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Spatial Dependence of the Impact of Economic Policy Uncertainty on Carbon Emissions

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Abstract

In recent years, the escalating threat of global warming associated with climate change has heightened concerns about carbon emissions. This paper focuses on exploring the spatial dependence of the impact of Economic Policy Uncertainty (EPU) on carbon emissions. A theoretical framework is constructed using the IPAT equation and the STIRPAT model to investigate the relationship between EPU and carbon emissions. Following the Environmental Kuznets Curve (EKC) hypothesis, variables such as EPU, population size, economic development, industrial structure, and the square term of GDP are introduced into the model to explore the influencing factors of carbon emissions. Balanced panel data from 24 countries spanning from 2003 to 2020 are selected. This paper employs the Maximum Likelihood Ratio test to choose the Spatial Durbin model with fixed effects for analysis. The results of the Spatial Durbin model analysis are utilized to explore the direct, indirect, and feedback effects of EPU on carbon emissions in the 24 sampled countries. The findings indicate a strong spatial dependence in the direct impact of EPU on carbon emissions. In the short term, the indirect effect of EPU on carbon emissions outweighs the direct effect, prompting many countries to control carbon dioxide emissions at the expense of increased EPU.

Keywords

EPU; CO2 Emission; Spatial Dubin Model; Spillover Effect.

1. Introduction

Carbon dioxide emissions are widely recognized as the primary cause of global warming, exerting profoundly adverse effects on human society's survival and progress. The international community has convened United Nations climate change conferences multiple times to address the environmental crisis posed by global warming[1, 2]. Establishing "a sound green, low-carbon, and circular economic system" and a "clean, low-carbon, safe, and efficient energy system" have been set as China's long-term development goals. During the annual political meetings, the concepts of carbon peaking and carbon neutrality were included in the government work report for the first time. China has pledged that its carbon emissions will no longer increase by 2030 and will gradually decrease after reaching the peak. Some scholars argue that Economic Policy Uncertainty (EPU) not only influences the macroeconomy and financial markets but also has an impact on the environment. EPU refers to the inability of economic agents, as the subjects of economic activities, to accurately understand whether policymakers will change existing economic policies, when these changes might occur, and how they will be implemented. On one hand, EPU might prompt enterprises to adopt traditional production methods detrimental to the environment, thereby increasing carbon dioxide emissions [3]. On the other hand, EPU can affect consumption and investment, consequently reducing carbon dioxide emissions [4]. Moreover, policy uncertainty can have significant implications for carbon emissions in different countries. The correlation between the external

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policy environment in which businesses operate and policy uncertainty is closely intertwined. Changes in the external policy environment can lead to shifts in corporate strategies, thereby impacting regional total carbon emissions. Therefore, the relationship between EPU and carbon emissions cannot be overlooked.

Climate change has consistently been a global issue of paramount concern, and research on carbon dioxide emissions has become increasingly extensive. Regarding the factors influencing carbon emissions, numerous scholars agree that output is the primary driver of carbon emission growth [5, 6]. Reducing carbon emissions primarily relies on energy efficiency, and factors such as urbanization levels and household income can also lead to an increase in carbon emissions. Studies on the impact factors of carbon emissions show that researchers widely consider output as the primary cause of carbon emission growth. Reduction in carbon emissions primarily hinges on energy efficiency, while levels of urbanization and household income can also contribute to an increase in carbon emissions. Richmond and Kaufmann [7] found that fuel mix, income indicators, and the level of economic development influence the relationship between economic activities, energy use, and carbon emissions. Soytas and Sari [8] explored the connections between the Turkish economy, carbon emissions, and energy use through Granger causality tests. The results indicated that, in the long run, there was no causality between income and emissions, suggesting that reducing carbon emissions in Turkey might not require sacrificing economic growth. Bekhet and Othman [9] employed ecological modernization and an enhanced Cobb-Douglas production theory to study the bi-directional causal relationships between carbon emissions, urbanization growth, energy consumption, GDP, domestic investment, financial development from 1971 to 2015. They also examined the unidirectional causality from financial development to carbon emissions.

However, research on the impact of Economic Policy Uncertainty (EPU) on carbon emissions is not yet widely explored. Jiang et al. [10] utilized industry-level carbon emissions data in the United States and estimated the relationship between EPU and carbon emissions for the first time. They propose that EPU exerts influence over carbon emissions by altering environmental governance and impairing corporate performance. On the one hand, companies might reduce their efforts to decrease emissions. On the other hand, a company's emissions performance might be ambiguous: low emissions might indicate subpar performance, while high emissions could result from a switch to cheaper, yet more polluting fuels. They found that EPU in the United States not only impacts carbon emission uncertainty but also positively influences the tail of the emission growth distribution. Adedoyin and Zakari [11] studied the energy consumption emissions framework in the United Kingdom using annual data from 1985 to 2017. This paper indicated that low EPU reduces the short-term growth of carbon dioxide emissions, while the long-term impact is favorable. A higher EPU impedes corporate investment and economic growth, mitigating environmental issues. In times of economic recession, industries compensate for reduced liquidity by turning to low-cost energy production. However, as these industries' incomes grow over time, they may transition to cleaner energy production, thus reducing emissions.. Adams et al. [12] analyzed the World Uncertainty Index spanning from 1996 to 2017 to investigate the long-term correlation between the EPU and energy consumption in countries characterized by elevated geopolitical risks. The findings suggest that energy consumption and economic growth are factors contributing to carbon dioxide emissions. Furthermore, in the long run, a significant association exists between economic uncertainty and carbon emissions. Using the panel non-causality testing method based on Dumitrescu and Hurlin [13], the analysis indicates the existence of bidirectional relationships among carbon emissions, energy consumption, EPU, and economic growth.

