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## Dynamics of Environmental Pollution in the Presence of Micro plastics Contamination, Energy Transition, and Demographic Pressure

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### Abstract

*the study aims to investigate the influences of urbanization, investment in technology and innovation, micro-plastic, gross domestic product per capita, foreign direct investment, and urban land area on environmental pollution. The study has applied an econometrical model spatial lag model (SLM), spatial Durbin model (SDM), and spatial error model (SEM) to analyze the data from 2005 to 2023. The results revealed that the effects of urbanization, gross domestic product per capita and micro-plastic are mitigating factors for environmental degradation. There are no observable benefits to reducing carbon emissions from investment in technology and innovation, foreign direct investment. In both interaction and no-interaction scenarios, the upgrading of the urban land area structure has a major knock-on effect on environmental pollution. The study's conclusions advise policymakers to concentrate their efforts on funding green innovation technologies and to slow the flow of people from rural to urban regions by creating employment opportunities in rural areas.*

**Keywords:** *Micro-plastic, Transportation, Urbanization, GDP per capita, investment in technology, spatial lag model, spatial Durbin model*

### 1. Introduction

Over the past 10 years, there has been a correlation between global warming and spring cooling and winter warming. A significant causative aspect of environmental transformation is the growth in CO<sub>2</sub> emissions caused by the excessive use of energy for economic growth. The population of industrial cities is growing quickly due to economic growth, which deteriorates the environment. The percentage of the population that lives in cities is a metric of urbanization, which has a significant influence on global warming (Liu and Han, 2021). To support industrial restructuring, foreign direct investment (FDI), gross domestic product per capita (GDPPC), micro-plastic (MP), investment in technological and innovations (ITC), urbanization (UP), and growth in urban land areas (ULA) are the main factors driving energy consumption sources (ECS), which cause environmental pollution (ENV). Suki et al. (2022) claim that environmental deterioration is a result of investments in new technical advancements since CO<sub>2</sub> emissions increase in line with productivity improvements brought about by technology. FDI has a positive impact on the environment by reducing ecological emissions (Wang and Liu, 2019). Long-run financial development contributes to the reduction of natural corruption and the improvement of ecological quality, while the growth of the population worsens ecological degradation (Adem et al., 2020). There is a significant correlation between environmental pollution and economic factors (Khan and Liu, 2022). Financial growth has a direct impact on the amount of energy consumed, and this energy consumption plays a

significant role in driving the process of globalization, globalization also has consequences for CO<sub>2</sub> emissions (Rahman, 2020). The extension of urban areas has a significant negative impact on air pollution. The negative influence of population extension and land urbanization on provincial CO<sub>2</sub> emissions has been realized in complete indirect instruments (Chen et al., 2022). In instruction to improve the concern of acceptable growth and low-carbon economic growth, the study objectives are to observe the effects of GDPPC, UP, FDI, ULS, MP, and ITC on environmental pollution. The study examines the significance of urbanization, recognizing the being of a non-direct relationship between urbanization, urban land area extension, and an increase in the use of fossil fuels. The study also aims to evaluate the correlation between UP, GDPPC, ITC, and ULS relative to the growth of CO<sub>2</sub> emissions. The study presented the following open-ended queries: What impact does technological advancement have on alterations in the environment? What connections exist between pollution in the environment and urbanization? How does the growth of urban land area react to variations in the climate? What impact does the use of electricity have on pollution in the environment? What effects does foreign direct investment have on the environment? What connection exists between CO<sub>2</sub> emissions and GDP growth per capita? Does the link between carbon dioxide emissions and urbanization exhibit nonlinearity? Does governance cut the carbon dioxide emissions brought on by urbanization? The study examines the direct and indirect effects of urbanization on the nation's environmental quality. Based on statistical data, policy objectives, and existing study and simulations, the study calculates the parameters. This has led to the use of the spatial Durbin model (SDM), spatial error model (SEM), and spatial lag model (SLM) in the study. There are three scenarios with distinct probability distributions for GDP per capita, urbanization, and foreign direct investment, each with a unique urbanization strategy. Validating the method, the data support the association between technological innovations, GDP per capita, micro-plastic, urbanization, and rise in CO<sub>2</sub> emissions. Foreign direct investment and urban land area growth have a strong positive correlation with environmental pollution.

The remainder of the study is organized as: Section 2 describes the literature review; study methodology, data collection sources, and study design have been discussed in Section 3. Section 4 explains the results and discussions. Section 5 concludes the study findings and suggests future study options.

## 2. Literature Review

Lee et. al. (2023) claim that the ability to encourage urbanization and lower CO<sub>2</sub> emissions increases with the level of development in the financial, government, and technological sectors. Ogunbode et. al. (2023) examined that technology innovations and energy consumption were affecting pollution in the metropolises. Awan and Azam (2022) found that the increase in GDP per capita also increases CO<sub>2</sub> emissions. Huang and Hsu (2022) discovered that FDI had a stronger and more significant impact than political risk, the effective corporation tax rate, and the degree of economic growth. Le et al. (2022) looked at the disproportionate effects of environmental degradation and foreign direct investment on the short- and long-run growth of an emerging nation's economy. In African and Asian rising nations, Munir and Ameer (2022) discovered the long- and short-run nonlinear effects of urbanization, trade liberalization, economic growth, and technology on environmental pollution. Information technology investment and green innovation have a significant relationship, according to Wang and Wang (2022) there is a good correlation between the quantity of IT expenditure and the emergence of green patents in Chinese heavy-polluting industries. Investors make judgments on where to place their investments based on court rulings and environmental rules (Sitawati et al., 2022). To reveal the environmental implications of Turkey's urbanization for its sustainable development, Udemba and Keleş (2022) implemented Granger causality estimates, structural breaks, and dynamic autoregressive distributed lag (ARDL)-bound estimations in Turkey. There is a considerable amount of inertia in the growth rates of China's GDP and SO<sub>2</sub> emissions (Yan et al., 2022). The penetration of ICTs is associated with economic development and micro-plastic (Magazzino et al., 2021). Since renewable energy promotes growth, the relevant authorities should support and encourage its usage (Nosheen et al., 2021). According to Gerritsen et al. (2020), FDI inflows, technological innovation, green industrial transformations, environmental legislation, and study and development investment are potential mediators between carbon emissions and Pakistan's reduced carbon

