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Abstract

This study, focusing on the water pollutions in terms of chemical oxygen demand (COD) and ammonia nitrogen by industrial and household discharges in Chinese provinces, investigates the contribution of capacity shortage for pollution control to the provincial pollution levels, by conducting a factor analysis to the heterogeneity of provincial pollutions under the environmental Kuznets curve (EKC) framework. The study's contribution to the literature lies in its framework of analyzing the heterogeneity of Chinese provinces' EKCs in terms of their positions (not their shapes) by using a fixed-effect model to extract the province-specific pollution effects. The main finding of this study is that the capacity shortage for pollution control accounts for around 30% as a pollution factor of industrial COD and ammonia nitrogen, and accounts for around 60% and 80% as a pollution factor of household COD and ammonia nitrogen, respectively. It suggests that China has still much policy space and room to mitigate the water pollutions, by building the capacity for pollution control through developing human resources and training them.

Keywords: water pollutions, pollution-control capacity, Chinese provinces, chemical oxygen demand (COD), ammonia nitrogen, environmental Kuznets curve
JEL Classification: Q53, Q58, O53

1. Introduction

China's growth has significantly improved the country's living standards since its Open and Reform Policy in 1978. The economic status of China was promoted from low-income category to lower-middle-income one in 1997 and further to upper-middle-income one in 2010, based on the World Bank income classification[1]. On the other hand, this rapid economic development has brought serious damages to its environment through industrialization and urbanization. Water pollution is one of the vital issues influencing the survival of human beings and the development of socio-economic systems. According to the Environmental Performance Index[2], China remains at the 80th place out of 180 countries in the field of water resources. To address the water pollution, the Chinese government has set the numerical targets to reduce the two main water pollutants: chemical oxygen demand (COD) discharge since the 11th Five-Year Plan (2006-2010) and ammonia nitrogen discharge since the 12th Five-Year Plan (2011-2015). The current 14th Five-Year Plan (2021-2025) contains binding targets to reduce COD and ammonia nitrogen discharges by 8% during the planed period, respectively. Although these targets have been almost achieved through the policy efforts, the pollution discharges still remain massive, keeping the water quality at a low level: the groundwater supplies in more than half of Chinese cities were categorized as "bad to very bad", while more than a quarter of China's major rivers were considered "unfit for human contact" (e.g., Cai et al. 2020, Zhang et al. 2017).

Aside from the nation-wide issue of water pollution, another concern in China is the regional heterogeneity in the pollution levels and the factors affecting the pollution (see Table 1). According to the China Statistical Yearbook[3] in 2020, the industrial discharge of COD per million persons varies in the range from 65 ton in Beijing to 700 ton in Jiangsu; the household discharge of COD from 1,848 ton in Beijing to 11,488 ton in Guangxi; the industrial discharge of ammonia nitrogen from 2 ton in Beijing to 36 ton in Jiangxi; and the household discharge of ammonia nitrogen from 94 ton in Tianjin to 1,149 ton in Guangxi. Regarding the economic factors affecting the pollution, gross regional product (GRP) per capita at 2010 prices differs from 127,816 yuan in Beijing to 28,171 yuan in Gansu; the secondary industry's value added as a percentage of GRP affecting industrial discharges from 46.2% in Fujian to 16.0% in Beijing; and the urban population as a percentage of total population affecting household discharges from 89.3% in Shanghai to 35.8% in Tibet. There are also the policy priority areas where the Chinese

[1] See the website: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519.
[2] See the website: https://epi.yale.edu/.
[3] See the website: https://spc.jst.go.jp/statistics/stats_index.html.

government designates them as key regions for water pollution control and has imposed a variety of regulations to improve water quality: the three rivers (i.e., Huai, Hai, and Liao) and three lakes (i.e., Tai, Chao, and Dianchi) basins (hereafter, 3Rs3Ls) that involves 11 provinces as shown in the last column of Table 1 (Wang et al. 2018)[4].

This study, focusing on the water pollutions (COD and ammonia nitrogen by industrial and household discharges) in Chinese provinces, aims to investigate the contribution of capacity shortage for pollution control to the provincial pollution levels, by conducting a factor analysis to the heterogeneity of provincial pollutions under the analytical framework of the environmental Kuznets curve (EKC). Specifically, this study takes the following steps: first, estimating the EKC econometrically with provincial panel data by a fixed-effect model; second, extracting the province-specific pollution effect from the fixed effect, which is not affected by the provincial income level on the EKC; third, re-estimating the alternative EKC by replacing the fixed-effects with the possible contributors to the province-specific pollution, i.e., the capacity for pollution control, industrialization degree (for industrial discharges), and urbanization degree (for household discharges), and finally, quantifying the contribution of capacity shortage for pollution control to the province-specific pollutions.

The main finding of this study is that the capacity shortage for pollution control accounts for around 30% as a pollution factor of industrial COD and ammonia nitrogen, and accounts for around 60% and 80% as a pollution factor of household COD and ammonia nitrogen, respectively. It suggests that China has still much policy space and room to mitigate the water pollutions in terms of COD and ammonia nitrogen.

The remainder of the paper is structured as follows. Section 2 reviews the literature related to the EKC issues including water pollution in China and clarifies this study's contributions. Section 3 conducts empirics consisting of the EKC econometric estimations using provincial panel data and the factor analysis to the heterogeneity of the province-specific water pollutions. Section 4 summarizes and concludes the paper.

2. Literature Review and Contributions

This section reviews the literature related to the EKC issues including water pollution EKC in China and clarifies this study's contributions.

The EKC provides an analytical framework to examine how economies deal with environmental issues. It postulates an inverted-U-shaped relationship between pollution and economic development. Kuznets's name was apparently attached to the curve by

[4] The author identifies 11 provinces based on Wang et al. (2018).

Grossman and Krueger (1993) who noted its resemblance to Kuznets inverted-U relationship between income inequality and development. Dasgupta et al. (2002) describes the EKC dynamic process as follows: In the first stage of industrialization, pollution worsens rapidly because people are more interested in jobs and income than in clean air and water, and environmental regulation is correspondingly weak. Along the curve, pollution falls in wealthy societies, because leading industrial sectors become cleaner, people value the environment, and regulatory institutions become more effective.