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2. Materials and Methods

2.1. STIRPAT Model

To assess environmental pressure, Ehrlich and Holdren [14] introduced the IPAT equation. The IPAT model incorporates variables related to population, wealth, and technology to explain their impact on environmental quality. Although this model is straightforward, it requires controlling variables. It assumes that other variables remain constant to analyze the influence of a single variable on the environment, which limits its use in some studies. To address the shortcomings of the IPAT model, scholars have proposed the STIRPAT model. In This paper, the impact of EPU on carbon dioxide emissions is investigated within the framework of the STIRPAT model. The basic form of the STIRPAT model is as follows:

$$I_{it} = a \times P_{it}^{b} \times A_{it}^{c} \times T_{it}^{d} \times e_{it} \tag{1}$$

Where I represents environmental pressure, P represents the population factor variable, A represents the per capita wealth variable, T represents the technological level variable, a represents the overall coefficient before the model, b, c, d are the exponents for the three variables mentioned above, and e represents the random disturbance term.

For ease of analysis, the STIRPAT model is typically logarithmically transformed on both sides, making it a multivariate linear model. The log-transformed STIRPAT model has a well-defined economic interpretation, reduces the impact of heteroskedasticity in the model, and is more suitable for regression and analysis. This results in the following equation:

$$\ln I_{it} = a_0 + b \ln P_{it} + c \ln A_{it} + d \ln T_{it} + \ln e_{it} \tag{2}$$

The basic model mentioned above analyzed the influence of population size, economic development, and industrial structure on the environment. However, it overlooked other significant factors affecting carbon dioxide emissions, such as EPU. In order to make further efforts explore the influence of economic policy nondeterminacy on the environment, EPU is introduced into Equation (2). Additionally, following the Environmental Kuznets Curve (EKC) hypothesis, environmental quality is assumed to be a function of both GDP and GDP squared. Therefore, the STIRPAT model is revised by incorporating economic policy uncertainty and GDP squared into the set of factors, thus allowing for a more comprehensive analysis of the relationship between these variables.

$$\begin{aligned} \ln(CO_{2it}) &= a_0 + b\ln(pop_{it}) + c\ln(pgdp_{it}) + d\ln(pgdp_{it})^2 \\ &+ e\ln(indus_{it}) + f\ln(epu_{it}) + gCV_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{3}$$

where epu represents economic policy uncertainty. Specifically, CO_2 represents per capita carbon dioxide emissions (hereinafter referred to as carbon emissions or simply emissions), pop is the total population, $pgdp$ per capita income. The total population and GDP per capita measure the influence of population and economic factors. $indus$ represents industrial structure (expressed as the percentage of industrial value-added to GDP), μ_i represents individual fixed effects, controlling all spatially specific non-time-varying variables, ignoring which might lead to coefficient estimation bias, ε_i is the error term, CV representing the control variables suggested on determinants of carbon dioxide emissions.

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2.2. Spatial Panel Model

The spatial econometric model is frequently employed in empirical studies mainly because it clearly describes the heterogeneity between individuals, reduces multicollinearity, and increases degrees of freedom.All attributes of indicators on the geographical surface are interrelated, but indicators closer to each other have stronger correlations than those farther away. No region can be isolated. Ignoring spatial correlation in econometric analysis when variables are spatially related can lead to biases, and incorporating spatial relationships into the data can introduce potential spatial autocorrelation issues. Therefore, this paper aims to use spatial econometric models to examine the impact of EPU on carbon emissions through an enhanced STIRPAT model.