intensity. The micro-plastic is higher in the retail and relaxation administration sectors, as well as in private designs, due to particulate matter air pollution (He et al., 2020). Asian countries must establish plans regarding FDI inflows and the environment to achieve sustainable economic growth and development (Khan and Ozturk, 2020). Monetary strategy changes are crucial for aligning FDI inflows in a more environmentally friendly direction. According to Kong and Khan (2019), there is a clear association between coat let and the development of GDPPC in the modern area, but it only applies in the short term and one direction. According to Nguyen and Moehrle (2019), they used Innovation DNA on US patents, which represent the most advanced market in the world. There is a purposeful categorization of advancements in this field based on patent classes. Phuong (2018) presented compelling statistical support for the general idea that there is an inverse U-shaped relationship between Vietnam's environmental deterioration and per capita income. Zhang and Li (2020) discovered that by fostering economies of scale and the use of non-fossil energy, urbanization lowers carbon emissions. Urbanization studies the nonlinear impact on greenhouse gas emissions, according to discovered that new economic strategies led to decreased CO<sub>2</sub> emissions (Demircan et al., 2021). According to Chen et al. (2020), there could be a relationship between the innovation signal and the transportation sector's CO<sub>2</sub> emissions. its indices of technical innovation had comparable impacts at different intensities, indicating that the collective use of similar technology-based strategies for emission reduction makes sense. According to Niu (2021) analyses done with the fixed-effect model, technological advancements boost the Chinese economy and reduce CO<sub>2</sub> emissions at the same time. CO<sub>2</sub> emissions increase more as a result of urbanization than economic growth (Zhang et al., 2021). China's urban agglomerations are unconnected to the country's overall economic growth (Ma et al., 2019). According to Kazemzadeh (2022), China and India scored lower than Turkey and Hungary in runs of resources and energy efficiency. There is no correlation between China's urban agglomerations and the nation's overall economic growth. Huo et al. (2021) examined the geographical, economic, and demographic consequences of urbanization on carbon emissions.

### **3. Study Methodology**

#### **3.1 Data Collection**

The study has collected the data of study variables such as urban population, urban land area, foreign direct investment, GDP per capita, micro-plastic, investment in technology and CO<sub>2</sub> emissions from 2011 to 2023. The Provincial Statistical Yearbook of China and the National Bureau of Statistics of China database "https://data.stats.gov.cn" were the sources of the data of 28 provinces of China. Data collected at the provincial level in China's Provincial Statistical Yearbook provides information about regional variations within the country.

#### **3.2 Study Design**

The study has applied the geographical panel model consisting of spatial lag model, spatial error model, spatial Durbin model, and spatial panel model to test the data set of study variables. Figure 1 represents the study framework of statistical methods that have been applied to examine the relationships between variables through the utilization of data analysis.

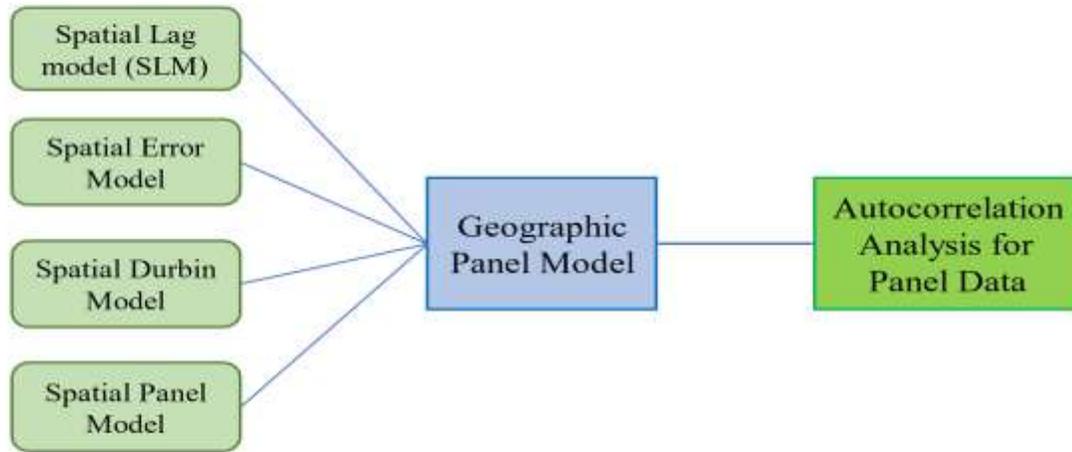


Figure 1. Research Framework of Statistical Models

The study measures the effects of urbanization, urban land area, FDI, GDPPC, and ITC on environmental pollution using different data analysis methods, and the function of dependent and independent variables has been shown in equation 1.

$$ENV = f(ITC, UP, GDPPC, FDI, MP, ULS) \quad (1)$$

Whereas environmental pollution is represented as ‘ENV’, which is a dependent variable. The urban population is denoted as ‘UP’, investment in technology and innovations as ‘ITC’, and ‘EC’ represents the micro-plastic. GDP per capita is presented as ‘GDPPC’, and foreign direct investment is shown as ‘FDI’. The regression equation of the variables is presented in equation 2 as follows:

$$EMV_{it} = \beta_0 + \beta_1 ITC_{it} + \beta_2 MP_{it} + \beta_3 ULS_{it} + \beta_4 GDPPC_{it} + \beta_5 UP_{it} + \beta_6 FDI_{it} + \beta_7 MPS_{it} + \epsilon_{it} \quad (2)$$