Since the report of World Bank (1992) initially discussed EKC issues, numerous empirical tests and theoretical debates have been intensified, supporting the applicability of the EKC for some regions and environment problems (e.g., Selden and Song 1994, Lopez 1994, Grossman and Krueger 1995, Stokey 1998). At the initial stage until the 1990s, most of empirical studies concentrated on validating the EKC hypothesis and its requirements by using cross-sectional data. Since the late 1990s, however, the EKC studies have shifted from cross-sectional analyses to time-series analyses, and more importantly, have examined the heterogeneity of individual economies' EKCs in terms of the curve's shapes and positions. In this context, Dasgupta et al. (2002) presented three different EKC scenarios from the conventional inverted-U EKC: Race to the Bottom (pessimistic with continuation of the highest level of pollution), New Toxics (pessimistic with higher curve by newly emerging pollutants), and Revised EKC (optimistic with lower and flatter curve by better management of pollution), and these scenarios have also been put in empirical tests (e.g., Dinda 2004, Mukhopadhyay and Chakraborty 2005, Taguchi and Murofushi 2010, Taguchi 2012). Sarkodie and Strezov (2019) comprehensively reviewed the heterogeneity of the EKC modalities in terms of the curve's shapes and positions.

Although there has been a large body of literature on the EKC studies for several countries and for several environmental quality as shown above, it is in recent times since the 2000s that the studies on the EKC of China have increasingly appeared in the literature. Thus, there are relatively a limited number of the EKC studies, particularly, on water pollution in China, covering total provinces or specific areas, as listed in Table 2. Their estimation shows ambiguous and mixed outcomes: some studies identify the validity of inverted-U shaped EKC (Zhang et al. 2017, Zhao et al. 2017, Li et al. 2016, Jayanthakumaran and Liu 2012, Shen 2006), while the others demonstrate that the EKC modality depends on regions and pollutants (Cai et al. 2020, Liu et al. 2019, Wang et al. 2017, Liu et al. 2016, Liu et al. (2007).

Regarding the heterogeneity of Chinese provinces' EKCs, Cai et al. (2020), for instance, demonstrates the several types of EKCs depending on provinces: "good EKCs" (negative monotonic shape, inverted N-shape, inverted U-shape and M-shape), "bad EKCs" (positive monotonic shape, N-shape and U-shape) and "transition EKC" (positive monotonic and flat-tailed shape). To the best of the authors' knowledge, however, no studies investigate the "positions" of provincial EKCs, which reflect the province-specific pollution effects that are not affected by the provincial income levels. Thus, this study's contributions are directly to analyze the heterogeneity of Chinese provinces' EKCs in terms of their positions by using a fixed-effect model in the EKC panel estimation in order to extract the province-specific pollution effects, and to reveal the factors affecting the province-specific pollutions, focusing particularly on the provincial capacity for controlling the pollutions.

3. Empirical Analyses

This section conducts empirics consisting of the EKC econometric estimations using provincial panel data and the factor analysis to the heterogeneity of the province-specific water pollutions. The section starts with the description of methodology and data.

3.1 Methodology and Data

This study basically follows the original form of the EKC, i.e., the standard nonlinear model where water pollution per capita is regressed by income per capita and its square. The first specification in Equation (1) applies a fixed-effect model for provincial panel-data estimation in order to explicitly demonstrate the province-specific pollution effects, and also runs the alternative models in Equation (2) and (3) by replacing the fixed-effects with possible pollution contributors (pollution-control capacity, industrialization, and urbanization) to the province-specific pollution effects. The equations for the estimation are specified as follows.

$$\ln (codi_{it}, codh_{it}, anti_{it}, anth_{it}) = \alpha_0 + \alpha_1 \ln ypc_{it} + \alpha_2 (\ln ypc_{it})^2 + f_i + f_t + \varepsilon_t \quad (1)$$

$$\ln (codi_{it}, anti_{it}) = \beta_0 + \beta_1 \ln ypc_{it} + \beta_2 (\ln ypc_{it})^2 + \beta_3\, edu_{it} + \beta_4\, ind_{it} + f_t + \varepsilon_t \quad (2)$$

$$\ln (codh_{it}, anth_{it}) = \gamma_0 + \gamma_1 \ln ypc_{it} + \gamma_2 (\ln ypc_{it})^2 + \gamma_3\, edu_{it} + \gamma_4\, urb_{it} + f_t + \varepsilon_t \quad (3)$$

where the subscripts *i* and *t* denote sample 31 Chinese provinces and years for 2003-2019, respectively; *codi*, *codh*, *anti*, and *anth* represents the water pollutants: industrial COD, household COD, industrial ammonia nitrogen and household ammonia nitrogen, expressed as the ton per million persons; *ypc* shows gross regional product (GRP) per capita in terms of yuan at constant prices in 2010; *edu* denotes the number of graduates of higher education per million persons; *ind* shows the secondary industry value added as a percentage of GRP; *urb* represents the urban population as a percentage of total population; f_i and f_t show a time-invariant country-specific fixed effect and a country-invariant time-specific fixed effect, respectively; ε denotes a residual error term; $\alpha_{0\ldots2}$, $\beta_{0\ldots4}$, and $\gamma_{0\ldots4}$ represent estimated coefficients, respectively; and ln shows a logarithm form, which is set to avoid scaling issues for the water pollutants and GRP per capita. The data source of all the variables is the China Statistical Yearbook. The study constructs a set of panel data of sample 31 provinces and period for 2003-2019.[5] The variable list and the descriptive statistics for the variable data are displayed in Table 3 and 4, respectively.

The notes on the specifications of the estimation models in (1), (2) and (3) are needed to describe additionally as follows. Regarding Equation (1), it applies a fixed-effect model represented by f_i and f_t, respectively, for provincial panel-data estimation. From the statistical perspective, the Hausman-test statistic is generally utilized for the choice between a fixed-effect model and a random effect one (Hausman 1978). This study, however, places a premium on demonstrating province-specific pollution effects explicitly, and also needs to consider time-specific factors such as economic fluctuations due to external shocks such as the Asian financial crises in 1997–1998 and the global financial crises in 2008–2009. In addition, adopting the fixed-effect model contributes to alleviating the endogeneity problem by absorbing unobserved time-invariant heterogeneity among the sample provinces. The estimation sets Beijing as a benchmark province for extracting the province-specific pollution effects, because Beijing shows the best performance in water pollution control as shown in Table 1. The significantly positive coefficient of the province-specific fixed-effects would suggest that the province's water pollution is more serious than that of Beijing. The ordinary hypothesis of EKC postulating the inverted-U-shaped path between water pollution and GRP per capita would be verified if α_1, β_1, $\gamma_1 > 0$ and α_2, β_2, $\gamma_2 < 0$ are significant with reasonable levels of turning points.

