental protection are found to be effective to improve environmental quality (Khan and Chang 2018).

Numerous studies have shown that meteorological conditions play a key role in the formation and variation of water pollution and air pollution (Xu, Sun et al. 2019). More importantly, China is the third-largest country in the world, variations in meteorological and uneven development likely result in spatial heterogeneity in pollution patterns across the country (Qiao, Wu et al. 2019). Regarding water quality, precipitation can be the most important driver of water quality changes over time and can be affected by short- or long-term changes in climate (Sprague and Lorenz, 2009). Precipitation seems to be one of the major factors that influence the spatial-temporal distribution of API (Xiaofei, Mingjun et al. 2012, Huiwang, Jinling et al. 2014, Guijie, Peng et al. 2015). Qiao, Wu et al. (2019) found the temperature was one of the dominant factors influencing air quality year-round, and the correlation between the API and temperature showed a pattern inversion between seasons. Air quality may be better on days with more sunshine, higher wind speed, temperature, relative humidity, and precipitation(Liu, Fang et al. 2017, Qin, Wang et al. 2020).

2.3 EKC in China

The remarkable growth in China’s population and economy over the past several decades has come at a tremendous cost to the country’s environment since the late 1970s, because of rapid growth in energy consumption and thus pollution emissions. (Gleick 2009). China has making a great effort to improving the environmental quality, including strengthening industrial emission standards, upgrade on industrial boilers, and promoting clean fuels in the residential sector, and so on. Although China is still facing severe environmental problems, evidence is emerging to show that both the water quality and air quality are improving in recent years. Ma, Zhao et al. (2020) found the water quality of China's major rivers, lakes, and coastal waters is improving, even though the water ecology is not optimistic in general. According to a recent estimate, Zhang, Zheng et al. (2019) found national emissions of SO2, NOx and primary PM2.5 decreased by 59%, 21%, and 33%, respectively from 2013 to 2017.

In addition, the economic growth in China has a great regional difference. The economic has been developed more rapidly in the coastal regions of eastern China. Environmental pollution has presented regional differences as well and was found to be associated with economic growth and population density. Water pollution, water scarcity are unevenly distributed across China and are relatively severe in north and northeast China (Ma, Sun et al. 2020). Qiao, Wu et al. (2019) illustrated that the API exhibited clear seasonal and regional patterns, influenced by heterogeneity in urbanization and industrialization, as well as variability in meteorological conditions based on a study for 64 Chinese cities during 2005-2012.

Furthermore, as Carson (2010) indicated, the EKC was initially proposed to model the concentrations of pollutants, however, most subsequent studies have concentrated on pollution emissions, in particular carbon dioxide and sulfur dioxide. Most researchers have also examined pollution emissions rather than concentrations when conducted EKC studies for China (Tao, Zheng et al. 2008, Stern and Zha 2016, Ma, Tian et al. 2020). Only a few studies for Chinese EKC analysis have used concentration data(Stern and Zha 2016).

Regarding water quality, most of the previous studies on the relationship between water quality and economic development usually focused on specific water bodies or local regions. Fewer empirical investigations explored nationally, but have not estimated the relationship under the EKC framework. Yang (2017) estimated the EKC hypothesis for the Jiulong River basin, located in the south of Fujian province, by using water quality automatic monitoring data from 2005 to 2015. All three water quality indicators did not show the inverted U-shaped relationship with per capita GDP. NH3-N concentration presented an upward trend with economic development, CODMn concentration presented a u-shaped curve, and TP concentration presented a downward trend. Cheng (2012) conducted an empirical analysis on the relationship between water quality and economic development of the Taihu Lake area using time series data between 1979 and 2010. The results indicated that an inverted U-shaped relationship exists for total phosphorus, total nitrogen, and potassium permanganate index, while the relationship between chlorophyll a and chemical oxygen demand and economic development should be described by the right half of the inverted N-shaped curve. Qin, Su et al. (2014) investigates the causes of water quality changes over the rapid urbanization period of 1985–2009 in the Shenzhen River catchment, the results indicated that water quality deteriorated rapidly during the earlier urbanization stages before gradually improving over recent years and that rapid increases in domestic discharge were the major causes of water quality deterioration. Ma, Zhao et al. (2020) analyzed the nationwide variability of inland water quality across China from 2003 to 2017 and its responses to anthropogenic discharges and found that water quality has been improved markedly or was maintained at favorable levels over the country because of reduced discharges in the industrial, rural, and urban residential sectors. However, growing discharges from the agricultural sector threaten these gains. Liu, Feng et al. (2017) assessed the effects of total emission control policies (TEC) on surface water quality in China during 2004 and 2014, they suggested that TEC is inadequate to recover the status of surface water quality in China and highlighted the importance to consider the pollution sources when decision-makers draft future water management policies for China.

With respect to air pollutant concentration, there are few studies of the spatial-temporal evolution of comprehensive air quality in China over a long time interval (Xu, Sun et al. 2019, Xie, Mao et al. 2021). On the one hand, that's because of the implementation of a new air quality standard. The monitoring of PM2.5, CO, and O3 was not included in China's National Ministry of Environmental Protection (MEP) until 2013, and the new version of air quality assessment indicator, the Air Quality Index (AQI), was not available until 2014 in most prefecture-level cities where the Air Pollution Index (API) was used previously (Xu, Sun et al. 2019, Xie, Mao et al. 2021). Therefore, research on air quality in China used to focus on short time and individual air pollutants. On the other hand, research on a large spatial scale with long time series has usually based on satellite data, which is limited to reflect the near-ground air pollution (Xu, Sun et al. 2019). Zhan et al. (2018) investigated the air quality index across Chinese cities in 2015 and indicated that the air pollution levels in China are still high on the whole, with PM2.5, PM10, and O3 as the major primary pollutants. In addition, they also found air pollution presents a U-shape over the year and spatial clustering. W. Wang (2018) analyzed the relationship between the air quality index and the per capita GDP with panel data of 41 major cities between 2000-2015, In the form of the traditional two-square EKC model, the two variables are satisfied with the U-shaped relationship. By the co-integration analysis, the results show that under the three-square EKC model, the relationship between the AQI and GDP per capita satisfies the N-typed environment Kuznets curve and there exist two turning points. Luo, Chen et al. (2014) found decreasing trend of API for 41 province's capital cities during 2003 and 2012 as well. Kong studied the spatial and temporal distribution of the Air Pollution Index (API) in Chinese major cities. They found average daily API state in northern China is higher than the southern region, the eastern coastal region is higher than the western inland regions. Y. Wang and Komonpipat (2020) conducted an EKC test for prefecture-level and above cities of China, results showed that except for the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing, economic growth has a complex impact on PM2.5 concentration in most cities during the study period, rather than a simple inverted U-shaped pattern. Moreover, only in recent years has smog pollution shown an average decrease. Based on a spatial analysis for 150 Chinese cities in 2014, Jiang, Zhou et al. (2018) found that there is no evidence of an inverted U-shaped curve between income and air pollution. As income levels increase, air quality continues to worsen. At the same time, this study suggests that foreign direct investment is negatively related to air pollution in China and densely populated cities tend to demand better environmental quality.