The variables in the equation are: "ECS" (energy consumption structure), "i" (province), "t" (year), and "ε" (error factor). The study logarithmically transforms the variables and adjusts Equation 3 to reduce heteroscedasticity.:

$$\ln EMV_{2it} = \beta_0 + \beta_1 \ln ITC_{it} + \beta_2 \ln MP_{it} + \beta_3 \ln ULS_{it} + \beta_4 \ln GDPPC_{it} + \beta_5 \ln UP_{it} + \beta_6 \ln FDI_{it} + \beta_7 \ln MPS_{it} + \epsilon_{it} \quad (3)$$

### 3.3 Geographical Panel Models

The report uses ENV's geographical correlation to create a spatial panel model to study ITC and ISO's effects on ENV. Below, the study explores the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM).

#### 3.3.1 Spatial Lag Model

Through the spatial transmission mechanism, SLM believes that all descriptive factors across adjacent provinces would impact near industrial areas. SLM considers a geographical spillover effect to analyze how main explanatory factors affect neighboring provinces. Equation 4 presents the SLM expression as follows:

$$\ln EMV_{it} = \sigma \sum_{j=1}^M X_{ij} \ln EMV_{it} + \beta_0 + \beta_1 \ln ITC_{it} + \beta_2 \ln MP_{it} + \beta_3 \ln ULS_{it} + \beta_4 \ln GDPPC_{it} + \beta_5 \ln UP_{it} + \beta_6 \ln FDI_{it} + \beta_7 \ln MPS_{it} + \omega_t + \mu_t + \epsilon_{it} \quad (4)$$

$$\epsilon_{it} \sim i.i.D(0, \sigma^2)$$

The investment in technology and innovation development includes industrial production growth efficiency. If ITC and ISO interact, equation (5) will be written as:

$$\ln EMV_{it} = \sigma \sum_{j=1}^M X_{ij} \ln EMV_{it} + \beta_0 + \beta_1 \ln MP_{it} + \beta_2 \ln ULS_{it} + \beta_3 \ln GDPPC_{it} + \beta_4 \ln UP_{it} + \beta_5 \ln FDI_{it} + \beta_6 \ln MPS_{it} + \beta_7 \ln EFFCH_{it} + \beta_8 \ln TMPH_{it} + \beta_9 \ln TMPH_{it} \times \ln MP_{it} + \beta_{10} \ln TMPH_{it} \times \ln ULS_{it} + \omega_t + \mu_t + \epsilon_{it} \quad (5)$$

$$\epsilon_{it} \sim i.i.D(0, \sigma^2)$$

In the model, ‘i’ signifies provinces, ‘t’ signifies the number of years, ‘σ’ denotes the spatial autoregressive coefficient (range: [-1, 1]),  $\ln \ln ENV_{it}$  represents the ENV of province ‘i’ in year ‘t’,  $\beta_0$  is the constant run,  $\beta_0 \sim \beta_7$  is the coefficient of the main explanatory variables, and  $\ln ENV_{it}$  represents the interaction effect of the explanatory variables.

### 3.3.2 Spatial Error Model

SEM supposes a geographical link among unobserved explanatory factors; therefore, provinces' spatial spillover effects are random shocks. The spatial autocorrelation of the error component during model creation, as shown in Equation 6, results in a biased model:

$$\ln EMV_{it} = \beta_0 + \beta_1 \ln ITC_{it} + \beta_2 \ln MP_{it} + \beta_3 \ln ULS_{it} + \beta_4 \ln GDPPC_{it} + \beta_5 \ln UP_{it} + \beta_6 \ln FDI_{it} + \beta_7 \ln MPS_{it} + \omega_t + \mu_t + \Phi_{it} \quad (6)$$

$$\Phi_{it} = \psi \sum_{j=1}^M X_{ij} \ln EMV_{it} + \epsilon_{it}, \epsilon_{it} \sim i.i.D(0, \sigma^2)$$

Equation 7 represents the relationship between investment in technology and innovations, and factors affecting environmental pollution:

$$\ln EMV_{it} = \beta_0 + \beta_1 \ln MP_{it} + \beta_2 \ln ULS_{it} + \beta_3 \ln GDPPC_{it} + \beta_4 \ln UP_{it} + \beta_5 \ln FDI_{it} + \beta_6 \ln MPS_{it} + \beta_7 \ln EFFCH_{it} + \beta_8 \ln TMPH_{it} + \beta_9 \ln TMPH_{it} \times \ln MP_{it} + \beta_{10} \ln TMPH_{it} \times \ln ULS_{it} + \omega_t + \mu_t + \Phi_{it} \quad (7)$$

$$\Phi_{it} = \psi \sum_{j=1}^M X_{ij} \ln EMV_{it} + \epsilon_{it}, \epsilon_{it} \sim i.i.D(0, \sigma^2)$$

The spatial autocorrelation error run is represented by ‘ $\Phi_{it}$ ’, and the spatial autocorrelation coefficient of the run is ‘ $\psi$ ’. The coefficient represents the degree to which a single province is affected by the random influence of 'ENV' in the provinces and takes values between [-1, 1].