Equations (2) and (3) represent the alternative models for industrial discharges and household discharges, respectively. Equation (2) replaces the province-specific fixed effects with possible pollution contributors to the fixed-effects: pollution-control capacity (*edu*) and industrialization (*ind*), and Equation (3) replaces them with pollution-control capacity (*edu*) and urbanization (*urb*). This study uses the number of graduates of higher education (*edu*) to represent the capacity to control pollutions because the pollution controllability depends highly on human resources and capitals to address pollution in each province. In fact, the importance of human capitals in controlling environmental

[5] This study excludes the year of 2020 when the COVID-19 seriously affected economic activities.

pollutions has been studied in a number of previous studies (e.g., Lan et al. 2012, Wang et al. 2019, Haini 2021). The adoption of industrialization (*ind*) and urbanization (*urb*) is based on Liu et al. (2019), which argues that secondary industry output can be a main indicator for industrial water use, and urban population can be an indicator for household water use. No multicollinearity problem exists in the regressors' combinations in Equations (2) and (3), namely, (*ypc*, *edu*, *ind*) and (*ypc*, *edu*, *urb*). It is because the variance inflation factors (VIF), a method of measuring the level of collinearity between the regressors, indicate lower values than the criteria of collinearity (ten points) in each equation.[6] The pollution-control capacity (*edu*) is expected to equip a negative coefficient on water pollutions because the higher capacity enables the pollutions to mitigate. The coefficients of industrialization (*ind*) and urbanization (*urb*), which deteriorate water pollutions, are supposed to be positive in the respective equations.

The explanatory variables in Equation (1) – (3), *ypc*, *ind*, and *urb* are lagged by one year. It comes from the need to avoid the issue of reverse causality in the model specifications including the endogenous interaction between dependent and independent variables. Regarding the pollution-control capacity (*edu*), ten-year lag is applied because it takes a long time for graduates of higher education to be trained for the capacity building for pollution control. Figure 1 displays the magnitudes of negative coefficients of the pollution-control capacity (*edu*) by time-series lag patterns in Equation (2) and (3) estimated on each water pollutant, and shows that the impacts of the capacity on pollutions are negatively maximized around at ten-year lag.

As for the estimation technique, this study applies the ordinary least squares (OLS) estimator and the Poisson pseudo-maximum likelihood (PPML) estimator. The reason for applying the PPML estimator is that the sample data with the heterogeneity in provincial properties would be plagued by heteroskedasticity and autocorrelation; in which cases, the OLS estimator leads to bias and inconsistency in estimates. The PPML estimator corrects for heteroscedastic error structure across panels and the presence of autocorrelation with panels, as Silva and Tenreyro (2006) and Kareem et al. (2016) suggest. Therefore, both estimators are applied to ensure the robustness of the estimations. This study uses EViews (version 12) as software to process the data and conduct all the estimations in this study.

3.2 Panel Unit Root and Cointegration Tests

[6] The VIF values of (*ypc*, *edu*, *ind*) in Equation (2) are (2.793, 2.765, 1.017), and those of (*ypc*, *edu*, *urb*) in Equation (3) are (5.417, 2.737, 4.111), according to the author's estimation.

For the subsequent estimation, this study investigates the stationary property of the constructed panel data by employing panel unit root tests, and if needed, a panel cointegration test for a set of variables' data. The panel unit root tests are firstly conducted on the null hypothesis that a level and/or a first difference of the individual data have a unit root. In case that the unit root tests reveal that each variable's data is not stationary in the level, but stationary in the first-difference, a set of variables' data corresponds to the case of $I(1)$, and then can be further examined by a co-integration test for the "level" data. If a set of variables' data are identified to have a co-integration, the use of the "level" data is justified for a model estimation.

For the panel unit root tests, this study applies the Levin, Lin, and Chu test (Levin et al. 2002) as a common unit root test; and the Fisher-ADF and Fisher-PP tests (Maddala and Wu 1999, Choi 2001) as individual unit root tests. The common unit root test assumes that there is a common unit root process across cross-sections, and the individual unit root test allows for individual unit root processes that vary across cross-sections. For a panel co-integration test, the study conducts the Pedroni residual co-integration test (developed by Pedroni, 2004). All of the test equations contain individual intercept and trend with the lag length being automatic selection.

Table 5 presents the test results: the common unit root test rejects the null hypothesis of a unit root at the conventional significance levels in all the variables; however, the individual tests do not reject a unit root in their levels except *edu* while rejecting it in their first differences, thereby the variables almost following the case of $I(1)$. Then, the panel co-integration test is conducted further on the combinations of variables in Equations (2) and (3). The panel PP and ADF tests suggest that the level series of a set of variables' data are co-integrated in the respective combinations. Thus, the study utilizes the level data for the estimation.

3.3 Estimation Results

Tables 6 – 9 report the results of OLS estimation and PPML one in the form of log-link function for industrial and household COD and industrial and household ammonia nitrogen, respectively. Column (i) and (ii) display the outcomes of the fixed-effect models, and Column (iii) and (iv) present the results of the alternative models containing pollution-control capacity (*edu*) and industrialization (*ind*) for industrial discharges and pollution-control capacity (*edu*) and urbanization (*urb*) for household discharges instead of the fixed-effects. Both of OLS and PPML estimations show similar results in the sign and significance of each coefficient, and thus the subsequent description focuses on the result of PPML estimations that adjusts heteroskedasticity and autocorrelation. The findings from the estimation results are summarized as follows.

First, the EKC hypothesis, which assumes the inverted-U-shaped relationship between water pollution level and GRP per capita, is confirmed in all the water pollutants from Tables 6 – 9 and in all the estimations from Columns (i) – (iv). They are confirmed by the estimation results that the coefficients of GRP per capita are significantly positive and those of its square are significantly negative; and the turning points fall within the reasonable ranges of GRP per capita between its minimum level and its maximum one in the samples shown in Table 4, except for the estimations in Column (i) and (ii) in Table 6 (the turning point is computed by $-\alpha_1/2\alpha_2$, $-\beta_1/2\beta_2$, or $-\gamma_1/2\gamma_2$ in Equations). The main research focus in this study is, however, the provincial EKC positions rather than their shapes as in the subsequent description.