2.4 Research gaps and main contribution

There are increasing numbers of studies trying to explore the relationship between economic growth and environmental degradation. Despite the mixed results of the previous studies, several observations can be made. First, there seems to be an empirical relationship between environmental quality and economic growth. Even though emerging evidence shows that environmental degradation tends to fall as income grows for some pollutants, which supports the EKC hypothesis. However, it is not certain that unambiguous turning points exist for all pollutants. Second, other factors apart from income growth could influence environmental pollution and improvement in environmental quality as well. Third, China is receiving special attention in studies of the EKC, in particularly emissions of environmental pollution. Lack of studies focused on dynamic environmental quality and pollutant concentration in China. Besides, it is necessary to consider the specific characteristic of cities given the great regional difference in socioeconomic and natural characteristics across China.

The main contribution of this paper is to explore whether and why EKC does or does not occur for various environmental aspects across China. Firstly, we would estimate the relationship between economic growth and environmental quality from two facets, water quality and air quality by using CODMn and NH3-N concentration, and Air Pollution Index (API) using monitoring data at the prefecture-city level between 2003-2018. Secondly, this study makes a methodological contribution by undertaking the OLS estimator, fixed effect model, and random effect model. The latter two models, compared to OLS regression, make it possible to capture the specific characteristics of cities. Thirdly, we would like to identify how other factors affect environmental quality by incorporating socioeconomic, demographic, and geographic conditions in the local area. Finally, with the results of the estimated relationship between environmental quality and the socioeconomic and natural factors, as well as the turning points, we would find ways to maintain better environmental quality.

3 Data and Methodology

3.1 Data

3.1.1 Environmental quality indicators

Water quality data between 2004 and 2018, was obtained from the China National Environmental Monitoring Center, containing water quality data from around 140 surface water monitoring sites, which covers the majority of the National Surface Water Quality Automatic Monitoring System. The water quality data were measured according to the Technical Specification Requirements for Monitoring of Surface Water (GB 3838–2002) (China Ministry of Environmental Protection, 2003). The Water quality is taken on weekly mean concentrations on monitoring site-level. Potassium permanganate index (CODMn) and ammonium nitrogen (NH3-N) are chosen as the water quality pollutants because they were the most serious water quality indices in China river basins(Zhou, Ma et al. 2017, Ma, Zhao et al. 2020). The monitoring sites that have weekly water quality data at least 20 weeks distributed evenly per year would be included in our study. Then those monitoring sites were located at the prefectural cities where they are, and the annual averages of each pollutant in each prefectural city are calculated.

Regarding air quality, two indexes have been used to measure air quality in the past two decades in China, i.e. Air Pollution Index (API) and Air Quality Index (AQI). China released the newest Ambient Air Quality Standard (GB 3095-2012) in 2012 to replace GB 3095-1996. According to the newest air quality standard, six pollutants and AQI started to releasing every day, at the same time, API was stopped to be released. We adopted Air Pollution Index (API) as the measurement in this paper to cover a longer study period. Daily API was collected by China National Environmental Monitoring Center before 2013. We calculated the daily API between 2014-2018 by using SO2, NO2, and PM10 according to Ambient air quality standards (GB3095-1996). Only cities that have daily mean API of at least 324 days per year and have annual mean API of at least 10 years from 2003 to 2018 would be included in this study.

For all three pollutants, only cities with data available for a minimum of 10 years are included in this study. This is helpful to ensure that the study period is long enough to capture changes in the pollution-economic relationship over time while retaining a sizeable number of observations(Wong and Lewis 2013). The higher the value for pollutant concentration, the worse the environmental quality. The spatial distribution of the study samples with their corresponding multi-year annual mean values for the three pollutants are displayed in Figure.3 respectively (a, b, and c). Finally, a total of 74 cities for CODMn and NH3-N, and a total of 83 cities were analyzed. The multi-yearly average concentration of CODMn is ranged from 1.23 to 57; NH3-N is ranged from 0.07 to 12.8; API is ranged from 37.3 to 102. The ranges were divided into 5 grades according to the natural break methods. On the other hand, we also get a consistent nationally annual data series during the study period (Fig.1d). Table 1 provides a for the sample cities by region and city level (CBN 2019).

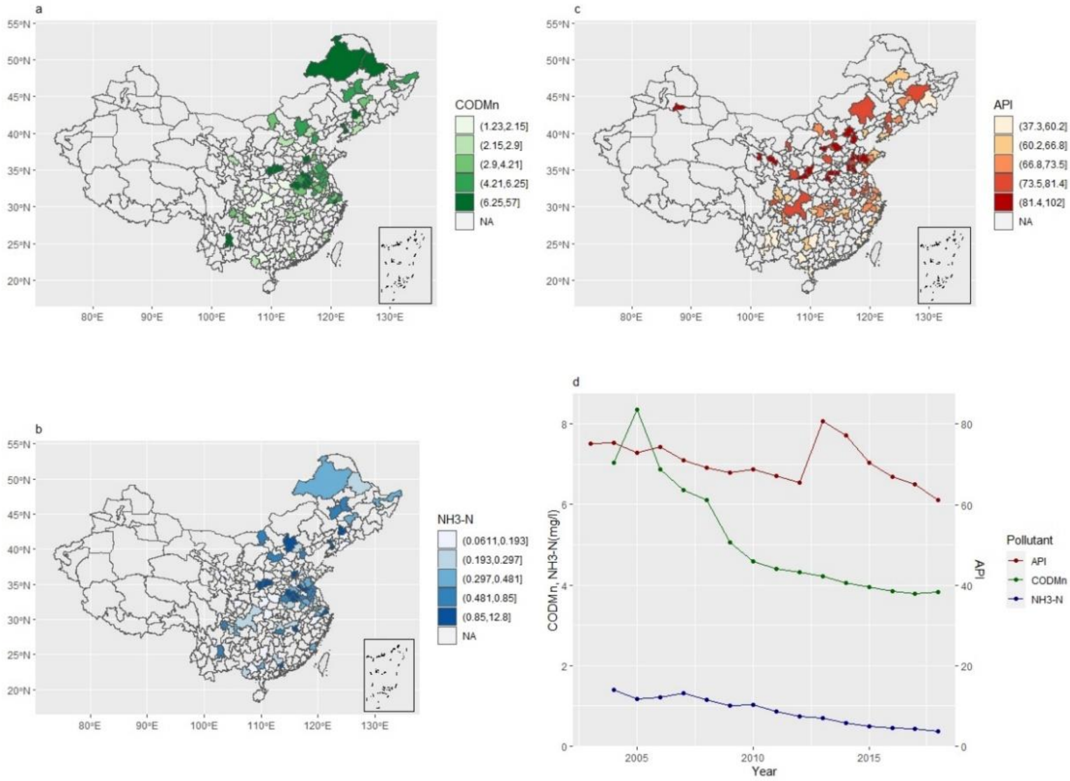

Figure. 3. Spatial-temporal variation of three pollutants at the prefectural scale in 2003-2018. Spatial distribution of study samples with corresponding multi-year annual mean concentration, (a) CODMn; (b) NH3-N; (c) API. (d) National trends in the annual mean concentration of three pollutants.

Table.1 Number of sample cities by region and city level

	Water quality		Air quality	
Region	**Number**	**Proportion**	**Number**	**Proportion**
Eastern	24	0.33	24	0.29
Central	22	0.30	35	0.42
Western	17	0.22	16	0.19
Northeastern	11	0.15	8	0.10
Total	74	1.00	83	1.00
City Level	**Number**	**Proportion**	**Number**	**Proportion**
I	3	0.04	4	0.05
II	19	0.26	36	0.43
III	19	0.25	26	0.31
IV	23	0.32	13	0.16
V	10	0.14	4	0.05
Total	74	1.00	83	1.00

3.1.2 Explanatory variables

The following variables have been chosen for the analysis because they represent important concepts concerning environmental quality. The socioeconomic data for the prefectural cities were derived from China Urban Statistical Yearbook. The natural factors are obtained from statistical yearbooks of provinces and cities. Table 2 describes all the variables used in this study. All the variables are in logarithmic form, except for the proportion of secondary industry.

