Nitrogen Oxide Emission, Economic Growth and Urbanization in China: a Spatial Econometric Analysis

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Abstract. This research studies the nexus of nitrogen oxide emissions and economic development/urbanization. Under the environmental Kuznets curve (EKC) hypothesis, we apply the analysis technique of spatial panel data in the STIRPAT framework, and thus obtain the estimated impacts of income/urbanization on nitrogen oxide emission systematically. The empirical findings suggest that spatial dependence on nitrogen oxide emission distribution exist at provincial level, and the inverse N-shape EKC describes both income-nitrogen oxide and urbanization-nitrogen oxide nexuses. In addition, some well-directed policy advices are made to reduce the nitrogen oxide emission in future.

Keywords: Nitrogen oxide emission; Urbanization; Sustainable development; EKC; Spatial effects

1. Introduction
The relationship between economic development and environmental quality of the literature is extensive in the field of environmental economics. This empirical study rely on the Environmental Kuznets Curve (EKC) hypothesis carried out by Grossman and Krueger [1] because its’ expanded form has the potential to be a policy tool for sustainable development [2].

The studies of the relationship between nitrogen oxide emission and socioeconomic factors have explored through quantitative empirical approaches in the context of China, even though such empirical analyses are sorely urgent. Such analyses can shed some new light on the driving forces and precise regularities for the pollutants emission level and the estimated parameter and function could be very helpful for policy makers to implement suitable policies for precise emission reduction. Brajer, et al. [3] carried out the sole related study through panel data. The spatial dependence is a problem in many panel data sets in which the individuals of subject are not sampled in random. In reality, an observation in a cross-sectional sample is always related to some other observations from the same sample [4]. Anselin and Griffith [5] illustrated this phenomenon as the existence of a relation between what occurs at one spot in space and what occurs somewhere else, which violates the pre-assumption for standard regression analysis: the independence among sampled observations. According to recent studies on air pollution, air pollutants of China show a spatially correlated pattern [6]. For the research on EKC, regional samples located nearby may have interactions caused by spillovers of economic factors and pollutant emission regulations [7].

The objectives of this paper are to estimate the impacts of income/urbanization on nitrogen oxide emission systematically. Comparing with previous researches, this paper mainly contributes to
literature in these aspects. Firstly, we investigate the relationship between nitrogen oxide emission and economic growth/urbanization. As far as we know, this research is the empirical estimation for the socioeconomic influential factors on nitrogen oxide emission in China within EKC and STIRPAT framework. Secondly, the proper spatial econometric tools are applied for the empirical analysis so that the spatial dependence of nitrogen oxide emission could be taken into account, then the biased estimators caused by omitting spatial effects could be avoided. No prior quantitative analysis on nexus of socioeconomic factors and nitrogen oxide emission has utilized spatial econometric tools. Thirdly, since the finally adopted spatial Durbin model (SDM) contains the spatially lagged dependent variable as the explanatory variable, we rectify the previous way of calculating the turning points in some EKC studies that has utilized spatial econometric approach.

2. The Framework and Methodology

2.1. EKC Hypothesis

EKC is originally an empirical hypothesis that characterizes an inversely U-shaped curve for the relationship between environmental quality and the economic development: Various indices of environment degenerate with economic growth until reaching a threshold after which the environment deterioration starts to come down [1]. Generally, the considered model for the EKC is a polynomial function type as follows:

$$Y = \alpha + \beta_1X + \beta_2X^2 + \beta_3X^3 + \beta_4Z + \varepsilon. \quad (1)$$

Here $Y$ represents the indices of environmental degradation while $X$ refers to economic development level, usually measured by per capita GDP and $Z$ are other influential factors of environment. The polynomial function form of EKC offers an adequate tool for us to estimate nonlinear relationship between economic growth/urbanization and pollutants emission.