Second, the fixed-effect models in Columns (i) and (ii) identify the positive coefficients as the province-specific fixed-effects at conventional significant levels, in all the provinces for industrial COD in Table 6 and for household ammonia nitrogen in Table 9, and in the majority of provinces for household COD (except Hebei, Shandong, Henan, Chongqing, and Ningxia) in Table 7 and for industrial ammonia nitrogen (except Tibet) in Table 8. The positive provincial fixed-effects mean the provincial EKCs are located upward from that of Beijing as the benchmark, suggesting that the province-specific pollution effects (not affected by the provincial income level on the EKC) are larger than the pollution of Beijing. These results are in line with the simple observations on water pollutions per capita in all the provinces in Table 1. The degree of the water pollutions is shown by the magnitude of the coefficients of provincial fixed-effects: the industrial COD in Tianjin by PPML estimation (Column (ii) in Table 6), for instance, is exp. (1.825) = 6.203 times larger than that of Beijing. The provincial fixed-effects also reveal that the pollution levels in the policy propriety areas (3Rs3Ls) shown in Table 1 are not necessarily higher than the average levels among the 31 provinces in all the water pollutants, thereby implying that the government policies have controlled well the water pollutions in the priority area.

Third, turning to the alternative model containing pollution-control capacity (*edu*), industrialization (*ind*), and urbanization (*urb*) in Column (iii) and (iv), the coefficients of *edu* is significantly negative in all the pollutants and estimations in Table 6 – 9, and those of *ind* for industrial discharges in Tables 6 and 8 and those of *urb* for household discharges in Tables 7 and 9 are significantly positive in any estimations. These results are in line with the hypothesis of Liu et al. (2019) that secondary industry output and urban population can be main indicators of industrial and household water use, respectively.

More importantly, the negative coefficients of *edu* in all the pollutants suggest that the pollution-control capacity has really affected the provincial pollution levels, and that the heterogeneity of provincial pollutions can be explained by the difference in provincial pollution-control capacity. The joint estimation outcomes of the province-specific pollution effects and the workability of pollution-control capacity lead to the question on the quantitative contributions of provincial capacity shortage for pollution control to the provincial pollution levels.

3.4 Factor Analysis on Pollution-Control Capacity

This section quantifies the contributions of provincial pollution-control capacity to the province-specific pollution effects (hear, also based on the PPML estimation). Tables 10 and 11 denote the analytical outcomes for COD and ammonia nitrogen discharges, respectively. Columns (a) and (b) redisplay the provincial fixed-effects (only significant coefficients) in Tables 6 – 9 representing the province-specific pollutions from industrial and household discharges, respectively; Column (c) presents the period-average of provincial pollution-control capacity indicators (*edu*); Column (d) computes the *edu* deviations from that of Beijing (the benchmark); Columns (e) and (f) obtain the *edu* contributions to provincial industrial and household discharges by multiplying the *edu* deviations with the estimated *edu* coefficients in Tables 6 – 9; and Columns (g) and (h) finally demonstrate the *edu* contribution ratios to provincial industrial and household pollutions by dividing Columns (e) and (f) by Columns (a) and (b).

The average *edu* contribution ratios among total provinces except those with insignificant fixed effects are 0.263 for industrial COD, 0.623 for household COD, 0.329 for industrial ammonia nitrogen, and 0.838 for household ammonia nitrogen. It suggests that the capacity shortage for pollution control accounts for around 30% as a pollution factor of industrial COD and ammonia nitrogen, and accounts for around 60% and 80% as a pollution factor of household COD and ammonia nitrogen, respectively. The strategic implication of this result is the significance in building the capacity for water pollution control by developing human resources and training them. The capacity building contributes to water-pollution mitigation through various channels by: enhancing environmental awareness (e.g., Niu et al. 2022), developing environmental technologies (e.g., Zhao et al. 2017, Aboelmaged and Hashem 2019), and raising regulatory powers and governances of environmental policies (e.g., Cai et al. 2020, Liu et al. 2019).

4. Conclusion

This study focused on the water pollutions in terms of COD and ammonia nitrogen by industrial and household discharges in Chinese provinces, and investigated the contribution of capacity shortage for pollution control to the provincial pollution levels, by conducting a factor analysis to the heterogeneity of provincial pollutions under the EKC framework. The study's contribution to the literature lies in its framework of analyzing the heterogeneity of Chinese provinces' EKCs in terms of their positions (not their shapes) by using a fixed-effect model in the EKC panel estimation to extract the province-specific pollution effects, and conducting a factor analysis to uncover the contribution of provincial pollution-control capacity to the provincial pollutions.

The main findings from empirical estimations are summarized as follows. First, all the EKC estimations with provincial panel data identify the existence of the inverted-U-shaped relationship between water pollutions and income with reasonable turning points. Second, the fixed-effect models confirm that the majority of provinces have more serious water pollutions as province-specific effects than Beijing as the benchmark has. Third, the alternative models reveal that industrial and household pollutions are associated with industrialization and urbanization degrees, respectively, and, more importantly, that both of pollutions are significantly affected by pollution-control capacity. Fourth, the factor analysis demonstrates that the capacity shortage for pollution control accounts for around 30% as a pollution factor of industrial COD and ammonia nitrogen, and accounts for around 60% and 80% as a pollution factor of household COD and ammonia nitrogen, respectively.

The policy implication is, therefore, that China has still much policy space and room to mitigate the water pollutions in terms of COD and ammonia nitrogen by building the capacity for pollution control through developing human resources and training them. The capacity building contributes to water-pollution mitigation through various channels by: enhancing environmental awareness, developing environmental technologies, and raising regulatory powers and governances of environmental policies.

The limitation of this study is the shortage of detailed researches on individual provinces and regions. As shown in the introduction, China has its regional heterogeneity in pollution levels and factors affecting them, and also its policy priority areas such as the 3Rs3Ls. Examining the complexity of pollution mechanisms and the policy performances in specific regions through detailed case studies would make it possible to produce region-specific and concrete recommendations and prescriptions on the water-pollution management in China.