Economic development: GDP per capita is used to reflect the economic development of China cities. To eliminate price factors in this study, the data of GDP were converted into real GDP as the base year of 2000. Besides, in this study we also take into account the quadratic term of GDP per capita, to examine if there is an inverted U-shaped curve between income and environmental quality. We do not expect in terms of the sign of the relationship between GDP per capita and environmental quality indicators, as we would use a quadratic or cubic functional form for the per capita GDP, there's a possibility of getting either linear, quadratic, or cubic significant link.

Population density: Population density is measured as the number of people per km^2. The expected sign of the relationship between environmental quality and population density is positive, which means the higher the population density, the higher level of environmental degradation.

Share of industries: Proportion of secondary industry to local GDP is used to measure the industrial structure. The energy was consumed largely and the environment was polluted seriously during the process of industrialization, thus, the expected sign for the share of industry is positive.

Foreign direct investigation (FDI): FDI is measured by effective utilization of foreign capital. FDI exhibits either an effective channel of advanced technological transfer from developed to developing countries or pollution haven effect. Since manufacturing has been the biggest FDI recipient sector in China, which is high pollution-intensive, we would expect a positive sign for FDI.

Technique: Expenditure for science and technology is used to measure technique development. The assumption is that higher expenditure for science and technology would promote technology development and economic structure upgrade. The expected sign for technique is negative.

Natural factors: natural factors are measured by annual mean temperature and annual total precipitation in the cities. It is important to introduce natural factors as explanatory variables because it influences the dissolution of environmental pollutants.

Time trend: the inclusion of a time trend in the model is designed to capture changes in pollution levels due to time-variant factors unrelated to economic growth such as technology development and public environmental awareness (Wong and Lewis 2013, Olale, Ochuodho et al. 2018)

Table 2. List of variables and their sources

	Description	Unit	Source
Dependent variables			
lnCODMn	Logarithm of CODMn concentration	mg/l	NEMN
lnNH3N	Logarithm of NH3-N concentration	mg/l	NEMN
lnAPI	Logarithm of API		NEMN
Independent variable			
lnGDPPC	Logarithm of the GDP per capita, derived from growth rate at 2000 constant prices	Yuan	CCSY
Control variables			
lnPD	Logarithm of Population density	Persons/km^2	CCSY
SECONDARY_IND	Proportion of the added value of secondary industry to GDP	%	CCSY
lnEXPDTECH	Logarithm of expenditure for science and technology	10000 yuan	CCSY
lnFDI	Logarithm of the foreign direct investment in the city	USD 10000	CCSY
lnPRE	Logarithm of annual total precipitation	mm	SY
lnTMP	Logarithm of annual average temperature	°C	SY
TIME	Time trend		

Data resources note: NEMN refers to National Environmental Monitoring Network, CCSY refers to China City Statistical Yearbook, SY refers to statistical yearbooks of provinces and prefectural cities.

3.2 Methodology

In this section, the methods used in this study would be introduced. At first, we apply panel unit root tests, namely Augmented Dickey-Fuller (ADF) tests, to test if there are unit roots in our panel data sets. Afterward, we proceed to estimate the EKC with the OLS, fixed effect model, and random effect model. Among the three kinds of models, the F test and Hausman test are used to estimate a preferred model. Finally, Generalized Method of Moments (GMM) estimation, which is available to correct for heteroscedasticity and autocorrelation (Fatima, Shahzad et al. 2020), was implied to give a robustness test.

Currently, the study of the EKC curve is mostly using the logarithmic linear model of its square, and a few scholars consider adding three squares to analyze it (Wang 2018). Based on the previous practice, the basic EKC equation could be specified in quadratic form as equation (2) in this study,

$$lnEQ_{it} = \beta_0 + \beta_1 lnGDPPC_{it} + \beta_2 lnGDPPC_{it}^2 + \epsilon_{it} \tag{2}$$

where i represents the prefectural-level city and t denotes the year; EQ represents the indicators of environmental quality, in this paper, COD, NH3-N, and API; GDPPC refers to the GDP per capita (in 2000 constant Chinese yuan); ε refers to the disturbance term with zero mean and finite variance.

The parameters βi indicate the estimated coefficients of the variables. For the EKC inverted-U shaped to hold, $\beta1 > 0$, $\beta2 < 0$, $\beta3 = 0$, and must be statistically significant. As mentioned above, other cases are possible in the environmental quality-economic relationship.

As we mentioned above, an EKC may be established within the context of the conventional quadratic specification, and yet there is the possibility of another turning point. In other words, it is theoretically plausible to have a situation whereby the economic increases beyond a threshold and environmental quality begins to deteriorate thereafter. In such a case the EKC equation will assume a cubic term as displayed in equation (3). Numerous previous studies have included the cubic term when studying the EKC hypothesis(Grossman and Krueger 1995, Orubu and Omotor 2011, Wang and Komonpipat 2020). In this paper, we would introduce a cubic term into our model when necessary.

$$lnEQ_{it} = \beta_0 + \beta_1 lnGDPPC_{it} + \beta_2 lnGDPPC_{it}^2 + \beta_3 lnGDPPC_{it}^3 + \epsilon_{it} \tag{3}$$

It is also necessary to incorporate with other control variables. Therefore, our full extended models are equation (4):

$$\begin{gathered} lnEQ_{it} = \beta_0 + \beta_1 lnGDPPC_{it} + \beta_2 lnGDPPC_{it}^2 + \beta_3 lnGDPPC_{it}^3 + \beta_4 lnPD_{it} + \\ + \beta_5 SECONDARYIND_{it} + \beta_6 lnEXPDTECH_{it} + \beta_7 lnFDI_{it} + \\ \beta_8 lnPRE_{it} + \beta_9 lnTMP_{it} + \beta_{10} TIME_{it} + \epsilon_{it} \end{gathered} \tag{4}$$

In the conventional inverted-U-shaped EKC, the turning points display the level of economic development where pollution declines, which means after this threshold, higher economic growth will accompany lower environmental degradation. The estimated turning points are relevant to the chosen pollutant (Al-Rawashdeh, Jaradat et al. 2014). The turning point is obtained based on equation (5) and equation (6) for the quadratic and cubic specification equation, respectively. In the cubic form equation, we could get two turning points only for the real roots of the equation (Mythili and Mukherjee 2011).

$$t = exp(\frac{-\beta_2}{2\beta_1}) \tag{5}$$

$$t = exp(\frac{-\beta_2 + \sqrt{\beta_2^2 - 3\beta_1\beta_3}}{3\beta_1}) \tag{6}$$

Firstly, we would employ a pooled OLS model. The use of panel data in this paper also allows us to conduct fixed effect model and random effect model. Pooled regression restricts the estimated intercept to be identical across cities. Conversely, the fixed effect model allows the estimated intercept term to be unique for each city. The intercept could capture some specific factors for cities, including geography, resource endowments, business climate, or government policies that may affect the environmental quality(Orubu and Omotor 2011, Wong and Lewis 2013). If these variables are correlated with any of the independent variables, their omission from the models will generate biased and inconsistent estimated. The random effect model assumes that the individual effects are randomly distributed and as such, no correlation exists between individual effects and the error term.