2.2. STIRPAT Model

We use the STIRPAT model as our theoretical foundation to test Environmental Kuznets Curve existence for nitrogen oxide emission as related to affluence. York, et al. [8] refined the stochastic version of IPAT known as STIRPAT, expressed by

$$I_i = \alpha P_i^b A_i^c T_i^d \varepsilon_i \quad (2)$$

Here $I$ represent environmental impact. $P, A$ and $T$ respectively indicates human activities: population, affluence and technological influences (per unit of economic activity). $\alpha, b, c, d$ are coefficients to be estimated. $\varepsilon$ is the error term. Indicated by the subscript $i$, quantities of $I, P, A, T$ and $\varepsilon$ vary across observations. Its regression form for estimation and hypothesis test is carried out by logarithmic transformation of the variables in Eq. (3). In this case, the coefficients $b, c, d$ stands for the Ecological Elasticity (EE) that is defined as the proportion of change on environmental impacts due to its significant determinants. Since being highly flexible and amenable to various functional forms, a quadratic or higher terms of affluence can enter STIRPAT equation [8]. Therefore, one can extend the Eq. (3) to Eq. (4) and (5) for research purpose:

$$\ln I = \alpha + b \ln A + c \ln P + d \ln T + e \quad (3)$$

$$\ln I = \alpha + b_1 \ln A + b_2 (\ln A)^2 + c \ln P + d \ln T + e \quad (4)$$

$$\ln I = \alpha + b_1 \ln A + b_2 (\ln A)^2 + b_3 (\ln A)^3 + c \ln P + d \ln T + e \quad (5)$$

According to our study purpose and modernization theories, per capita GDP and the percentage of urban population are used as the proxies of affluence; energy intensity is explained as the indicator of technology impacts. Environmental impact refers to pollutants emission amount.
2.3. **Spatial Panel Data Model**

Before the statistics of model specification is carried out, three currently prevailing spatial panel model were considered: the spatial Durbin model (SDM), spatial lag model (SLM) and the spatial error model (SEM). SDM model, SLM model and SEM model can be written in matrix form as

\[
Y = \delta (I_T \otimes W_N) Y + X \beta + \gamma (I_T \otimes W_N) X + (\tau_T \otimes I_N) \mu + (I_T \otimes \tau_N) \eta + u, \quad u \sim N(0, \sigma^2 I_{NT}) \tag{6}
\]

\[
Y = \delta (I_T \otimes W_N) Y + X \beta + (\tau_T \otimes I_N) \mu + (I_T \otimes \tau_N) \eta + u, \quad u \sim N(0, \sigma^2 I_{NT}) \tag{7}
\]

\[
Y = X \beta + (\tau_T \otimes I_N) \mu + (\tau_N \otimes I_T) \eta + u, \quad u \sim N(0, \sigma^2 I_{NT}) \tag{8}
\]

The dependent variable \(Y\) is substantively an \(NT \times 1\) vector of nitrogen oxide emission amount at provincial level. \(X\) is the independent variable composed of an \(NK \times K\) matrix corresponding to independent variables of equation (1) to (3). \(\mu\) controls for the unknown individual effects of the 30 provinces while \(\eta\) controls for the time effects, the constant whole trend of nitrogen oxide emission levels.

\(\delta\) is the spatial autocorrelation and \(\rho\) is the spatial autocorrelation exists in the error term \(\varepsilon\). Both of them reflects the strength of the characteristics’ spatial autocorrelation that refers to the average impacts of observations from the neighboring ones. Parameter \(\beta\) indicates the responsiveness of the dependent variable to a change in the independent variables. \(\gamma\) is the coefficient showing the spillover effects of the independent variables on the dependent variable. \(\tau_N\) is a column vectors of all ones in the length of \(N\) and \(\tau_T\) represents a column vectors of all ones in the length of \(T\). \(I_N\) and \(I_T\) are \(N \times N\) and \(T \times T\) dimension identity matrixes respectively.