### 3.3.3 Spatial Durbin Model

To define the interactions between provinces in the spatial Durbin model, a combination of SLM (Spatial Lag Model) and SEM (Spatial Error Model), rather than only relying on either model and Equation 8 SDM is as follows.

$$\ln EMV_{it} = \sigma \sum_{j=1}^M X_{ij} \ln EMV_{it} + \beta_0 + \beta_1 \ln MP_{it} + \beta_2 \ln ULS_{it} + \beta_3 \ln GDPPC_{it} + \beta_4 \ln UP_{it} + \beta_5 \ln FDI_{it} + \beta_6 \ln MPS_{it} + \varphi \sum_{j=1}^M X_{ij} y_{ijt} + \omega_t + \mu_t + \epsilon_{it} = \sigma \sum_{j=1}^M X_{ij} \ln EMV_{it} + \beta_0 + \beta_1 y_{it} + \varphi \sum_{j=1}^M X_{ij} y_{ijt} + \omega_t + \mu_t + \epsilon_{it} \quad (8)$$

$$\epsilon_{it} \sim i.i.D(0, \sigma^2)$$

When there is a relationship between ITC and ISO, so, the Equation (9) will be written as

$$\ln ENV_{it} = \sigma \sum_{j=1}^M X_{ij} \ln ENV_{it} + \beta_0 + \beta_1 \ln MP_{it} + \beta_2 \ln ULS_{it} + \beta_3 \ln GDPPC_{it} + \beta_4 \ln UP_{it} + \beta_5 \ln FDI_{it} + \beta_6 \ln MPS_{it} + \beta_7 \ln EFFCH_{it} + \beta_8 \ln TMPH_{it} + \beta_9 \ln TMPH_{it} \times \ln MP_{it} + \beta_{10} \ln TMPH_{it} \times \ln ULS_{it} + \varphi \sum_{j=1}^M X_{ij} y_{ijt} + \omega_t + \mu_t + \epsilon_{it} = \sigma \sum_{j=1}^M X_{ij} \ln ENV_{it} + \beta_0 + \beta_1 y_{it} + \varphi \sum_{j=1}^M X_{ij} y_{ijt} + \omega_t + \mu_t + \epsilon_{it} \quad (9)$$

$$\epsilon_{it} \sim i.i.D(0, \sigma^2)$$

Where ‘ $\varphi$ ’ represents the spatially lag explanatory variable coefficient, while ‘ $x$ ’ represents the primary explanatory variable. The simplification of SDM into SLM is achievable when  $\varphi = 0$ , whereas SEM is possible when  $\varphi + \sigma\beta = 0$ . A spatial interaction effect of  $ENV_{it}$  exists between nearby provinces with a high significance level of  $\sigma$ . A positive  $\sigma$  indicates beneficial interaction between nearby provinces. Interaction is negative otherwise.

### 3.3.4 Investigation of SPM Autocorrelation

Prior to constructing the spatial econometric model, it is important to examine the dependent and independent variables for any signs of spatial autocorrelation. The study starts with a mixed panel data model that disregards spatial autocorrelation and employs OLS estimation as shown in equation 10:

$$\ln ENV_{it} = \beta_0 + \beta_1 \ln ITC_{it} + \beta_2 \ln MP_{it} + \beta_3 \ln ISO_{it} + \beta_4 \ln GDPPC_{it} + \beta_5 \ln UP_{it} + \beta_6 \ln FDI_{it} + \beta_7 \ln MPS_{it} + \omega_t + \mu_t + \epsilon_{it}, \quad (10)$$

$$\epsilon_{it} \sim i.i.D(0, \sigma^2)$$

The  $\epsilon_{it}$  represent the error run,  $\omega_t$  and  $\mu_t$  represent the spatial fixed effects, and the remaining variables are specified as in the previous model. The study selects a spatial, temporal, or double fixed effect model using the likelihood ratio test.

### 3.4 Environmental Pollution

Energy usage and industrial sector choices are key to environmental pollution (ENV) calculation. First, the article selects 27 industrial categories from China's "Industry Classification and Coding of National Economy" to calculate CO<sub>2</sub> emissions. Second, this study uses the latest China Energy Statistical Yearbook to calculate 17 industrial production use fossil fuels. These fuels are coal, petroleum, and natural gas. According to International Panel Climate Change (IPCC) criteria in the equation (11), the environmental pollution (ENV) is calculated as follows:

$$ENV_i = \sum_k^K E_{ik} \times MCV_k \times CC_k \times COF_k \times TC = \sum_k^K E_{ik} \times MCV_k \quad (11)$$

The index  $k$  represents the kind of fossil fuel, with  $k = 1, 2, \dots, K$ ; In the industrial sector,  $ENV_i$  represents carbon dioxide emissions.  $MCV_k$  represents the average low calorific value of fossil fuel  $k$ ,  $CC_k$ , its carbon content,  $COF_k$  represents the carbon oxidation rate, TC represents the conversion coefficient, and  $CMP_k$  shows the carbon emission coefficient.

### 3.5 Investments in Technology and Innovations

The Investments in Technology and Innovations (ITC) of modern is calculated using a comprehensive factor efficiency approach. An analysis using the Data Envelopment Analysis (DEA)- Malmquist approach is employed to assess the Total Factor Productivity (TFP) of the industrial sector. The approach avoids any biases or errors related to endogeneity or data issues. It analyzes ITC by separating it into two components: manufacturing technology services (MTS) and industrial technology advancements (INTECH).

### 3.6 Industrial Construction Progression

The study derives MP index using the angles between the three industrial industry-level percentage vectors. ‘ $\varphi_1$ ’ signifies a transformation of industrial production from low to middle, and middle to high level, whereas ‘ $\varphi_2$ ’ signifies the industrial production from middle to high level. An increased industrial industry structure index ( $EC = \varphi_1 + \varphi_2$ ) indicates stronger industrial upgrading, calculate  $\varphi_1$  and  $\varphi_2$ . The study evaluates low, middle, high, and total industrial production values by  $y_1 = (y_{1,0}, y_{2,0}, y_{3,0})$ . Since  $\omega_1$  and  $\omega_2$  represent the angle between  $Y^1$  besides the (0, 0, 1), and (0, 1, 0) vectors.  $\varphi_1 = \pi - \omega_1 - \omega_2$ . If  $\delta$  is the angle between  $Y^2$  ( $Y_{2,0}, Y_{3,0}$ ) and vector (0, 1), then  $\varphi_1 = \frac{\pi}{2} - \delta$ . Here's the Equation 12 calculates as follows:

$$\varphi = \arccos \left[ \frac{\sum_{i=1}^3 (x_{i,j} x_{i,0})}{(\sum_{i=1}^3 (x_{i,j^2}))^{1/2} (\sum_{i=1}^3 (x_{i,0^2}))^{1/2}} \right] \quad (12)$$

Statistics' geographical autocorrelation and heterogeneity effect independent variable regression coefficients and statistical inference. Check for data autocorrelation and heterogeneity before using the spatial econometric model. To find ENV geographical correlation, studiers evaluate global and local spatial autocorrelation.