Among OLS, fixed effect model, and random effect models, firstly we would use the F test to identify whether we need to consider the individual effect in the model to select a better-fitted model between the OLS model and fixed effect model. Then a Hausman test would be applied to identify a preferred model between fixed effect model and random effect model. At last, we could identify which model is the best fitted.

4 Results

4.1 Descriptive results, correlation, and unit root examination

Table 3. presents descriptive statistics of the variables for water quality and air quality used in this study, including mean, median, maximum, minimum, and standard deviation. Table 4 provides a correlation matrix that displays the relationships between environmental indicators and relevant explanatory variables. The results for unit root tests were reported in Table 5, the null hypothesis of non-stationarity can be rejected for all the variables using the ADF test, therefore all variables were found to be stationary.

Table 3. Descriptive statistics of the variables.

a. Water quality

	Mean	Min	Median	Max	Std.Devc	N.Valid
lnCODMn	1.29	-0.17	1.24	4.89	0.66	1074
lnNH3N	-0.98	-3.76	-1.13	3.18	1.11	1075
lnGDPPC	10.17	7.84	10.15	12.13	0.85	1077
lnGDPPC^2	104.16	61.45	102.93	147.19	17.37	1077
lnPD	5.94	2.28	6.08	7.75	0.89	1077
SECONDARY_IND	0.48	0.15	0.48	0.86	0.11	1077
lnEXPDTECH	9.95	4.08	9.91	15.27	1.95	1077
lnFDI	10.30	1.10	10.34	14.94	1.97	1077
lnPRE	6.76	4.36	6.84	8.01	0.53	1077
lnTMP	2.70	0.34	2.83	3.22	0.41	1077
TIME	8.13	1.00	8.00	15.00	4.26	1077

b. Air quality

	Mean	Min	Median	Max	Std.Dev	N.Valid
lnAPI	4.23	3.41	4.24	5.33	0.23	1250
lnGDPPC	10.41	8.47	10.37	12.61	0.76	1250
lnGDPPC^2	108.97	71.79	107.63	158.91	15.95	1250
lnGDPPC^3	1146.63	608.23	1116.57	2003.29	252.50	1250
lnPD	6.14	3.90	6.29	7.86	0.70	1250
SECONDARY_IND	0.47	0.18	0.48	0.68	0.09	1250
lnEXPDTECH	10.27	5.38	10.24	15.53	1.92	1250
lnFDI	10.74	2.77	10.92	14.94	1.86	1250
lnPRE	6.78	4.32	6.83	8.01	0.55	1250
lnTMP	2.67	1.22	2.78	3.23	0.39	1250
TIME	7.93	0.00	8.00	15.00	4.40	1250

Table 4 Correlation matrix

a. Water quality

	lnCODMn	lnNH3N	lnPD	lnGDPPC	SECONDARY_IND	lnEXPDTECH	lnFDI	lnPRE	lnTMP	TIME
lnCODMn	1.00									
lnNH3N	0.75***	1.00								
lnPD	0.05*	0.19***	1.00							
lnGDPPC	-0.16***	-0.22***	0.16***	1.00						
SECONDARY_IND	-0.02	-0.02	0.15***	0.17***	1.00					
lnEXPDTECH	-0.14***	-0.14***	0.40***	0.68***	-0.09**	1.00				
lnFDI	-0.06*	-0.04	0.49***	0.60***	0.01	0.73***	1.00			
lnPRE	-0.32***	-0.18***	0.39***	0.06*	-0.04	0.23***	0.31***	1.00		
lnTMP	-0.29***	-0.06*	0.64***	0.01	0.18***	0.24***	0.25***	0.61***	1.00	
TIME	-0.11***	-0.20***	0.03	0.47***	-0.15***	0.59***	0.20***	0.09**	0.01	1.00

b. Air quality

	lnAPI	lnGDPPC	lnPD	SECONDARY_IND	lnEXPDTECH	lnFDI	lnPRE	lnTMP	TIME
lnAPI	1.00								
lnGDPPC	-0.12***	1.00							
lnPD	-0.01	0.37***	1.00***						
SECONDARY_IND	0.15***	-0.05*	0.12***	1.00**					
lnEXPDTECH	-0.03	0.77***	0.39***	-0.08	1.00				
lnFDI	0.02	0.66***	0.51***	-0.04	0.67***	1.00			
lnPRE	-0.57***	0.18***	0.38***	0.03	0.18***	0.21***	1.00		
lnTMP	-0.38***	0.10***	0.55***	0.10***	0.15***	0.16***	0.71***	1.00	
TIME	-0.15***	0.52***	0.01***	-0.20***	0.63***	0.14***	0.06*	0.00	1.00

Table 5. Results for panel unit root testing

	Variable	Level
	lnCODMn	-8.6159***
	lnNH3N	-9.1555***
	lnGDPPC	-9.1688***
	lnGDPPC^2	-9.0768***
	lnPD	-6.3679***
Water quality	SECONDARY_IND	-7.204***
	lnEXPDTECH	-11.577***
	lnFDI	-10.207***
	lnPRE	-10.411***
	lnTMP	-6.9367***
	TIME	-15.756***
	lnAPI	-12.87***
	lnGDPPC	-10.393***
	lnGDPPC^2	-10.237***
	lnGDPPC^3	-10.083***
	lnPD	-6.7869***
Air quality	SECONDARY_IND	-8.6665***
	lnEXPDTECH	-13.168***
	lnFDI	-10.194***
	lnPRE	-11.059***
	lnTMP	-7.4418***
	TIME	-16.604***

4.2 Regression results

In this section, we present and analyze the regression estimates of the basic and extended ordinary least squares (OLS) models, with their corresponding fixed effect models and random effect models. Firstly, the Wald test is used to choose the more appropriate model between quadratic and cubic specification EKC for CODMn, NH3-N, and API respectively. Next, the F test and Hausman test are carried out to identify a preferred model among OLS, fixed effect and random effect models. In addition, turning points are reported for the equations with statistically significant coefficients. The F statistical tests indicated that individual effects exist for all the three pollutants in both the reduced and extended form model. The Hausman tests have inconsistent results. In all, a U-shape relationship is estimated between GDP per capita and water quality, measured by CODMn and NH3-N concentration. An inverted-N relationship is estimated between GDP per capita and air quality, measured by API.

As we mentioned aforesaid, there may be various functional forms for the EKC. In order to choose the most appropriate one between the quadratic and cubic specification, we first run both the reduced-form quadratic and cubic specification models for the three pollutants, then the Wald test is performed to detect a preferred one. The results for the Wald test are shown in Table 6. According to the Wald test, the quadratic specification can be adequate for CODMn and NH3-N, while the cubic specification is preferred for API.

Table 6. The results of the Wald test for the alternative quadratic and cubic model

	CODMn	**NH3-N**	**API**
OLS	0.094	0.021	34.265***
FE	0.413	3.762	28.738***
RE	0.559	4.4801*	35.244***

4.2.1 Results for CODMn

The results for CODMn are summarized in Table 7. The results for the basic OLS model indicate that the EKC performs a U shape for CODMn, with a negative and significant coefficient for the logarithm of per capita GDP and a positive and significant coefficient for the square of the logarithm of per capita GDP. For the corresponding basic fixed and random effect model, the Hausman statistic suggests that the random effect model is more consistently estimated, relative to the fixed effect model. The coefficients are also properly signed and statistically significant, thus the result of EKC, in this case, is U-shaped. The estimated turning point for the basic OLS model is 52,840 yuan, 27,265 and, and 48,047 yuan for the fixed and random effects model respectively.