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Table 1 Water Pollution and its Influential Factors in Chinese Provinces in 2020

	codi	*codh*	*anti*	*anth*	*ypc*	*ind*	*urb*	*3Rs3Ls*
Beijing	65	1,848	2	119	127,816	16.0	87.5	*
Tianjin	203	2,423	7	94	79,377	35.1	84.7	*
Hebei	351	4,823	11	228	37,909	38.2	60.1	*
Shanxi	138	5,386	5	326	40,851	43.2	62.5	*
Inner Mongolia	365	4,290	19	224	56,765	40.0	67.5	*
Liaoning	310	3,893	13	209	46,399	37.4	72.1	*
Jilin	392	5,894	15	215	39,585	35.2	62.6	
Heilongjiang	671	5,672	32	313	33,595	25.3	65.6	
Shanghai	346	2,255	8	100	121,299	26.3	89.3	
Jiangsu	700	5,336	30	407	93,882	43.4	73.4	*
Zhejiang	686	6,299	14	491	78,860	40.8	72.2	*
Anhui	268	8,085	16	477	49,455	40.0	58.3	*
Fujian	471	10,412	18	811	83,630	46.2	68.7	
Jiangxi	459	8,124	36	672	44,234	43.1	60.4	
Shandong	457	5,140	19	368	56,397	39.1	63.1	*
Henan	161	5,821	8	347	42,522	41.0	55.4	*
Hubei	389	7,674	20	611	56,788	37.1	62.9	
Hunan	219	7,542	10	728	49,459	38.4	58.8	
Guangdong	324	7,162	12	632	68,259	39.5	74.2	
Guangxi	312	11,488	11	1,149	33,915	31.9	54.2	
Hainan	437	8,250	11	631	41,565	19.3	60.3	
Chongqing	290	4,126	11	511	62,176	39.8	69.5	
Sichuan	307	9,413	15	848	45,290	36.1	56.7	
Guizhou	122	6,329	17	558	36,729	35.1	53.2	
Yunnan	224	5,746	9	435	40,611	34.2	50.0	
Tibet	49	9,214	3	786	39,917	37.6	35.8	
Shaanxi	239	6,951	8	563	51,742	43.1	62.7	
Gansu	179	3,998	8	134	28,171	31.5	52.2	
Qinghai	274	10,516	19	821	38,082	38.0	60.1	
Ningxia	436	5,576	17	325	43,180	40.7	65.0	
Xinjiang	424	8,215	23	721	41,769	34.7	56.5	

Notes:
codi: Industrial Chemical Oxygen Demand (COD), ton per million persons
codh: Household Chemical Oxygen Demand (COD), ton per million persons
anti: Industrial Ammonia Nitrogen, ton per million persons
anth: household Ammonia Nitrogen, ton per million persons
ypc: Gross Regional Product (GRP) per capita, 2010 prices, yuan
ind: Secondary industry, percent of GRP
urb: Urban population, percent of total population
3Rs3Ls: Three rivers (i.e., Huai, Hai, and Liao) and three lakes (i.e., Tai, Chao, and Dianchi) basins
Sources: China Statistical Yearbook

Table 2 Literature Review of EKC on Water Pollution in China

	Sample Areas	Pollutants	Summary
Cai et al. (2020)	31 provinces	WW, COD, NH_4-N	Modality of EKC depends on regions
Liu et al. (2019)	Shandong	WW, COD, NH_3-N	Modality of EKC depends on pollutants
Zhang et al. (2017)	27 provinces	COD, NH_3-N	Inverted-U shaped EKC is identified
Zhao et al. (2017)	31 provinces	water use	Inverted-U shaped EKC is identified
Wang et al. (2017)	Urumqi	WW, COD, NH_3-N	Modality of EKC depends on pollutants
Li et al. (2016)	28 provinces	WW	Inverted-U shaped EKC is identified
Liu et al. (2016)	Zaozhuang	WW, COD, NH_3-N	Modality of EKC depends on pollutants
Jayanthakumaran & Liu (2012)	31 provinces	COD	Inverted-U shaped EKC is identified
Liu et al. (2007)	Shenzhen	TPH, etc.	Modality of EKC depends on pollutants
Shen (2006)	31 provinces	COD, Arsenic, Cadmium	Inverted-U shaped EKC is identified

Notes:
WW: Waste water discharge
COD: Chemical Oxygen Demand
NH_3-N, NH_4-N: Ammonia Nitrogen
TPH: total petroleum hydrocarbon
Sources: Author’s description

Table 3 List of Variables

Variables	Description
Dependent Variable	
codi	*Industrial Chemical Oxygen Demand (COD), ton per million persons, log term*
codh	*Household Chemical Oxygen Demand (COD), ton per million persons, log term*
anti	*Industrial Ammona Nitrogen, ton per million persons, log term*
anth	*household Ammona Nitrogen, ton per million persons, log term*
Explanatory Variables	
ypc	*Gross Domestic Product (GDP) per capita, 2010 prices, RMB, log-term, one-year lagged*
edu	*Number of graduate of higher education (regular undergraduate and specialized) per million persons, log-term, ten-year lagged*
ind	*Secondary industry, percent of GDP, one-year lagged*
urb	*Urban population, percent of total population, one-year lagged*

Sources: Author's description

Table 4 Descriptive Statistics

Variables	Obs.	Median	Std. Dev.	Min.	Max
Dependent Variable					
codi	527	7.700	1.046	4.159	9.800
codh	527	8.672	0.458	6.984	9.724
anti	527	7.648	1.295	0.000	7.648
anth	527	6.583	0.584	3.689	7.532
Explanatory Variables					
ypc	527	10.298	0.620	8.435	11.761
edu	527	8.351	0.536	6.463	9.214
ind	527	42.340	8.895	15.989	63.254
urb	519	50.970	14.626	22.198	89.600