\(W_N\) is another \(N \times N\) weight matrix in which the elements represent the contiguity of provinces: the element on the \(i\)th row and \(j\)th column equals 1 if the \(i\)th province and \(j\)th province have a mutual border, otherwise it equals 0. Before applied to the econometric model, \(W_N\) was row normalized. Thus, its elements are between 0 and 1 and should be interpreted as the averaging values between local and neighbor regions [9]. To capture the spatial autocorrelation and spillover effects in the model with panel data sets, the weight matrix is constructed as \(W_{NT} = I_T \otimes W_N\) where \(\otimes\) indicates the Kronecker product.

3. **Data and Variables**

This paper investigates the nexus of income/urbanization and nitrogen oxide emission through a balanced panel dataset of 30 provinces in China, spanning from 2010-2015 (Data of Tibet autonomous, Taiwan province, Hong Kong and Marco special administrative regions are not available for regression analysis). The data on 2010-2015 nitrogen oxide emission, income (per capita GDP), urban population, and total population all originate from the National Bureau of Statistics of China. The nitrogen oxide emission amount in 2010 is obtained from the webpage of Ministry of Environmental Protection of the People’s Republic of China. Energy consumption (kg of coal equivalent) data is collected from the China Energy Statistical Yearbook. The per capita GDP data is converted into 2003 constant price. Table 1 lists all the definition and descriptive statistics of the variables. All variables are processed with logarithm in case of data’s large changing range and the potential estimation bias caused by the ignorance of other trivial factors.
### Table 1. Definition and descriptive statistics of variables

| Variable | Definition | Mean   | Std. Dev | Min  | Max  |
|----------|------------|--------|----------|------|------|
| log I    | Nitrogen oxide emissions (ton) in natural logarithm | 13.292 | 0.703    | 11.2 | 14.4 |
| log GDP  | Real GDP per capita (RMB) in natural logarithm (in 2003 constant price) | 10.332 | 0.560    | 9.01 | 11.7 |
| log UR   | Percentage of urban population in the total population (%) in natural logarithm | 3.9793 | 0.221    | 3.52 | 4.49 |
| log P    | Population in natural logarithm | 8.188  | 0.739    | 6.33 | 9.29 |
| log EI   | Energy intensity (kg of coal equivalent/10000 GDP) | 7.052  | 0.486    | 6.08 | 8.26 |

### 4. Empirical Results and Discussion

#### 4.1. Spatial Distribution of Nitrogen Oxide in China

We firstly explore the possible existence of the nitrogen oxide emission’s spatial autocorrelation (geographic relationship) during the data interval with Global Moran’s I statistics. All the empirical results in this study are generated through Matlab and ArcGIS. Table 2 illustrates the Global Moran’s I of nitrogen oxide emission from 2010 to 2015.

| Year | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|------|------|------|------|------|------|------|
| Moran’s I | 0.212 | 0.190 | 0.186 | 0.173 | 0.173 | 0.182 |
| Z-Score | 2.327 | 2.121 | 2.080 | 1.959 | 1.963 | 2.052 |
| P-value | 0.020 | 0.034 | 0.038 | 0.050 | 0.050 | 0.040 |

Note: For the consistency with the regression analysis, the spatial weight matrix W for the Moran’s I test was also row normalized.

Clearly, the Z scores and P values clearly states that the spatial autocorrelation effects in nitrogen oxide emission are significant at 5% level over 6 years. The positive Moran’s I values indicates that the areas with high nitrogen oxide emission (provinces in the high-high groups) tend to locate together, so do the low emission areas (provinces in the low-low groups). During 2010-2015, decreased Global Moran’s I suggests a declining tendency of agglomeration on nitrogen oxide emission in China.