In the expanded models, the coefficients of GDP per capita and the squared of GDP per capita still suggest a U-shape relationship between CODMn and GDP per capita. The Hausman test reports the fixed effect model fits better than the random effect model. The turning points turned into 109,087, 101,093, and 78,267 yuan for OLS, fixed effect model, and random effect model, respectively. In terms of population density, the OLS model suggests a significantly positive relationship between population density and CODMn concentration. However, the positive sign changed in the fixed effect model. The proportion of secondary industry in GDP and FDI report a significantly positive association with CODMn concentration under fixed effect model. Expenditure for science and technology is negatively and statistically significantly associated with CODMn concentration under the OLS model and the fixed effect model. In the OLS models, natural factors which measured by precipitation and temperature are negatively associated with CODMn concentration, but the natural factors change sign and lose significance in fixed effect model. Time trend is positively and statistically significant associated with CODMn in the extended models.

4.2.2 Results for NH3-N

Table 8 presents results for the water quality indicator NH3-N. It provides similar results for EKC-type shape as of CODMn. A U-shape relationship is estimated between NH3-N concentration and GDP per capita under the OLS model, fixed effect model, and random effect model. In the case of NH3-N concentration, the Hausman test suggests fixed effect models fit better than random effect models in both the reduced-form model and stepwise extended models. The turning points are at 41019, 8551, 38457 yuan per capita for the OLS model, fixed effect model, and random effect model respectively, and changed to 62148, 41306, 82974 yuan after introducing control variables.

In the extended OLS model, population density and FDI are positively and statically significantly associated with NH3-N concentration. The natural factors, precipitation and temperature, show negative and statically significant association. While in the extended fixed effect model, the proportion of secondary industry shows a statistically significant relationship with NH3-N, and the sign is positive as we expected. In addition, the time trend is found to be negative and statistically significant.

4.2.3 Results for API

The results of cubic specification models for API are summarized in Table 9. The results suggest an inverted-N shaped curve for the relationship between economic and API. Because the estimation coefficients for GDP per capita, GDP per capita squared, and GDP per capita cubic are statistically significant in all models and have the signs fitted to an inverted-N shape curve. F test indicated that the individual effect exists. The Hausman test suggests choosing fixed effect models, compared to random effect models. Therefore, the fixed effect model is the preferred model in the API case. In the basic cubic OLS model, the first turning point is at 10123 yuan and the second turning point is at 49367 yuan. In the basic cubic fixed effect model, the first turning point occurs at 9667 yuan and the second turning point occurs at 67249 yuan; the turning points turned into 8464 and 87523 in the extended fixed effect model. In the basic cubic random effect model, the first turning point occurs at 11236 yuan and the second turning point occurs at 55931 yuan; the turning points turned into 14158 and 51277 in the extended fixed effect model. Although inverted-N relationships significantly exist in the extended OLS model, the turning points are unable to be calculated because of the coefficient problem.

Regarding the control variables, population density is statistically significantly associated with API in the extended OLS regression and fixed effect regression. The proportion of secondary industry in GDP is statistically significant positive with API in OLS regression, while turn to insignificantly in the fixed effect model. It implies that the higher proportion of secondary industry will aggravate air pollution, but it's not significantly within a city. Expenditure for science and technology is found to be positive and statistically significant in the OLS regression, but found to be negative and statistically insignificantly in the fixed effect model. It suggests that increasing expenditure for science and technology within a city is benefical to improve air quality, but the effect is still not significant. Precipitation is negative and statistically significant in both OLS regression and fixed effect model. Temperature shows a negative and statistically significant relationship with API in the OLS regression, but the relationship becomes positive and significant in the fixed effect model. Time trend has a negative coefficient and is statistically significant.

4.2.4 Robust test

The literature has provided two types of solutions to the endogeneity in the dynamic panel model: the difference of the generalized method of moment (DIFF-GMM) and the system of generalized method of moment (SYS-GMM) (Kong and Khan 2019, Zheng and Kamal 2020). In the DIFF-GMM method, the difference of the original equation is estimated to eliminate the individual fixed effect, and the lagged terms of the independent variables are used as the instrument variables to avoid endogeneity. In the SYS-GMM method, both the difference equation and the level equation are estimated. Moreover, the lagged terms of the different variables are used in the level equations as instruments. Compared with the Diff-GMM method, the SYS-GMM method includes more instrument variables, which enhances the accuracy of the estimation (Roodman 2009). Thus, the SYS-GMM method would be used in this paper to estimate the dynamic panel model for robust tests. In addition, to judge the validity of estimation results, the residuals and the Sargan test of excessive overidentification are necessary (Roodman 2009).

Table 10 gives a summary result for SYS-GMM estimation for CODMn, NH3-N, and API. Both CODMn and NH3-N passed the regression diagnostic of the Sargan tests and residual tests with p-value over 0.05. Therefore, the SYS-GMM estimation for CODMn and NH3-N are valid. Moreover, the coefficients of the core independent variables have the same sign and statistical significance as the fixed effect model, thus the results of fixed effect model are robust and valid. Therefore, the U-shaped curves are valid for CODMn and NH3-N.

However, API only accepts the Sargan test, but does not pass the AR(2) test. It might because of the unbalanced panel datasets. Therefore, there still exists an autocorrelation between the variables and the residuals (Roodman 2009). However, the SYS-GMM estimator supports an inverted-N relationship between economic development and air pollution index.

Table 7. Summary of quadratic specification results for CODMn

	OLS (1)	FE (1)	RE (1)	OLS (2)	FE (2)	RE (2)
Predictors	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*
(Intercept)	10.78 *** (2.42)		6.50 *** (1.35)	12.60 *** (2.34)		13.40 *** (1.75)
lnGDPPC	-1.75 *** (0.48)	-0.92 *** (0.26)	-0.96 *** (0.26)	-1.74 *** (0.46)	-2.49 *** (0.33)	-2.29 *** (0.32)
lnGDPPC^2	0.08 *** (0.02)	0.05 *** (0.01)	0.04 *** (0.01)	0.08 *** (0.02)	0.11 *** (0.02)	0.10 *** (0.02)
lnPD				0.30 *** (0.03)	-0.36 (0.22)	0.03 (0.07)
SECONDARY_IND				0.40 * (0.19)	1.72 *** (0.24)	1.45 *** (0.22)
lnEXPDTECH				-0.04 * (0.02)	-0.03 ** (0.01)	-0.04 ** (0.01)
lnFDI				0.06 *** (0.02)	0.02 * (0.01)	0.02 * (0.01)
lnPRE				-0.32 *** (0.04)	0.04 (0.04)	-0.00 (0.04)
lnTMP				-0.58 *** (0.06)	0.05 (0.09)	-0.12 (0.08)
TIME	-0.01 (0.01)	-0.02 (0.01)	-0.01 (0.01)	0.01 * (0.01)	0.03 ** (0.01)	0.02 * (0.01)
Observations	1074	1074	1074	1074	1074	1074
R^2 / R^2 adjusted	0.038 / 0.036	0.091 / 0.021	0.088 / 0.086	0.271 / 0.265	0.145 / 0.075	0.132 / 0.125
AIC	2123.583	32.903	110.114	1837.955	-21.803	86.285
Shape	U	U	U	U	U	U
Turning points	52,840	27,265	48,047	109,087	101,093	78,267
F-test		81.66 ***			62.84***	
Hausman test		1.28			45.09***	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 8. Summary of quadratic specification results for NH3-N