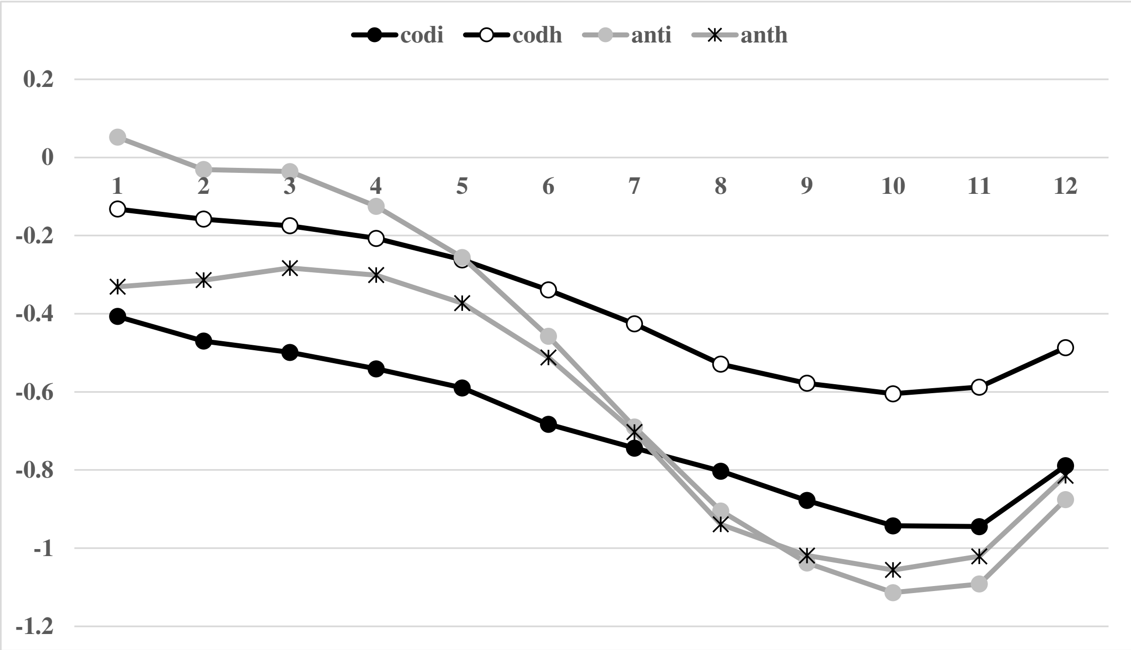
Sources: Author's calculation

Table 5 Panel Unit Root Tests

	Unit Root Test		Panel Cointegration Test	
	Level	1st difference		
	Levin, Lin and Chu			
codi	-3.959 ***	-		
codh	-3.445 ***	-		
anti	-3.277 ***	-		
anth	-3.089 ***	-		
ypc	-2.223 **	-	-	
ypc^2	-1.365 *	-		
edu	-2.895 ***	-		
ind	-3.290 ***	-		
	Fisher-ADF		Panal ADF	Panel PP
codi	30.454	178.523 ***	Group of *codi*	
codh	33.619	219.161 ***		
anti	37.407	200.169 ***	-3.661 ***	-0.863 ***
anth	9.257	181.955 ***		
ypc	21.936	145.492 ***	Group of *codh*	
ypc^2	17.626	149.354 ***		
edu	79.095 *	113.663 ***	-4.102 ***	-4.037 ***
ind	70.484	201.233 ***		
	Fisher-PP		Panal ADF	Panel PP
codi	26.552	265.096 ***	Group of *anti*	
codh	36.131	290.202 ***		
anti	33.946	277.300 ***	-3.248 ***	-2.121 **
anth	4.284	204.084 ***		
ypc	29.065	150.792 ***	Group of *anth*	
ypc^2	20.094	141.915 ***		
edu	425.975 ***	131.504 ***	-3.223 ***	-2.116 **
ind	60.512	264.166 ***		

Note: ***, **, and * denote statistical significance at 99, 95 and 90 percent level, respectively.
Sources: Author’s estimation

Figure 1 Lag pattern of Pollution-Control Capacity



Note: The vertical line denotes the coefficient value of pollution-control capacity (*edu*), which is defined as the number of graduates of higher education per million persons, and the horizontal line indicates yearly-time lags of the *edu* variable: edu_{-1}, edu_{-2}, edu_{-3}…edu_{-n}.

Sources: Author's estimation

Table 6 Estimation Results: Industrial COD (*codi*)

Estimation Methodology	(i) OLS	(ii) PPML	(iii) OLS	(iv) PPML
ypc	2.603 **	2.796 **	12.333 **	13.404 **
	(2.336)	(2.229)	(2.692)	(2.216)
ypc^2	-0.104 *	-0.112 *	-0.567 **	-0.618 **
	(-1.747)	(-1.663)	(-2.653)	(-2.207)
ind			0.019 ***	0.020 ***
			(5.994)	(3.262)
edu			-0.940 ***	-0.943 ***
			(-17.758)	(-6.774)
Dummy for fixed effect				
Tianjin	1.856 ***	1.825 ***		
Hebei	2.484 ***	2.468 ***		
Shanxi	2.549 ***	2.543 ***		
Inner Mongolia	2.947 ***	2.970 ***		
Liaoning	2.654 ***	2.676 ***		
Jilin	2.903 ***	2.924 ***		
Heilongjiang	2.646 ***	2.680 ***		
Shanghai	1.363 ***	1.381 ***		
Jiangsu	2.562 ***	2.603 ***		
Zhejiang	2.618 ***	2.630 ***		
Anhui	2.239 ***	2.276 ***		
Fujian	2.262 ***	2.298 ***		
Jiangxi	2.705 ***	2.775 ***		
Shandong	2.207 ***	2.227 ***		
Henan	2.273 ***	2.262 ***		
Hubei	2.313 ***	2.316 ***		
Hunan	2.691 ***	2.721 ***		
Guangdong	2.155 ***	2.178 ***		
Guangxi	3.427 ***	3.419 ***		
Hainan	2.001 ***	2.067 ***		
Chongqing	2.443 ***	2.458 ***		
Sichuan	2.466 ***	2.493 ***		
Guizhou	1.662 ***	1.701 ***		
Yunnan	2.603 ***	2.632 ***		
Tibet	0.918 **	1.044 **		
Shaanxi	2.547 ***	2.548 ***		
Gansu	2.773 ***	2.840 ***		
Qinghai	3.089 ***	3.089 ***		
Ningxia	4.140 ***	4.157 ***		
Xinjiang	3.429 ***	3.441 ***		
Turning Point (*ypc*)	12.456	12.457	10.872	10.842
Cross-sections	31	31	31	31
Periods	2004-2019	2004-2019	2013-2019	2013-2019
Total observations	496	496	217	217

Note: ***, **, and * denote statistical significance at 99, 95 and 90 percent level, respectively.
Sources: Author’s estimation

Table 7 Estimation Results: Household COD (*codh*)