In order to visualize and depict the spatial clustering pattern of nitrogen oxide emission at provincial level more intuitively, Fig. 1 demonstrates the emission distribution in provinces during 2010-2015:

![Figure 1. Annual nitrogen oxide emission distribution.](image)

As shown above, the high-high (HH) cluster is mostly located in the east and north regions of China and can be classified into two categories. One category is located in areas with dense population, high urbanization and developed economy, mostly eastern parts of China (Henan, Shandong, Jiangsu, Shanghai, Zhejiang etc.). The other category located in the areas where heavily rely on heavy and
mining industry in terms of economy, especially the Northeastern regions (Jilin, Liaoning, Hebei, Shanxi provinces etc.). For the low-low (LL) cluster regions of nitrogen oxide emission, they are mainly located in areas of undeveloped and low-dense population, particularly north, middle and south parts in China (Gansu, Ningxia, Shanxi, Chongqing, Guizhou, Guangxi, Yunnan etc.)

To sum up, the geographical agglomeration of nitrogen oxide emission is statistically significant during our study period and the discharge of pollutants seemingly correlate with economic development and population effects. Specifically, the provinces/cities with developed economy and large population are generally characterized by high nitrogen oxide emissions and vice versa. This phenomenon is corresponding to the STIRPAT model’s theory. We are about to explore the specific quantitative relationship between the nitrogen oxide emission and its driving forces in the next sub-section.

**4.2. Econometric Results and Analysis**

**4.2.1. Non-spatial Panel Data Results.** To determine the most appropriate model specification, this part firstly apply the non-spatial panel model to calculate classical LM and robust LM statistics for model specification (SLX or SEM). If the (robust) LM tests reject the non-spatial models, we further determine which spatial panel model is the most appropriate one. Once the most appropriate panel data model is determined, we estimate the driving forces’ direct and indirect marginal influences on the nitrogen oxide’s emission, and then make explanation and discussion according to these results.

**Table 3.** Non-spatial panel model results.

|          | GDP-NOx |     | URB-NOx |     |
|----------|---------|-----|---------|-----|
|          | M1      | M2  | M3      | M1  | M2  | M3   |
| LM test no spatial lag | 6.3766** | 7.1485 | 10.4617* | 15.8132* | 15.3210* | 16.8318* |
| robust LM test no spatial lag | 0.0136 | 0.2819 | 0.0079 | 2.2739 | 2.7814* | 1.1501 |
| LM test no spatial error | 8.0278*** | 7.7327 | 13.1395* | 13.5398* | 12.5722* | 15.9735* |
| robust LM test no spatial error | 1.6647 | 0.8661 | 2.6858 | 0.0005 | 0.0326 | 0.2917 |
| LR-test spatial fixed effects | 749.78*** | 740.04 | 747.044* | 713.583* | 715.3909 | 732.152* |
| LR-test time fixed effects | 186.77*** | 175.43 | 179.243* | 154.725* | 155.5018 | 157.157* |
| N | 180 | 180 | 180 | 180 | 180 | 180 |
| R-bar-squared | 0.4877 | 0.4561 | 0.4253 | 0.3268 | 0.3291 | 0.3268 |

Note: M1, M2 and M3 refers to estimated results of model (5), (4) and (3). Parameter estimates are omitted due to the limitation of space, readers can request from the corresponding author if interested. Numbers in the parentheses are t-stat. *: P<0.1; **: P<0.05; ***: P<0.01.

Table 3 depicts the results of non-spatial regression models that control for both spatial fixed and time fixed effects (two-way fixed effects) in two fields: GDP- nitrogen oxide and URB- nitrogen oxide. As we can see, the LR (Likelihood ratio) test results in Table 3 overwhelmingly rejects the null hypothesis of spatial fixed effects as well as time-period fixed effects. Therefore, the two way fixed effects are preferred over spatial/time fixed effects in both GDP- nitrogen oxide and Urbanization-nitrogen oxide models.

LM tests reject the null hypothesis of no spatially lagged dependent variable and no spatially auto-correlated error term significantly for GDP- nitrogen oxide and Urbanization-nitrogen oxide models, however the robust LM tests do not. This gives very ambiguous evidence on spatial model
selection. The final determination of which spatial panel model fits our data best needs to consider the LR and Wald tests results. We illustrate these tests results in the following section.