	OLS (1)	**FE (1)**	**RE (1)**	**OLS (2)**	**FE (2)**	**RE (2)**
Predictors	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*
(Intercept)	27.39 *** (3.93)		5.30 * (2.34)	25.31 *** (4.05)		10.00 ** (3.06)
lnGDPPC	-5.34 *** (0.77)	-0.96 * (0.45)	-1.13 * (0.45)	-4.58 *** (0.79)	-1.97 *** (0.59)	-2.09 *** (0.56)
lnGDPPC^2	0.25 *** (0.04)	0.05 * (0.02)	0.05 * (0.02)	0.21 *** (0.04)	0.09 *** (0.03)	0.09 *** (0.03)
lnPD				0.48 *** (0.05)	-0.66 (0.39)	0.21 (0.12)
SECONDARY_IND				0.19 (0.34)	1.10 ** (0.42)	1.04 ** (0.38)
lnEXPDTECH				-0.05 (0.03)	0.01 (0.02)	0.00 (0.02)
lnFDI				0.07 * (0.03)	-0.01 (0.02)	-0.01 (0.02)
lnPRE				-0.50 *** (0.07)	-0.05 (0.07)	-0.09 (0.06)
lnTMP				-0.41 *** (0.10)	0.06 (0.16)	-0.07 (0.13)
TIME	-0.03 *** (0.01)	-0.06 *** (0.01)	-0.05 *** (0.01)	-0.00 (0.01)	-0.04 * (0.02)	-0.03 * (0.01)
Observations	1075	1075	1075	1075	1075	1075
R^2 / R^2 adjusted	0.098 / 0.095	0.215 / 0.155	0.202 / 0.200	0.228 / 0.221	0.223 / 0.159	0.211 / 0.204
AIC	3173.739	1214.704	1299.126	3018.726	1215.367	1308.882
Shape	U	U	U	U	U	U
Turning points	41,019	8,551	38,457	62,148	41,306	82,974
F-test		70.59 ***			58.88***	
Hausman test		12.53***			11.89***	

* *p<0.05* ** *p<0.01* *** *p<0.001*

Table 9. Summary of cubic specification regression results for API

	OLS(1)	**FE(1)**	**RE(1)**	**OLS(2)**	**FE(2)**	**RE(2)**
Predictors	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*	*Estimates*
(Intercept)	47.35 ***		38.58 ***	44.91 ***		42.97 ***
	(8.61)		(6.28)	(6.74)		(6.27)
lnGDPPC	-13.06 ***	-9.65 ***	-10.28 ***	-11.63 ***	-11.31 ***	-11.32 ***
	(2.47)	(1.89)	(1.82)	(1.94)	(1.97)	(1.82)
lnGDPPC^2	1.31 ***	0.96 ***	1.02 ***	1.13 ***	1.12 ***	1.11 ***
	(0.24)	(0.18)	(0.18)	(0.18)	(0.19)	(0.18)
lnGDPPC^3	-0.04 ***	-0.03 ***	-0.03 ***	-0.04 ***	-0.04 ***	-0.04 ***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lnPD				0.08 ***	0.22 **	0.09 ***
				(0.01)	(0.07)	(0.02)
SECONDARY_IND				0.33 ***	0.17	0.20 *
				(0.06)	(0.11)	(0.09)
lnEXPDTECH				0.03 ***	-0.01	0.00
				(0.01)	(0.01)	(0.01)
lnFDI				0.00	-0.01	-0.00
				(0.00)	(0.00)	(0.00)
lnPRE				-0.22 ***	-0.06 ***	-0.11 ***
				(0.01)	(0.02)	(0.01)
lnTMP				-0.09 ***	0.14 *	-0.12 ***
				(0.02)	(0.07)	(0.04)
TIME	-0.01 ***	-0.01 **	-0.01 ***	-0.01 ***	-0.02 **	-0.01 *
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1250	1250	1250	1250	1250	1250
R^2 / R^2 adjusted	0.094 / 0.091	0.125 / 0.060	0.155 / 0.153	0.457 / 0.452	0.152 / 0.085	0.241 / 0.235
AIC	-222.792	-1892.908	-1807.607	-849.581	-1920.711	-1785.903
Shape	Inverted-N	Inverted-N	Inverted-N	Inverted-N	Inverted-N	Inverted-N
Turning points	10123;49367	9667;67249	11236;55931	-	8464;87523	14158;51277
F-test		39.60 ***			19.03***	
Hausman test		2.74***			67.16***	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 10. The result of the SYS-GMM model

	Dependent variable:		
	lnCODMn	lnNH3N	lnAPI
lag(., 1)	0.297***	0.275***	0.373***
	(18.29)	(20.69)	(85.99)
lnGDPPC	-2.743***	-3.865***	-9.085***
	(-6.70)	(-3.05)	(-12.78)
I(lnGDPPC2)	0.125***	0.177***	0.905***
	(6.18)	(2.99)	(13.05)
I(lnGDPPC3)			-0.030***
			(-13.25)
lnPD	0.129***	0.090	0.055***
	(4.33)	(0.86)	(6.17)
SECONDARY_IND	0.742***	3.330***	0.773***
	(6.22)	(14.50)	(35.08)
lnEXPDTECH	-0.000	-0.077***	-0.017***
	(-0.12)	(-6.13)	(-15.18)
lnFDI	-0.017***	-0.041***	0.007***
	(-5.57)	(-6.75)	(6.69)
lnPRE	-0.102***	-0.085***	-0.067***
	(-16.18)	(-4.20)	(-19.25)
lnTMP	-0.177***	-0.078	0.027*
	(-7.22)	(-0.70)	(1.70)
TIME	0.010***	0.049***	0.000
	(3.64)	(6.81)	(0.22)
cons	15.860***	19.613***	32.355***
	(7.68)	(2.74)	(13.47)
Observations	994	996	1166
Sargan	0.9476	0.9933	0.9971
AR(1)	0.0000	0.0000	0.0000
AR(2)	0.6754	0.7535	0.0007
Note:	*p<0.1; **p<0.05; ***p<0.01		

4.2.5 The EKC relationship in China

The EKC curves for the three pollutants were obtained based on the fitted models. All fitted curves are displayed in Figure 4, the scales in the x-axis refers to GDP per capita in logarithm and the scales on the y-axis denote fitted values of concentration of pollutants in logarithm. The OLS (1) are the fitted curves for reduced-form models, while the OLS (2) are the fitted curves for the extended models with adjusting the effect of the control factors. U-shaped curves exist for CODMn and NH3-N, and inverted-N shaped curves exist for API.

The differences are visible between the reduced- and extended form estimators. According to Figure 4a and Figure 4b, the water pollution is lower at the less developed economic level when incorporating the other factors, while is higher at the more developed economic level. In addition, the turning points appear at lower GDP per capita in the extended models than the reduced form models. As depicts in Figure 4c, as the economy develops, the air pollution under the extended form model first exceeds and then lower than the reduced form model.