Estimation Methodology	(i) OLS	(ii) PPML	(iii) OLS	(iv) PPML
ypc	3.461 ***	3.518 ***	5.497 ***	5.615 *
	(5.815)	(5.254)	(8.746)	(1.949)
ypc^2	-0.151 ***	-0.155 ***	-0.259 ***	-0.262 **
	(-4.731)	(-4.222)	(-8.681)	(-1.969)
urb			0.012 *	0.009 **
			(2.357)	(2.123)
edu			-0.615 ***	-0.605 ***
			(-21.443)	(-8.886)
dummy for fixed effect				
Tianjin	0.396 ***	0.380 ***		
Hebei	0.203	0.186		
Shanxi	0.524 ***	0.500 **		
Inner Mongolia	0.391 ***	0.363 **		
Liaoning	0.597 ***	0.573 ***		
Jilin	0.734 ***	0.702 ***		
Heilongjiang	0.969 ***	0.945 ***		
Shanghai	0.512 ***	0.503 ***		
Jiangsu	0.571 ***	0.570 ***		
Zhejiang	0.295 ***	0.289 ***		
Anhui	0.721 ***	0.702 ***		
Fujian	0.789 ***	0.783 ***		
Jiangxi	1.018 ***	0.995 ***		
Shandong	0.107	0.095		
Henan	0.218	0.198		
Hubei	0.812 ***	0.794 ***		
Hunan	0.940 ***	0.915 ***		
Guangdong	0.648 ***	0.645 ***		
Guangxi	1.115 ***	1.090 ***		
Hainan	1.017 ***	0.992 ***		
Chongqing	0.276 *	0.241		
Sichuan	0.731 ***	0.705 ***		
Guizhou	0.817 ***	0.785 ***		
Yunnan	0.438 **	0.405 *		
Tibet	0.795 ***	0.774 ***		
Shaanxi	0.414 **	0.389 **		
Gansu	0.530 **	0.493 **		
Qinghai	0.746 ***	0.720 ***		
Ningxia	0.312 *	0.298		
Xinjiang	0.639 ***	0.628 ***		
Turning Point (*ypc*)	11.452	11.356	10.612	10.713
Cross-sections	31	31	31	31
Periods	2004-2019	2004-2019	2013-2019	2013-2019
Total observations	496	496	217	217

Note: ***, **, and * denote statistical significance at 99, 95 and 90 percent level, respectively.
Sources: Author's estimation

Table 8 Estimation Results: Industrial Ammonia Nitrogen (*anti*)

Estimation Methodology	(i) OLS	(ii) PPML	(iii) OLS	(iv) PPML
ypc	4.038 ***	6.935 ***	17.671 **	21.456 **
	(2.647)	(3.318)	(2.109)	(2.383)
ypc^2	-0.178 **	-0.317 ***	-0.811 **	-0.989 **
	(-2.177)	(-2.804)	(-2.091)	(-2.375)
ind			0.023 **	0.024 ***
			(2.549)	(2.972)
edu			-1.098 ***	-1.114 ***
			(-6.128)	(-6.737)
Dummy for fixed effect				
Tianjin	2.283 ***	2.172 ***		
Hebei	2.556 ***	2.484 ***		
Shanxi	2.645 ***	2.570 ***		
Inner Mongolia	2.891 ***	2.906 ***		
Liaoning	2.473 ***	2.446 ***		
Jilin	2.366 ***	2.425 ***		
Heilongjiang	2.455 ***	2.459 ***		
Shanghai	1.631 ***	1.809 ***		
Jiangsu	2.546 ***	2.688 ***		
Zhejiang	2.515 ***	2.469 ***		
Anhui	2.432 ***	2.418 ***		
Fujian	2.241 ***	2.270 ***		
Jiangxi	2.707 ***	2.803 ***		
Shandong	2.148 ***	2.155 ***		
Henan	2.357 ***	2.260 ***		
Hubei	2.638 ***	2.584 ***		
Hunan	3.151 ***	3.142 ***		
Guangdong	1.726 ***	1.778 ***		
Guangxi	2.945 ***	2.929 ***		
Hainan	1.709 ***	1.811 ***		
Chongqing	2.374 ***	2.351 ***		
Sichuan	2.169 ***	2.198 ***		
Guizhou	1.664 ***	1.791 ***		
Yunnan	1.862 ***	1.926 ***		
Tibet	-0.336	0.108		
Shaanxi	2.168 ***	2.151 ***		
Gansu	3.257 ***	3.223 ***		
Qinghai	2.716 ***	2.757 ***		
Ningxia	4.052 ***	4.037 ***		
Xinjiang	2.999 ***	3.039 ***		
Turning Point (*ypc*)	11.327	10.922	10.891	10.844
Cross-sections	31	31	31	31
Periods	2004-2019	2004-2019	2013-2019	2013-2019
Total observations	496	496	217	217

Note: *** and ** denote statistical significance at 99 and 95 percent level, respectively.
Sources: Author's estimation

Table 9 Estimation Results: Household Ammonia Nitrogen (*anth*)

Estimation Methodology	(i) OLS	(ii) PPML	(iii) OLS	(iv) PPML
ypc	5.780 ***	6.078 ***	8.284 **	8.609 **
	(8.026)	(7.475)	(3.111)	(1.998)
ypc^2	-0.256 ***	-0.270 ***	-0.398 **	-0.413 **
	(-6.621)	(-6.343)	(-3.088)	(-2.058)
ind			0.026 **	0.026 ***
			(2.954)	(3.713)
edu			-1.054 ***	-1.056 ***
			(-19.299)	(-12.278)
Dummy for fixed effect				
Tianjin	0.381 ***	0.361 **		
Hebei	0.486 **	0.521 **		
Shanxi	0.874 ***	0.900 ***		
Inner Mongolia	0.716 ***	0.702 ***		
Liaoning	0.951 ***	0.957 ***		
Jilin	0.964 ***	0.973 ***		
Heilongjiang	1.191 ***	1.219 ***		
Shanghai	0.896 ***	0.922 ***		
Jiangsu	0.562 ***	0.596 ***		
Zhejiang	0.334 ***	0.354 **		
Anhui	0.765 ***	0.794 ***		
Fujian	0.764 ***	0.790 ***		
Jiangxi	1.014 ***	1.052 ***		
Shandong	0.378 **	0.400 **		
Henan	0.530 **	0.557 **		
Hubei	0.939 ***	0.968 ***		
Hunan	1.047 ***	1.078 ***		
Guangdong	0.784 ***	0.811 ***		
Guangxi	1.100 ***	1.140 ***		
Hainan	1.127 ***	1.159 ***		
Chongqing	0.534 ***	0.533 **		
Sichuan	0.828 ***	0.864 ***		
Guizhou	1.022 ***	1.073 ***		
Yunnan	0.613 **	0.641 **		
Tibet	0.992 ***	1.043 ***		
Shaanxi	0.654 ***	0.675 ***		
Gansu	0.836 ***	0.862 ***		
Qinghai	1.219 ***	1.253 ***		
Ningxia	0.881 ***	0.920 ***		
Xinjiang	1.098 ***	1.152 ***		
Turning Point (*ypc*)	11.294	11.256	10.412	10.435
Cross-sections	31	31	31	31
Periods	2004-2019	2004-2019	2013-2019	2013-2019
Total observations	496	496	217	217