4.2.2. Spatial Panel Data Results. Now we turn to the spatial econometric analysis. Tables 4 and 5 report the estimated results of SDM model that control for both spatial and time effects. Two fields (fixed effects estimates; random effects estimates) with triple columns contain these results in each table. In Table 4, the three columns in each field list and compare the results of three model specifications: the model with cubic term of GDP (M1), the model with quadratic term of GDP (M2) and the model with the linear term of GDP (M3). In a similar way, Table 5 compares the estimates results of the models with urbanization’s cubic quadratic and linear terms.

Table 4. Spatial panel model results (GDP as the indicator of affluence)

|                | fixed effects estimates | random effects estimates |
|----------------|-------------------------|--------------------------|
|                | M1          | M2          | M3          | M1          | M2          | M3          |
| δ              | 0.376***   | 0.350***   | 0.426***   | 0.313***   | 0.318***   | 0.425***   |
| (4.536)        | (4.120)     | (5.291)     |             | (3.731)     | (3.810)     | (5.614)     |
| θ              | 0.043***   | 0.045***   | 0.051***   |             |             |             |
| (5.481)        | (5.481)     | (5.482)     |             |             |             |             |
| Hausman        | 26.9213*** | 40.1047*** | 75.0638*** |             |             |             |
| N              | 180         | 180         | 180         | 180         | 180         | 180         |
| Rbar-squared   | 0.5397      | 0.5163      | 0.4263      | 0.7208      | 0.7131      | 0.7429      |
| WaldSpatial_lag| 16.0228*** | 13.3801*** | 3.3914      | 15.3446*** | 15.3468*** | 17.7147*** |
| LRSpatial_lag  | 16.9816*** | 15.3136*** | 2.7463      | 13.1342*** | 13.5632*** | 15.6328*** |
| WaldSpatial_error | 12.5273*** | 11.9753*** | 1.2424      | 8.5388      | 8.9657     | 5.5823      |
| LRSpatial_error | 15.2257*** | 14.8212*** | 1.3204      | 12.8468*** | 13.0801*** | 9.6568**   |

Note: M1, M2 and M3 refer to estimated results of model (5), (4) and (3). Parameter estimates are omitted due to the limitation of space, readers can request from the corresponding author if interested. Numbers in the parentheses are t-stat. *: P<0.1; **: P<0.05; ***: P<0.01.

Table 5. Spatial panel model results (urbanization as the indicator of affluence)

|                | spatial fixed effects | spatial random effects |
|----------------|-----------------------|------------------------|
|                | M1          | M2          | M3          | M1          | M2          | M3          |
| δ              | 0.343***   | 0.328***   | 0.469***   | 0.444***   | 0.410***   | 0.430***   |
| (4.068)        | (3.827)     | (6.094)     |             | (5.975)     | (5.318)     | (5.695)     |
| θ              | 0.044***   | 0.047***   | 0.050***   |             |             |             |
| (5.481)        | (5.481)     | (5.482)     |             |             |             |             |
| Hausman        | 26.426***  | 32.269***  | 22.014***  |             |             |             |
| N              | 180         | 180         | 180         | 180         | 180         | 180         |
| Rbar-squared   | 0.512       | 0.485       | 0.337       | 0.632       | 0.657       | 0.719       |
| WaldSpatial_lag| 35.5964*** | 26.9514*** | 4.1150      | 27.9652*** | 21.0943*** | 18.6102*** |
| LRSpatial_lag  | 39.2325*** | 30.8808*** | 4.5914      | 24.5783*** | 19.0932*** | 16.1401*** |
| WaldSpatial_error | 35.2548*** | 28.3682*** | 5.1504      | 13.3523*** | 9.2156     | 5.7002     |
| LRSpatial_error | 39.5535*** | 32.8361*** | 6.1206      | 16.9972*** | 12.0617*** | 8.6987**   |

Note: M1, M2 and M3 refers to estimated results of model (5), (4) and (3). Parameter estimates are omitted due to the limitation of space, readers can request from the corresponding author if interested. Numbers in the parentheses are t-stat. *: P<0.1; **: P<0.05; ***: P<0.01.