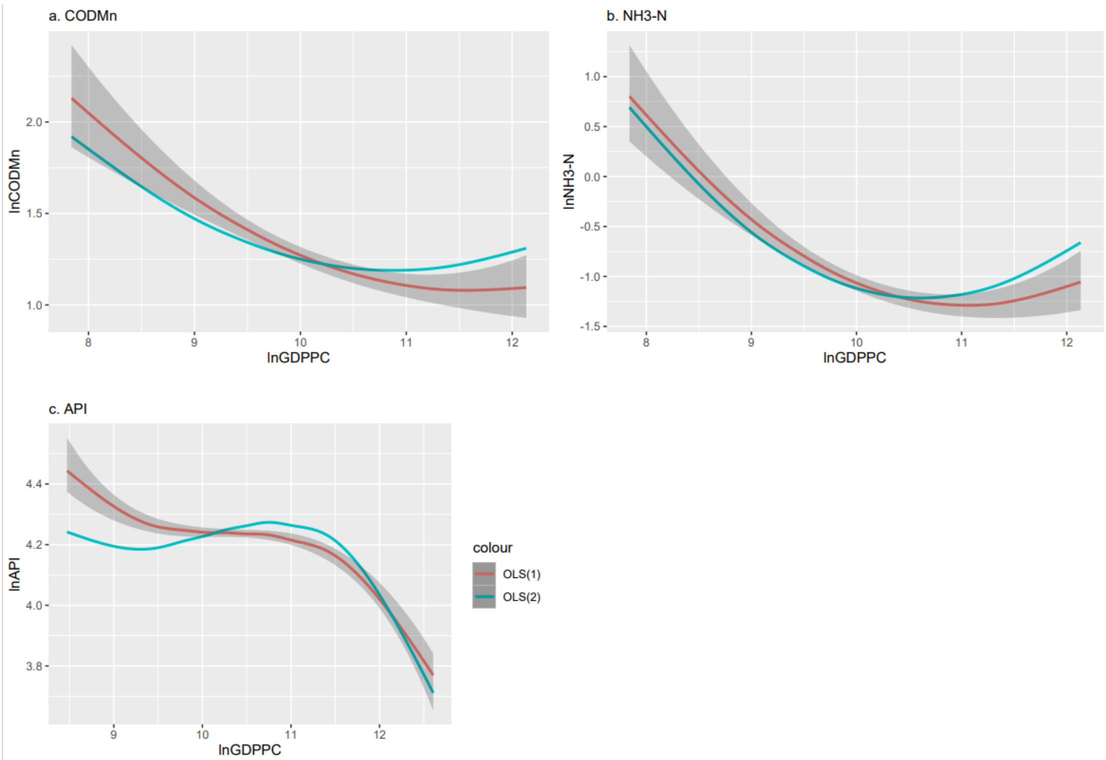

Figure 4. The environmental quality-economic development relationship for the three pollutants from the reduced and extended form estimators

5 Discussion and Conclusion

5.1 EKC for water and air quality

This paper estimated the relationship between economic growth and environmental quality in Chinese context. OLS model, fixed effect model, and random effect model are employed to conduct the analysis. Our empirical analysis suggests that no conventional inverted U-shaped curve exists for either water quality or air quality in China. For water quality, we find U-shaped curves for both CODMn and NH3-N concentration in China based on our study sample area, with turning points estimated, ranging from 12141 to 90090 yuan for CODMn; 27232 to 63927 yuan for NH3-N. For air quality, evidence was found in favor of an inverted N-shaped EKC in the cubic specification, with two turning points ranges between 9667 to 14158 yuan, and peak turning points ranging between 49367 to 67249 yuan. These findings also remind us to view the relationship between the economy and environmental quality from different aspects and for different pollutants (Orubu and Omotor 2011, Luo, Chen et al. 2014).

In terms of the EKC for water quality, the U-shaped curve implies that with the rise of economic growth, the water quality first declines, and then increases after arriving at the turning point. At present, most of Chinese cities are still experiencing the declining trend, only a few of cities have reached the turning point, such as Guangzhou, Shanghai, Tianjin, Hangzhou, et al. Most of the recent studies on water quality tend to highlight an improving water quality in China due to enormous investment in environmental remediation, reduced wastewater discharge in the industrial sector, and so on. After introducing a quadratic specification of the economic growth, we found there's a potential increase trend for the water quality. The U-shaped relationship is the same as the previous work of Yang (2017), who found a U-shaped curve for CODMn, and an upward trend for NH3-N in the Jiulong river basin. That might because even though pollution from industry sectors are decreasing because of industry upgrade and adjustment, the pollution from agricultural sectors offsets the reduction. Several scholars demonstrated big difficulties to treat wastewater in rural area, such as wastewater from livestock, irrigation, and rural household (Ma, Zhao et al. 2020). Conversely to our results, an inverted-U relationship was found for CODMn and total N in Tai Lake between 1979 and 2010 (Cheng 2012). Hao., Xinyu. et al. (2019) also find inverted-U relationships for CODMn and NH3-N in the Three Gorges Reservoir Area between 2008-2017. The former study covers a longer study period than our study, thus it could capture different stages of economic development and environmental quality, which would be helpful to fit the EKC curve. In the case of the Three Gorges Reservoir Area study, it received increasing investment in environmental protection from the government in recent years, which would be effective to improve water quality.

In terms of air quality, our results suggest an inverted-N shaped relationship between API and economic growth, that is to say, the air quality will continue to improve with the economic development first; when GDP per capita reaches the first turning point, the air quality will gradually deteriorate with the development of the economy; with the continuous economic development, the relationship will reach another turning point and the air quality will improve again. Our results for API are consistent with the results of Wang (2018), who found the relationship between the air quality index and GDP per capita satisfies the N-typed environment Kuznets curve and there exist two turning points under the cubic form EKC model. In addition, Xu, Sun et al. (2019) also found the air quality for all regions during 2005-2016 was characterized by an overall decrease in the pollution rating. However, some regions recorded a substantial increase in the frequency of pollution during 2012-2014. The slightly severer degradation of air pollution may be due to enormous energy consumption and increasing vehicles (Xu, Sun et al. 2019). Another possible reason might be China released a new air quality standard and implemented stricter policies on air quality monitoring work (Yang 2013). Besides, Luo, Chen et al. (2014) found a decreasing trend for API for 41 capital cities in China with technology innovation and modulation in industries together with policy implementation from the 1990s. Zhang, Zheng et al. (2019) observed improved PM2.5 air quality from 2013 to 2017 when China implemented the toughest-ever clean air policy. Take PM2.5 concentration as the environmental indicator, Wang and Komonpipat (2020) found different relationships for various level cities and the inverted-U hypothesis is only confirmed in first-tier cities, such as Beijing, Tianjin, Shanghai, and Chongqing. While N-shaped EKC is confirmed for other city levels, for relying on the development path of heavy industry and manufacturing. They also indicated that the reduction of haze pollution in Beijing is the result of the government’s efforts in environmental governance in the past years.

In summary, we highlight the importance to study the relationship between economic development and environmental quality under the framework of the EKC. Because the results indicated that the improving environmental quality might be temporal, and might turn into worsening in the future as the economic growth. Moreover, as the existing studies, our results also report the shape of EKC might be sensitive to the pollutants, the development stages of the study areas, and the social contexts and natural conditions of the region under study. In particularly, strengthening the environmental policy and increasing investment of environmental protection plays an effective role in mitigating environmental pollution.