### 3.7 Analysis of Worldwide Spatial Autocorrelation

The study performs the Moran's I measurement to measure worldwide ENV spatial autocorrelation:

$$Moran's\ I = \frac{\sum_{i=1}^M \sum_{j=1}^M Y_{ij} (y_i - \bar{y}) (y_j - \bar{y})}{P^2 \sum_{i=1}^M \sum_{j=1}^M Y_{ij}} \quad (13)$$

In the equation, ‘M’ represents the total number of Chinese provinces,  $y_i$  and  $y_j$  represents ENV values,  $\bar{y}$  and  $P^2$  indicate ENV mean and variance, and  $Y_{ij}$  denotes the column “i” and row “j” of the regulated spatial weight matrix ‘Z’. Moran's I am [-1,1], ECS values less than ‘0’ expression spatial negative association between provinces “ENV = 0” suggests independence, and more than ‘0’ suggests spatial agglomeration. Measurement of ENV's spatial correlation using Moran's I and the accompanying ‘Z’ statistic.

$$Z (Moran's\ I) = \frac{Moran's\ I - E(Moran's\ I)}{\sqrt{VAR(Moran's\ I)}} \quad (14)$$

$$\text{Where } E(Moran's\ I) = -\frac{1}{n-1}.$$

### 3.8 Worldwide Environment Moran’s Index

Table 1 presents the worldwide Moran's I values for the environmental variables (ENV) of China's 30 provinces from 2011 to 2023, together with the corresponding statistical test outcomes. The global Moran's I statistic exceeds 0.14 with high statistical significance, indicating that the variable ENV has a positive effect on geographical clustering and spatial correlation.

**Table 1:** Represents the Moran’s Index of international environmental pollution

Years	Moran I	E (Moran I)	SD (Moran I)	Weighed Value	P-value
2011	0.182	-0.037	0.127	1.853	0.035
2012	0.184	-0.037	0.123	2.234	0.048
2013	0.179	-0.037	0.127	1.795	0.053
2014	0.178	-0.037	0.124	1.846	0.064
2015	0.146	-0.037	0.128	1.578	0.201
2016	0.167	-0.037	0.123	1.645	0.063
2017	0.164	-0.037	0.127	1.523	0.084
2018	0.159	-0.037	0.126	1.956	0.082
2019	0.174	-0.037	0.124	1.856	0.079
2020	0.169	-0.037	0.125	1.745	0.084
2021	0.162	-0.037	0.134	1.745	0.087
2022	0.163	-0.037	0.142	1.654	0.084
2023	0.154	-0.037	0.132	1.698	0.079

### 3.9 Lag Spatial Autocorrelation Analysis

The lag spatial autocorrelation is determined by global Moran's I index, and it confirms variables ENV's spatial autocorrelation and shows local spatial agglomeration:

$$Moran's\ I_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})} \cdot \sum_{j=1}^M X'_{ij} (x_i - \bar{x}) \quad (13)$$

Where (Moran's  $I_i$ ) =  $-\sum_{j=1}^n X_{ij} / (n - 1)$  is the standard definition for standard space weight matrix and. A higher value of  $E$  (Moran's  $I_i$ ) indicates a greater degree of geographical clustering of ecological pollution in contemporary production.

## 4. Results and Discussions

The study reveals that the environmental conditions in 30 Chinese provinces exhibit significant spatial autocorrelation and spatial heterogeneity. This suggests that nearby areas typically have similar ENV values, indicating spatial clustering, while there are also significant variations in ENV values across regions. The conclusion highlights the importance of geological dispersion and spatial effect as crucial factors impacting the environmental variables in these regions.

**4.1 Spatial Autocorrelation Effects**

The study concepts a spatial econometric model utilizing the Lagrange multiplier forms to assess the conventional mixed panel model. Table 2 represents the SDM's reasonable test results.

**Table 2:** The results of spatial autocorrelation effects of variables

Details	Mixed-effects model	Spatial fixed-effects model	Time fixed-effects model	Spatial and time fixed-effects model
lnITC	-0.2357*** (-3.0548)	-0.2457*** (-2.0568)	-0.2145** (-1.5982)	-0.0782 (-1.6547)
lnMP	-1.2894*** (-9.7854)	-1.5324*** (-10.3257)	-0.7859*** (-3.8745)	-0.7844*** (-4.4256)
lnULS	-0.0401 (-1.3578)	-0.0265 (-0.8457)	-0.0024 (-0.8546)	0.0004 (-0.0056)
lnGDPPC	0.8562*** (31.7452)	0.8542*** (32.1004)	0.8562*** (30.8752)	0.6985*** (31.4217)
lnUP	-0.7451*** (-8.0104)	-0.7942*** (-8.8975)	-1.3145*** (-9.0235)	-1.3024*** (-8.5974)
lnFDI	-0.0325 (-1.0568)	-0.0452 (-0.7468)	-0.0523 (-1.2215)	-0.0314 (-0.7597)
lnMPS	-0.7846*** (-11.0597)	-0.8457*** (-12.0897)	-0.5479*** (-4.0568)	-0.5368*** (-4.6897)
Cons	-4.0148*** (-14.0245)			
$\delta^2$	0.2055	0.2359	0.0256	0.0745
$R^2$	0.8023	0.7985	0.8031	0.8453
LMLag	324.124***	319.032***	131.078***	131.54***
R-LMLag	52.027***	45.214***	5.0121**	4.875**
LMeror	338.56***	337.25***	169.564***	172.028***
R-LMeror	37.025***	48.054***	58.364***	57.024***
Obs.	525	525	525	525

Note: \* represents p-value < 0.10, \*\* shows the p-value < 0.05, and \*\*\* indicates the p-value < 0.01.