Note: *** and ** denote statistical significance at 99 and 95 percent level, respectively.
Sources: Author's estimation

Table 10 Provincial Pollutions and Pollution-Control Capacity (COD)

cod	fixed effect		*edu*	(c) - Benchmark	(d) × -0.943	(d) × -0.605	(e) / (a)	(f) / (b)
	codi	*codh*			*codi*	*codh*	*codi*	*codh*
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Tianjin	1.825	0.380	8.982	0.080	-0.075	-0.048	-0.041	-0.127
Hebei	2.468	-	8.225	-0.677	0.639	-	0.259	-
Shanxi	2.543	-	8.295	-0.607	0.573	-	0.225	-
Inner Mongolia	2.970	-	8.077	-0.825	0.778	-	0.262	-
Liaoning	2.676	0.573	8.459	-0.444	0.418	0.268	0.156	0.468
Jilin	2.924	0.702	8.447	-0.455	0.429	0.275	0.147	0.392
Heilongjiang	2.680	0.945	8.373	-0.529	0.499	0.320	0.186	0.339
Shanghai	1.381	0.503	8.594	-0.309	0.291	0.187	0.211	0.371
Jiangsu	2.603	0.570	8.447	-0.455	0.429	0.275	0.165	0.482
Zhejiang	2.630	0.289	8.213	-0.690	0.651	0.417	0.247	1.443
Anhui	2.276	0.702	8.147	-0.755	0.712	0.457	0.313	0.650
Fujian	2.298	0.783	8.184	-0.719	0.678	0.435	0.295	0.555
Jiangxi	2.775	0.995	8.370	-0.532	0.502	0.322	0.181	0.323
Shandong	2.227	-	8.285	-0.618	0.583	-	0.262	-
Henan	2.262	-	8.149	-0.753	0.710	-	0.314	-
Hubei	2.316	0.794	8.559	-0.343	0.324	0.207	0.140	0.261
Hunan	2.721	0.915	8.212	-0.691	0.651	0.418	0.239	0.456
Guangdong	2.178	0.645	7.980	-0.922	0.870	0.558	0.399	0.865
Guangxi	3.419	1.090	7.878	-1.025	0.967	0.620	0.283	0.568
Hainan	2.067	0.992	8.053	-0.849	0.801	0.513	0.388	0.518
Chongqing	2.458	-	8.286	-0.616	0.581	-	0.236	-
Sichuan	2.493	0.705	8.019	-0.884	0.834	0.534	0.334	0.757
Guizhou	1.701	0.785	7.638	-1.265	1.193	0.765	0.701	0.975
Yunnan	2.632	-	7.651	-1.251	1.180	-	0.448	-
Tibet	-	0.774	7.609	-1.294	-	0.782	-	1.011
Shaanxi	2.548	-	8.658	-0.244	0.230	-	0.090	-
Gansu	2.840	-	8.097	-0.805	0.759	-	0.267	-
Qinghai	3.089	0.720	7.569	-1.334	1.258	0.806	0.407	1.120
Ningxia	4.157	-	7.911	-0.992	0.936	-	0.225	-
Xinjiang	3.441	0.628	7.839	-1.064	1.003	0.643	0.292	1.024

Sources: Author’s estimation

Table 11 Provincial Pollutions and Pollution-Control Capacity (Ammonia Nitrogen)

ant	fixed effect		*edu*	(c) - Benchmark	(d) × -1.114	(d) × -1.056	(e) / (a)	(f) / (b)
	anti	*anth*			*anti*	*anth*	*anti*	*anth*
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Tianjin	2.172	-	8.982	0.080	-0.089	-	-0.041	-
Hebei	2.484	-	8.225	-0.677	0.755	-	0.304	-
Shanxi	2.570	0.900	8.295	-0.607	0.677	0.641	0.263	0.713
Inner Mongolia	2.906	0.702	8.077	-0.825	0.919	0.872	0.316	1.242
Liaoning	2.446	0.957	8.459	-0.444	0.494	0.469	0.202	0.490
Jilin	2.425	0.973	8.447	-0.455	0.507	0.481	0.209	0.494
Heilongjiang	2.459	1.219	8.373	-0.529	0.590	0.559	0.240	0.459
Shanghai	1.809	0.922	8.594	-0.309	0.344	0.326	0.190	0.354
Jiangsu	2.688	0.596	8.447	-0.455	0.507	0.481	0.189	0.806
Zhejiang	2.469	-	8.213	-0.690	0.769	-	0.311	-
Anhui	2.418	0.794	8.147	-0.755	0.841	0.798	0.348	1.005
Fujian	2.270	0.790	8.184	-0.719	0.801	0.759	0.353	0.961
Jiangxi	2.803	1.052	8.370	-0.532	0.593	0.562	0.212	0.534
Shandong	2.155	-	8.285	-0.618	0.688	-	0.319	-
Henan	2.260	-	8.149	-0.753	0.839	-	0.371	-
Hubei	2.584	0.968	8.559	-0.343	0.382	0.362	0.148	0.374
Hunan	3.142	1.078	8.212	-0.691	0.769	0.730	0.245	0.677
Guangdong	1.778	0.811	7.980	-0.922	1.028	0.974	0.578	1.201
Guangxi	2.929	1.140	7.878	-1.025	1.142	1.083	0.390	0.949
Hainan	1.811	1.159	8.053	-0.849	0.946	0.897	0.522	0.774
Chongqing	2.351	-	8.286	-0.616	0.686	-	0.292	-
Sichuan	2.198	0.864	8.019	-0.884	0.985	0.934	0.448	1.080
Guizhou	1.791	1.073	7.638	-1.265	1.409	1.336	0.787	1.245
Yunnan	1.926	-	7.651	-1.251	1.394	-	0.724	-
Tibet	-	1.043	7.609	-1.294	-	1.367	-	1.310
Shaanxi	2.151	0.675	8.658	-0.244	0.272	0.258	0.127	0.382
Gansu	3.223	0.862	8.097	-0.805	0.897	0.851	0.278	0.987
Qinghai	2.757	1.253	7.569	-1.334	1.486	1.409	0.539	1.125
Ningxia	4.037	0.920	7.911	-0.992	1.105	1.048	0.274	1.138
Xinjiang	3.039	1.152	7.839	-1.064	1.185	1.124	0.390	0.975

Sources: Author's estimation