In Tables 4 and 5, Hausman tests (against fixed effects) under three model specifications all reject the null hypothesis: the unobserved individual effects in provinces are uncorrelated with the independent variables in models. Thus, we only focus on the results of GDP- nitrogen oxide and urbanization- nitrogen oxide models with two-way fixed effects in the following discussion.

When including two-way fixed effects in M1 and M2, all the χ² statistics of all LR and Wald tests of GDP- nitrogen oxide and urbanization- nitrogen oxide models reject both hypothesis: H₀: γ=0 and H₀: γ+δβ=0, in other words: SDM model cannot be simplified to either SLM or SEM model if one of
the polynomial models is adopted. On the other hand, the Wald and LR tests in M3 (Tables 4 and 5) do not reject their null hypothesis. It is noteworthy that the independent variables’ direct and indirect (spillover) effects in SDM model need to be calculated by Eq. (9) and the estimate results are reported in Tables 6 and 7. Eq. (9) is derived from Eq. (10), Eq. (10) from Eq. (6). The reciprocal term \((I - \delta W)^{-1}\) is calculated by Eq. (11). All the parameters that need to be brought into Eq. (9) and (11) are already estimated in the process of generating results in Tables 4 and 5.

\[ Y_i = (I - \delta W)^{-1}(\mu + \eta) + (I - \delta W)^{-1}(X_i\beta + \gamma W X_i \eta) + (I - \delta W)^{-1}e_i \]  

\[ (9) \]

\[ (10) \]

### Table 6. Direct and spillover effects estimation

| Variable | M1 Direct | M1 Spillover | M2 Direct | M2 Spillover | M3 Direct | M3 Spillover |
|----------|-----------|-------------|-----------|-------------|-----------|-------------|
| logGDP   | -14.348** | 11.315      | 2.266***  | 2.092*       | 0.702***  | -0.167      |
|          | (-2.567)  | (0.594)     | (4.460)   | (1.851)      | (5.056)   | (-0.496)    |
| (logGDP)^2| 1.535***  | -1.136      | -0.098*** | -0.174**     |           |             |
|          | (2.825)   | (-0.601)    | (-3.568)  | (-2.393)     |           |             |
| (logGDP)^3| -0.053*** | 0.033       |           |             |           |             |
|          | (-3.038)  | (0.534)     |           |             |           |             |
| logPOP   | 0.332      | 0.803       | -0.152    | 0.855        | -0.903*** | -0.280      |
|          | (0.815)   | (0.805)     | (-0.398)  | (0.978)      | (-2.739)  | (-0.326)    |
| log EI   | 0.296**    | 0.365*      | 0.363***  | 0.294*       | 0.470***  | 0.187       |
|          | (4.232)   | (1.889)     | (5.231)   | (1.592)      | (7.109)   | (0.908)     |

Note: Numbers in the parentheses are t-stat. *: \(P<0.1\); **: \(P<0.05\); ***: \(P<0.01\); the direct and spillover effects of linear, square and cubic terms of logGDP are practically meaningless.

### Table 7. Direct and spillover effects estimation

| Variable  | M1 Direct | M1 Spillover | M2 Direct | M2 Spillover | M3 Direct | M3 Spillover |
|-----------|-----------|-------------|-----------|-------------|-----------|-------------|
| logURBEN  | -84.518** | 25.497      | 3.354*    | 29.433***   | 0.492**   | -0.361      |
|          | (-1.983)  | (0.189)     | (1.780)   | (4.166)     | (2.633)   | (-0.808)    |
| (logURBEN)^2| 22.565*** | -2.380      | -0.410    | -4.090***   |           |             |
|          | (2.010)   | (-0.068)    | (-1.618)  | (-4.192)    |           |             |
| (logURBEN)^3| -1.965**  | -0.218      |           |             |           |             |
|          | (-2.028)  | (-0.071)    |           |             |           |             |
| logPOP   | -0.407    | -1.230      | -0.488    | -1.402*     | -0.027    | -1.450      |
|          | (-1.347)  | (-1.674)    | (-1.489)  | (-1.780)    | (-0.087)  | (-1.566)    |
| log EI   | 0.239***  | 0.356*      | 0.294***  | 0.344*      | 0.401***  | 0.343       |
|          | (3.323)   | (1.853)     | (4.272)   | (1.878)     | (5.821)   | (1.448)     |