The results indicate that the Hausman test is better suited for a panel data analysis. The test suggests that the arbitrary impacts model is reliable and efficient, while the alternative hypothesis proposes that the decent impacts model is consistent and effective. The Hausman measurement value combined with a p-value < 0.01, provides strong evidence against the invalid hypothesis. The irregular impacts model is not favored, while the proper impacts model is considered more appropriate for reviewing information. The observed outcomes of the impacts model indicate that the factors are closely linked to the logical factors, and they are effectively represented in the assessment cycle.

**4.2 SDM Model Results without Interaction**

Table 3 indicates that the temporal fixed-effects SDM model's LR test statistic is the only one that is significant, indicating that the dual fixed-effects SDM model is not appropriate for this investigation. The time-fixed effects SDM model yields the most accurate results.

**Table 3:** The SDM model results without interaction

Details	Time fixed-effects		Spatial and time fixed-effects
	Spatial fixed-effects Model	mode	model
lnITC	-0.1045** (-2.23)	-0.132 (-1.12)	-0.0579 (-1.45)
lnMP	0.2521 -1.035	-1.7654*** (-11.087)	0.1325 -0.49
lnULS	-0.0177* (-1.352)	-0.0453** (-2.089)	-0.023* (-1.231)
lnGDPPC	0.4571*** -5.123	0.7542*** -23.48	0.2154*** -7.56
lnUP	1.2534*** -5.235	-0.4571*** (-3.258)	1.2387*** -5.02
lnFDI	-0.0544*** (-3.987)	-0.0421* (-1.45)	-0.0657*** (-4.324)
lnMPS	-0.0084* (-0.23)	-0.8754*** (-9.565)	0.1024 -0.85
Z×lnITC	0.145*** -1.789	0.121 -0.85	0.2247*** -2.24
Z×lnMP	1.0045** -2.04	-1.782*** (-3.894)	1.0049* -1.256
Z×lnULS	0.0247* -1.65	-0.0345 (-0.74)	0.0204 -0.66
Z×lnGDPPC	0.3985*** -4.98	0.2489*** -3.84	0.2478*** -3.54
Z×lnUP	-2.4723*** (-6.89)	-0.7245*** (-3.23)	-2.5682*** (-5.75)
Z×lnFDI	-0.0687** (-2.45)	-0.045 (-0.67)	-0.0978*** (-1.98)
Z×lnMPS	-0.2024 (-1.52)	-0.4012** (-2.23)	0.1892 -0.93
$\delta^2$	0.014	0.052	0.0452
$R^2$	0.523	0.8545	0.9541
LR	23.97	593.18***	

Note: \* represents p-value < 0.10, \*\* shows the p-value < 0.05, and \*\*\* indicates the p-value < 0.01.

The results revealed that the ITC has a negative influence on ENV, although the impact is less significant because of the rebound effect, which might result in higher energy use and carbon emissions. Therefore, the direction of the influence of ITC on ENV depends on how big this rebound effect. At the 1% level, EC's effect coefficient is statistically significant. The influence coefficient of ULS has a high significance level and an excellent inhibitory effect on ENV. The results indicate that EC has a more potent inhibitory impact on ENV when compared to ULS. Concerning the impact of control variables on ENV, the GDPPC's effect coefficient signifies a considerable increase of over 1%. This suggests that a rise in China's industrial production will nonetheless result in substantial energy consumption and raise the nation's ENV. The UP has an influence coefficient is significant above 1%. This indicates that improving UP can have a significant impact on the industrial industry's mode of production and level of innovation, speed up the aggregation of production factors, and significantly restrain the growth of ENV, and FDI has an inhibitory effect on ENV. The results of the study support the beneficial effects of FDI on the environment. The overall effect of FDI on ENV indicates a favorable shift as China works to tighten its environmental laws and prohibit the entrance of foreign businesses

with excessive energy usage, carbon emissions, and pollution. In contrast. As a result, encouraging China's industrial sector to grow at a high level can greatly lower ENV.

### 4.3 Spatial Spillover Effect Analysis

Table 4 shows the meaning of spatial cooperations among logical factors breeze through the importance assessments at the 1% or 5% level, demonstrating that each illustrative variable has various levels of spatial overflows. The immediate, roundabout, and complete impacts of each illustrative variable are determined according to the technique.

**Table 4:** The spatial spillover effects of variables without interaction

Details	Direct effect	Indirect effect	Total effect
lnITC	-0.2034 (-1.09)	0.0895 -0.78	-0.0245 (-0.06)
lnMP	-1.687*** (-11.025)	-1.492*** (-3.54)	-3.354*** (-7.85)
lnULS	-0.0345** (-2.06)	-0.0321 (-0.64)	-0.0428* (-1.81)
lnGDPPC	0.784*** -28.79	0.324*** -3.58	1.074*** -12.87
lnUP	-0.6124*** (-3.87)	-0.6502*** (-3.02)	-1.2025*** (-4.89)
lnFDI	7.09* (-1.63)	-0.0452 (-0.68)	-0.0954 (-1.53)
lnMPS	-0.6894*** (-8.985)	-0.3547** (-2.17)	-1.0845*** (-6.85)

Note: \* represents p-value < 0.10, \*\* shows the p-value < 0.05, and \*\*\* indicates the p-value < 0.01.