5.2 Influence of control factors

In this study, we also include a list of control variables, covering demographic characteristics, economic structure, trade openness, and natural factors, that are possible determinants of pollution. In terms of demographic variables, our results suggest that population density has a positive relationship with environmental pollution. which is consistent with the previous studies (Zhang, Zheng et al. 2019, Ma, Zhao et al. 2020). However, the negative signs in the fixed effect models show that the centralization of population in local cities is conducive to mitigating pollutant concentrations, but its influence is not strong enough to be statistically significant (Liu, Wang et al. 2019).

We would say the share of secondary industry is positively related to both water pollution and air pollution. it means that a higher proportion of secondary industry add value in GDP would accompany with worse water and air quality in China nowadays. It is the same as our expectation and theoretical hypothesis (Liu, Wang et al. 2019, Wang and Komonpipat 2020). However, several studies recently argued that pollution from the secondary industry is decreasing rapidly, however, pollution from agricultural sectors and household daily emission might offset the reduction (Yang 2017, Ma, Zhao et al. 2020). It is important to highlight to improve the management of pollution from the primary industry as well.

Based on our results, we would suggest that the expenditure on science and technology has a negative association with water quality and air quality which means that higher investment in technology would be benefit for water quality and air quality, especially in local cities. As same as the previous studies higher expenditure would be helpful for research on environmental protection and industrial upgrades (Kaika and Zervas 2013, Hao, Wu et al. 2018).

Trade openness measured by FDI is positively and statistically significantly associated with the water pollution and air pollution in the OLS models, while keeps its significantly positive association only in the fixed effect model for CODMn. FDI has a negative sign in the fixed effect models for NH3-N and API. Therefore, in global China, areas with higher FDI tend to have higher pollution. The result is the same as most of the past studies (Grossman and Krueger 1991, Dinda 2004). Because the majority of FDI inflows into the industrial sector, as well as in China. However, in local areas, higher FDI does not always aggravate environmental pollution. because foreign firms may tend to use environmentally-friendly technologies and clean energy and transfer advanced technology to China (Jiang, Zhou et al. 2018).

In terms of the natural factors, it is unsurprising to find statistically significant and negative effects of precipitation on CODMN, HN3-N, and API in the OLS models, which is agree with most of the previous studies that found the southern area of China where has more precipitation and higher temperature has better water quality and air quality than northern and northeastern China (Liu, Fang et al. 2017, Qiao, Wu et al. 2019). However, temperature was found to have a negative effect on API under the pooled OLS estimation while a positive effect in the fixed effect model. The positive effect is consistent with the studies that consider the spatial effect (Liu, Fang et al. 2017). In addition, Qiao, Wu et al. (2019) found the pattern of correlation with temperature was inverted in different seasons. The API was negatively correlated with temperature in northern China and positively in southern China in spring; however, the distribution was completely reversed in summer. Similarly, most cities showed a negative correlation in autumn and a positive correlation in winter.

Time trend displays a positive relationship with water pollution and a negative relationship with air pollution. It is consistent with the previous study of (Grossman and Krueger 1995), which found regards sulfur dioxide and smoke, urban air quality has tended to improve over time, however, the opposite situation is for most measures of river contamination. It implies that to some extent, water pollution has been worsened with time, while air pollution has been abating. The state of the environment may deteriorate with time if concentrations of pollutants accumulate or if consumer tastes shift towards pollution-intensive goods. The opposite may occur if technological innovation makes abatement less costly or if increasing awareness causes an autonomous shift in public demands for better environmental quality (Grossman and Krueger 1995).

5.3 Conclusion and policy implications

This study has drawn on an EKC framework in order to analyze the relationship between economic growth and environmental quality from water and air aspects in the Chinese prefecture-level cities. The study incorporated several factors affecting environmental quality, including demographic, social, and natural factors. Instead of pooling OLS estimator, we have also employed fixed effect model and random effect model to enhance our understanding of the relationship between economic growth and environmental quality, and that incorporation of controlling individual effect is a productive way of improving model specification. Overall, our results are consistent across models, which indicates the inverted-N relationship for API and U relationship for CODMn and NH3-N were robust to the inclusion of other factors and correction for individual effects. One of the main findings of this study is that the continued economic growth might helpful but does not guarantee a continued improvement in either water quality or air quality, and that the EKC relationship might be temporary. Therefore, to achieve an improving environmental quality, the societies needs to take many actions except for accelerating economic development, including optimize population management and improve population environmental awareness, implement effective environmental policies, and take advantage of the natural environment.

Nevertheless, several limitations of this study should be noted. First, this analysis is bound by the time period between 2003-2018. If data is available for a longer period of time, then there would capture longer and different stages of economic growth and environmental degradation, which may yield more accurate results (Olale, Ochuodho et al. 2018). Furthermore, our study sample is cities that have monitoring data for water quality or air quality for at least 10 years. Although it limited our sample to around 80 cities, our study sample covers cities distributed in all four regions and five city levels. The results are helpful for understanding the economic-pollution relationship in China. In addition, although the measures of pollution pertain to one or several sites on rivers, or specific cities, the GDP per capita is measured at the prefectural city level. That's because data on river or monitoring site level GDP per capita is not readily available. Similar situations are for the other variables. Therefore, we make use of the prefectural-level data as the previous studies (Grossman and Krueger 1995, Guo and Zhao 2011, Zhai, Xia et al. 2014, Liu, Feng et al. 2017). Finally, several socioeconomic factors, such as population structures, environmental policies, treatment abilities for pollution, pollution from different sources, and environmental awareness were excluded in this study, due to the lack of data. Thus, consider these factors in future studies would help to better understand their effect (Ma, Tian et al. 2020).

The detection of the EKC relationship between economic growth and environmental quality and diagnosing of potential contributing factors would provide a significant reference for environmental protection in the future. Based on our results and the existing literature, we should not be optimistic that the environmental quality would get better just depending on the economic growth, especially for the water quality. The societies also need a strong political will, adequate socioeconomic and environmental policies to achieve an improved environmental quality. Several factors could be taken into account while formulating environmental policies. Firstly, population dynamics could influence pollution, it is of great importance to improve environmental awareness to become more concerned about the environmental quality, promote environmental-friendly behaviors, and strive for more governmental support (Luo, Chen et al. 2014). Secondly, evidence shows that pollution reduction from secondary industry might be offset by increases from other sources. Pollution treatment capability should be improved in not only the industrialized sector but also the agricultural sector, especially rural areas. Thirdly, government investment has a positive impact to improve the environment, which suggests more investment in technology development and environmental protection. Fourthly, FDI might have both benefits and damage to the environment (Jiang, Zhou et al. 2018, Xu 2018). We should encourage FDI flow to high technology or service industries, and restrict FDI flow to high energy consumption and pollution industries to reduce the negative impact of FDI. Besides, the natural factors have great effects on environmental quality, thus, the local climate conditions must be taken into account in planning for urban construction, human production, and urban life through urban and regional planning practices (Liu, Wang et al. 2019). Last but not least, as we indicated great regional and individual effects across China, the environmental protection policies should be made at both the national level and the local level (Xu 2018).

In sum, the results of this study can increase our understanding of the relationship between economic growth and environmental quality in China under the framework of EKC. It is important to examine EKC from different aspects, such as water quality, air quality, solid waste, and land indicators. Future studies of this field should incorporate additional factors to enable the production of more robust explanatory models. In addition, with the development of China's environmental monitoring work, future studies could assess EKC with a larger study sample and a longer time period to get more comprehensive results.

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