Note: Numbers in the parentheses are t-stat. *: \(P<0.1\); **: \(P<0.05\); ***: \(P<0.01\); the direct and spillover effects of linear, square and cubic terms of logURB are practically meaningless.

The diagonal elements of the partial derivatives matrix in Eq. (9) indicates the direct effects of the \(k\)th explanatory variable and all the off-diagonal elements refer to its spillover effects. Consequently, if \(\gamma=0\) and \(\delta=0\), then spillover effects do not exist. Some prior EKC studies that applied the spatial econometric approaches either mistakenly reported the coefficient estimates as the direct and spillover effects, or avoid to report these effects in the SDM/SLX model [10].
Another issue that has never been correctly discussed is the calculation of the turning points in environmental Kuznets curve estimated by the SDM/SLM. Kang, et al. [10] applied spatial econometric approach and found an inverse-N shaped CO₂ EKC in China. However, they derived the turning points directly from the GDP’s coefficients estimates, which is invalid. In most situations, the EKC function is smooth thus the limit points of EKC function is the turning points. As for the SDM model, its right-hand side Eq. (6) contains the dependent variable, thus one need to firstly derive the Eq. (6) to Eq. (10), and then let the first-order derivative to explanatory variable be zero, so that the turning points of SDM specified EKC could be obtained. When fitting the EKC by SDM model, one needs to apply the direct effects estimated through Eq. (10) for calculating the turning points. Tables 6 and 7 report the direct and spillover effects. Model 1 (M1), Model 2 (M2) and Model 3 (M3) are respectively the GDP- nitrogen oxide/urbanization- nitrogen oxide models with cubic, quadratic and linear terms of GDP/urbanization. Turning attention to the GDP-nitrogen oxide model results, the cubic, quadratic and linear terms of GDP’s direct effects (Table 6, M1) are statistically significant at 5% level. Besides, the greater adjusted R2 and log-likelihood (Table 4, M1) of the cubic model suggests that Model 1 (Table 6) fits the data better than Models 2 and 3 (Table 6) do. The significant effects estimate of energy intensity has the expected signs in Model 1. As we mentioned in section 4.2.2, if we adopt polynomial model, SDM model should not be simplified to SLX or SEM. Therefore, the cubic GDP- nitrogen oxide model is the appropriate specification for the empirical analysis.

The finding shows that the estimated direct and spillover effects (elasticity) of energy intensity are highly significant at the 1% and 10% level respectively and their signs are positive as expected. The effect of 1% growth in local energy intensity will lead to an increase in local nitrogen oxide emission by 0.296%, other conditions hold constant. In other words, the impacts of a 1% growth in local energy intensity will on average cause a 0.365% increase on nitrogen oxide emission in neighbor provinces and vice versa, all else being equal [11]. On the other hand, both the direct and spillover effects of population are not significantly different from zero. The highly significant linear, quadratic and cubic terms of GDP per capita (Table 6, M1) points to an inversely N-shaped EKC for the nitrogen oxide emission and economic growth nexus, which is consistent to the findings in prior China’s SO2 EKC study [6]. Moreover, two turning points of the inverse N-shape trajectory are approximately 2788 (RMB) and 87139 (RMB) . These two turning point are estimated based on the polynomial equation:

\[ \ln NO_2 = -0.053(\ln GDP)^3 + 1.535(\ln GDP)^2 - 14.348 \ln GDP \]

Based on our sample, most of the economic developing provinces/cities (e.g. Guangxi, Xinjiang and Qinghai provinces) are in the upward phase after the first turning point. There exists the general uptrend in nitrogen oxide emission in such areas and the personal incomes in the areas are between these two turning points. On the contrary, several developed cities with GDP per capita over 87139 (RMB) (Beijing, Tianjin and Shanghai) are experiencing the persisting decline in nitrogen oxide emission. None of the per capita GDP in the observations is below 2788 (RMB). The lowest one is 8237 (RMB) found in Guizhou province 2010.