The MP has the largest direct effect, which suggests that MP plays a significant role in suppressing ENV. Meanwhile, ULS has the weakest direct effect, despite its negative impact on ENV, and the effect of ULS is not great. Meanwhile, UP and ECS have a negative direct impact, while the direct effect of ECS improvement is greater than that of UP improvement. The spatial overflow impacts of lnMP, lnGDPPC, lnUP, and lnMPS are remarkably substantial at a statistically significant level. The lnMP, lnUP, and lnMPS have negative spatial overflow impacts with values, indicating that the changes in these variables in one area have an inhibitory effect on ENV outflows in neighboring regions. The positive spatial overflow impact of lnGDPPC indicates that an increase in the level of industrial output in one area has adverse effects on the environment in its neighboring regions. The indirect effects of lnITC, lnULS, and lnFDI are insignificant for two reasons. ULS primarily strengthens the objective designation and effective utilization of territorial assets among enterprises and is limited to enhancing the coordination boundary among ventures within the same region. Therefore, the impact of ULS on spatial overflow is limited due to its focus on strengthening the coordination capacity among projects within the same region. The overall positive effects of lnMP, lnULS, lnGDPPC, lnUP, and lnMPS are of great importance. lnMP has the highest overall impact value and the strongest influence on ENV. The overall effects and benefits of lnGDPPC, lnUP, and lnMPS are slightly smaller, while lnULS has the smallest impact, suggesting that lnULS significantly influences ENV. The overall and immediate effects of the other informative factors are significant but not significantly large.

### 4.4 SDM Models Results with Interaction

Table 5 shows that lnMTS is not significant when ITC and ISO interact. The significant relationship of lnMTS×lnMP suggests that TECH and EC have a major inhibitory influence on ENV, with no direct effect from TECH. Thus, TECH may use MP's carbon reduction capabilities to decrease ENV. The EC reduces carbon

emissions through TECH because luxury industries encourage innovative technologies to improve energy efficiency, lower carbon emission intensity, and reduce ENV. However, TECH does not suppress ENV, suggesting that it decreases carbon emissions through MP rather than ULS. In runs of ULS's carbon emission reduction, lnULS still strongly inhibits ENV under interaction.

**Table 5:** The SDM model results with the interaction of study variables

Details	Direct effect	Indirect effect	Total effect
lnULS	2.0045	-2.47	0.0045
lnGDPPC	0.7923	30.52	0.024
lnUP	-0.6017	-4.87	0.053
lnFDI	-0.0402	-1.42	0.241
lnMPS	-0.6845	-9.87	0.03
lnINTECH	-0.1595	-2.03	0.09
lnMTS	0.7451	1.08	0.21
lnMTS×lnMP	-1.301	-3.01	0.001
lnMTS×lnULS	-0.0584	-1.03	0.401
Z×lnMP	-1.4892	-4.87	0.001
Z×lnULS	-0.0178	-0.63	0.721
Z×lnGDPPC	0.4213	4.06	0.003
Z×lnUP	-0.7124	-3.452	0.003
Z×lnFDI	-0.0376	-0.721	0.631
Z×lnMPS	-0.4128	-2.034	0.057
Z×lnINTECH	0.0503	0.347	0.689
Z×lnMTS	0.8507	1.597	0.348
Z×lnMTS×lnMP	-0.4055	-0.568	0.721
Z×lnMTS×lnULS	0.2104	0.864	0.432
$\delta^2$		0.1542	
$R^2$		0.7522	

The results show that ULS may directly affect production without TECH by cutting energy usage and improving resource allocation to minimize carbon emissions. Other control variables' effect on ENV is the same under ITC-ISO interaction without interaction. However, the impact varies. In particular, lnUP and lnMPS inhibit ENV better and have greater coefficients. Even after accounting for industrial industry structural optimization and ITC engagement, lnFDI does not suppress ENV. lnINTECH inhibits more than lnMTS, demonstrating that technological efficiency reduces energy use and carbon emissions. Table 5 results show how UP, ULS, ITC, and GDPPC contribute to geographic spillover effects in magnitudes. The results show that the ITC and industrial production growth interaction will affect GDPPC, UP, FDI, and INTECH in an area differently from surrounding ones. Tech and EC have no statistically significant effect on ENV, whereas INTECH and ULS do. Even while lnMTS has little direct impact, its shared words with lnMP and lnULS are significant. The impact of lnMTS ×lnMP is more direct than that of lnMTS ×lnULS. Other control variables like lnGDPPC, lnUP, lnFDI, and lnMPS have significant direct effects. While lnGDPPC has good direct impacts with an effect, lnUP, FDI, and ECS have negative ones. UP's direct effect has the biggest absolute value, suggesting it affects ENV most directly. ECS has the lowest absolute effect on ENV, indicating a negligible effect.

**4.5 Indirect Effect (Spillover Effect)**

No substantial geographical spillover effects of EC and ULS. However, the geographical spillover effect of INTECH is highly positive, implying that an increase in INTECH in one location will decrease ENV in other regions. Table 6 represents the direct, indirect, and total impacts of each of the ten explanatory variables.

**Table 6:** The direct, and indirect spatial spillover effects results of variables

Details	Spatial fixed-effects Model	Time fixed-effects mode	Spatial and time fixed-effects model
lnITC	-0.1356** (-2.47)	-0.0845 (-0.92)	-0.5455 (-0.75)
lnMP	-0.0927 (-0.53)	-1.712*** (-10.87)	-0.302 (-1.37)
lnULS	-0.0245 (-1.69)	-0.0503*** (-3.07)	-0.0206 (-1.57)
lnGDPPC	0.458*** -6.92	0.924*** -29.87	0.436*** -7.01
lnUP	1.419*** -6.032	-0.365*** (-3.87)	1.411*** -6.02
lnFDI	-0.0924*** (-5.002)	-0.07*** (-3.124)	-0.0848*** (-5.02)
lnMPS	-0.0007 0.0001	-0.8132*** (-7.9865)	0.2045* -1.89
Z×lnIP	0.308*** -3.53	0.502* -1.94	0.6211*** -4.02
Z×lnMP	0.843 -1.43	-0.528 (-0.97)	0.209 -0.31
Z×lnULS	0.0723*** -3.07	0.140*** -3.08	0.086* -2.06
Z×lnGDPPC	0.475*** -4.003	0.304* -2.0001	0.412** -2.235
Z×lnUP	-2.621*** (-6.22)	-1.212*** (-4.02)	-2.001*** (-4.35)
Z×lnFDI	0.0419 -0.83	-0.046 (-0.51)	0.0005 -0.06
Z×lnMPS	-0.307 (-1.56)	-0.622** (-2.58)	0.479 -1.53
$\rho^2$	0.53	0.231	0.423
$R^2$	0.845	0.738	0.827
LR	40.142	598.79***	

Note: \* represents p-value < 0.10, \*\* shows the p-value < 0.05, and \*\*\* indicates the p-value < 0.01.

The geographic spillover effect of TECH is small, implying that a rise in MTS has little influence on ENV in other regions. The indirect effects of  $\ln\text{MTS} \times \ln\text{MP}$  and  $\ln\text{MTS} \times \ln\text{ULS}$  are not significant, indicating no substantial spillover impact from ITC and ISO interaction in a province. The indirect effects of additional control variables differ slightly from those without interaction. The indirect impacts of  $\ln\text{GDPPC}$ ,  $\ln\text{UP}$ , and  $\ln\text{MPS}$  remain significant, but their magnitudes and orientations remain unaltered. EC, GDPPC, UP, FDI, and ECS have substantial influence. Under ITC and industrial production interaction, UP has the biggest direct effect on ENV with the highest absolute effect magnitude. The total effect of ECS has the smallest direct influence and lowest absolute effect magnitude, showing the least impact on ENV.

#### 4.6 Discussions

The study reveals that urbanization and the increase of urban land areas have significant adverse impacts on environmental deterioration. Prior study frequently dissects urbanization into many facets, including economic, land, and population urbanization, to assess its effects on carbon emissions (Ji et al., 2020). Huo et al. (2021)

conducted a study to investigate the impact of urbanization on carbon emissions in 30 Chinese provinces, focusing on the geographical, economic, and demographic factors. According to Adem et al. (2020), GDP growth slows unhappy normal deterioration, while population growth emergencies it. Similarly, Rahman et al. (2020) have established that both GDP per capita and EC have significant negative impacts on environmental pollution. This reveals that the increase in fossil fuel byproducts is regularly to the energy consumption associated with land urbanization. The results have been approved by Zhou et al. (2023) who recognized a strong correlation between the process of economic urbanization and the emissions produced by fossil fuels. The conclusions of the study highlight the importance of economic interests in ITC, GDP growth, and UP in determining the impact of environmental changes. The decrease in ITC and fossil fuel byproducts are interrelated since the execution of advanced technology in current production systems leads to a discount in environmental pollution. The production of results from fossil fuels increases proportionally with advancements in technology-driven efficiency. The results are confirmed by Suki et al.'s (2022) study, which investigated that the combination of increased industrial production and technological advancements contributes to the escalation of CO<sub>2</sub> emissions. The primary factor contributing to CO<sub>2</sub> emissions is the promotion of technological innovations aimed at growing industrial production. According to results confirmed Niu (2021) examined the levels of CO<sub>2</sub> emissions and the level of industrial growth in China. The results demonstrate a clear correlation between increased contemporary efficiency, CO<sub>2</sub> emissions, and technological growth. According to Chen et al. (2020), there is a suggested correlation between the development signal and the CO<sub>2</sub> emissions of transportation industrial. The results reveal that the contempt advancements in technology innovation activities continue in making detrimental effects on the climate, specifically in relative to the emissions of fossil fuels.

## 5. Conclusions and Recommendations

The study examines the interaction effects of ITC, UP, EC, GDPPC, and FDI on ENV. The study utilizes a geographic panel model that incorporates SLM, SDM, and SEM models to estimate the industrial data of 30 provinces in China spanning the years 2005 to 2023. The results reveal that urbanization and urban land area growth have significant negative impacts on environmental pollution. Similarly, the increase in micro-plastic and GDP per capita have also significant negative impacts on environmental pollution. The investment in technological innovations to increase industrial production is the major source of CO<sub>2</sub> emissions. The results of the analysis point to the importance of investment in technology innovations, economic growth, and urbanization growth in determining environmental changes due to industrial development. There is a connection between the ITC and the effect of lowering carbon emissions, the modernization technology in the industrial production structure has a limitation on the growth in ENV. The results also reveal that the advancements in technology innovations with the increase in industrial production also cause the increase in CO<sub>2</sub> emissions. The results reveal a direct correlation between technological advancements and increased industrial productivity growth in CO<sub>2</sub> emissions. The study represents the persistent pollution of the environment by industrial activities, even in the face of technological progress, particularly about CO<sub>2</sub> emissions. The presence of "INTECH" appears to have a substantial reduction impact on ENV. Specific technological developments are due to the implementation of cleaner technologies and more efficient operations, which are beneficial in reducing environmental pollution. MTS does not appear to have any impact in mitigating the increase of ENV. The MTS results represent that it is not as effective as INTECH in mitigating environmental pollution.

### 5.1 Future Study Suggestions

The object suggests possible teaching areas for the future in order to support sustainable urban and industrial expansion. Additionally, its promoters for the development of environmentally friendly low-carbon industries, the funding of eco-friendly technology, the application of radical urban preparation plans, and the inspiration of the growth of sustainable small companies. These principles' purpose to reduce environmental impact while indorsing long-term ecological welfare.

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