Now we turn to urbanization- nitrogen oxide model results. Similar with the GDP- nitrogen oxide model outcomes, all the polynomial terms of urbanization’s direct effects (Table 7, M1) are statistically significant. Besides, the greater adjusted R2 and log-likelihood (Table 5, M1) of the cubic model suggests that this model has the best explanatory power. Other than that, the energy intensity estimates keep positive, significant and almost unchanged (0.239 and 0.356). Statistically, the population’s direct and spillover effects on emission are still not different from zero. Namely, these results are in consistency with the cubic GDP- nitrogen oxide model results.

Due to the significant linear and polynomial terms of urbanization (Table 7, M1), we infer that there exists an inversely N-shaped EKC for the urbanization- nitrogen oxide nexus, which is somewhat different with a prior study of China’s urbanization and industrial pollution [12]. This is probably because this prior study did not apply the EKC model as the theoretical foundation for empirical
analysis and it applied different pollution indicators. Two turning points of the inverse N-shape trajectory are approximately 35.04% and 56.34% respectively. These two turning point are estimated based on the polynomial equation:

$$\ln NO_2 = -1.965(\ln URB)^2 + 22.365(\ln URB)^2 - 84.518 \ln URB$$

According to our sample interval, the urbanization levels of Beijing, Tianjin, Shanghai and Guangdong, Jiangsu provinces are already over 56.34% at the beginning and their local nitrogen oxide emission indeed experienced downward trends as urbanization proceed in the whole study period. Whereas emission in rest of the provinces in the sample firstly experienced upward trends and then decline after approximately reaching 56.34%.

Unlike the population term, the autoregressive parameters of $\delta$ in the SDM models (Tables 4 and 5) are positive and statistically significant at the 1% level, which further testify the spillover effects of nitrogen oxide emission among the neighboring provinces. Specifically, 1% increase and decrease of local nitrogen oxide emission would lead to about 0.35% corresponding variation in neighbor provinces and vice versa.

5. Conclusion
This paper examines the quantitative relationship between income/urbanization nitrogen oxide emission for China within the EKC hypothesis and STIRPAT framework through regression estimator of spatial panel data. Our results provide evidence suggesting that the relationships between income/urbanization and nitrogen oxide emission shape inverse N curves that are different from the classical inverted U shape EKC at current stage. In general, rapid economic growth and urban sprawl with great nitrogen oxide emissions will not last for a long time in China since most province’s personal income is either approaching or have already crossed the second turning points of per capita GDP and urbanization (87139 RMB, 56.34%). Even though the society’s affluence accumulation could enable government to put more investment on the pollution control and development of new energies to reduce pollutants emission, it is not wise to wait for the reaching of the turning point in the less developed provinces. Because the environmental system cannot withold the pollution influences if the pollution accumulation exceeds the threshold of total nitrogen oxide. It is imperative for both of the central and local governments to implement policies and measures to limit the amount of local nitrogen oxide emission instead of only favor the EKC hypothesis so that economic development and urbanization will benefit the environment.

In this paper, although we tend to have a cautious attitude toward them because there is still some limitation related to them. Given the fact that we applied a relatively short panel of sample in the analysis, the time span of data is limited and do not cover the first turning point of the inversely N shaped KEC. In this regard, further research with longer panel data can enhance the knowledge of the fluctuation at the beginning of the inversely N shaped curve. The average level of urbanization in China is just over 52%, further studies including data of recent years could provide more evidence for the proof of relation between urbanization and emission.

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