Currently, there are mainly three spatial econometric models: Spatial Lag Model (SLM), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). The SLM assumes that the value of the dependent variable observed at a specific location is partially determined by the spatially weighted average of adjacent dependent variables. This means that carbon emissions in a region are influenced by the carbon emissions in neighboring regions due to spillover effects. Therefore, this paper integrates SLM and SEM to form a comprehensive Spatial Durbin Model. The panel SDM model can be represented as follows:

$$y_{it}=\rho\sum_{j=1}^{N}w_{ij}y_{jt}+X_{it}\beta+\mu_i+\sum_{j=1}^{N}w_{ij}X_{jt}\gamma+\varepsilon_{it} \tag{4}$$

where y_{it} represents the per capita carbon emissions in country i at time t . $\sum_{j=1}^{N}w_{ij}y_{jt}$ represents the endogenous spatial interaction effect between the dependent variable y_{it} and y_{jt} in neighboring countries, i.e., the weighted average of carbon emissions in neighboring countries. The parameter ρ is the spatial autoregressive coefficient, indicating the influence of carbon emissions in nearby regions on the carbon emissions in the focal region. X_{it} is the matrix of independent variables, including per capita GDP, population size, industrial structure, urbanization level, and economic policy uncertainty. β is the vector of unknown parameters to be estimated. The error term ε_{it} is assumed to have a mean of zero, a variance of σ^2 , and to be independently and identically distributed. w_{ij} represents the elements of the spatial weight matrix.

2.3. Estimation Strategy and Interpretation of the Model

Due to spatial autocorrelation in spatial regression models, the coefficients of explanatory variables in the regression model cannot accurately reflect the marginal effects. When there are spatial lags of both the dependent variable and the independent variables in the model, the true overall impact of the unit explanatory variable on the unit dependent variable changes. This also includes the effects generated by neighboring countries through spatial correlation, which can be divided into direct (intra-regional) effects and indirect (spatial spillover) effects. The expectation of the Spatial Durbin Model (SDM) can be represented as follows:

$$E(Y_t)=(I_n-\rho W)^{-1}\mu+(I_n-\rho W)^{-1}(X_t\beta+WX_t\gamma) \tag{5}$$

where I_n is $n\times n$ matrix, and under certain stability conditions

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$$(I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots \tag{6}$$

Therefore, at a specific time point t , the partial derivative matrix of the dependent variables for different units relative to the k_{th} explanatory variable for different units is:

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdots \frac{\partial E(Y)}{\partial x_{Nk}}\right]_t = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix} = (I_n - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\gamma_k & \cdots & w_{1n}\gamma_k \\ w_{21}\gamma_k & \beta_k & \cdots & w_{2n}\gamma_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\gamma_k & w_{n2}\gamma_k & \cdots & \beta_k \end{bmatrix} \tag{7}$$

2.3.1. The Direct Effect

The direct effect (DE) is the average of the diagonal elements of the matrix in equation (7). If $A^{\bar{d}}$ represents row-wise averaging of the diagonal elements of matrix A , then DE can be expressed as:

$$DE = \left\{(I - \rho W)^{-1} \times (\beta_k I + \theta_k W)\right\}^{\bar{d}} \tag{8}$$

The direct effect illustrates how the dependent variable is influenced by the independent variables and the extent of this influence. Feedback effects are also embedded within the direct effect. Feedback effects mean that after one region affects other regions, those influenced regions, in turn, affect the original region. From a mathematical perspective, the sum of the model coefficients and the feedback effects equals the direct effect.

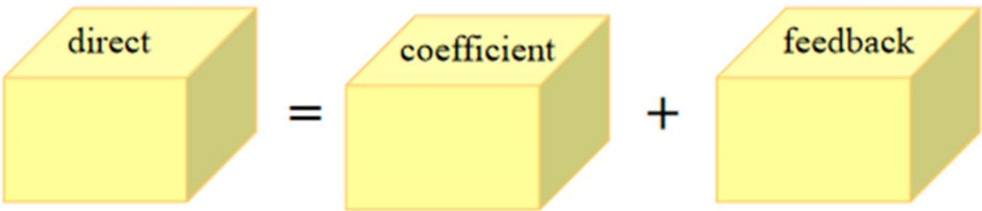

Figure 1. The direct effects and feedback effects.

2.3.2. The Indirect Effect

Indirect Effects (IE) are calculated as the row average of the matrix (7) excluding the diagonal elements. Here, if $A^{\overline{rsum}}$ represents row averages for the matrix A , then IE can be expressed as:

$$IE = \left\{(I - \rho W)^{-1} \times (\beta_k I + \theta_k W)\right\}^{\overline{rsum}} \tag{9}$$

Indirect Effects (IE) represent the key focus of This paper on spatial dependence. However, it is crucial to note that in empirical analysis, the significance of spatial autoregressive coefficients does not necessarily indicate the presence of spatial effects.

2.3.3. Total Effect

Total Effect (TE) is the sum of direct and indirect effects. In the SDM model, the coefficients are not equivalent to the marginal effects typically found in ordinary models. Therefore, when interpreting the model, using direct and indirect effects is more appropriate.

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3. The Spatial Dependence of the Impact of Economic Policy Uncertainty on Carbon Emissions

3.1. Pre-testing

This paper utilized a balanced panel sample comprising 24 developed and developing countries from the years 2003 to 2020. Restricting the sample to these 24 countries was done to ensure reliable data for various indicators, especially the data on Economic Policy Uncertainty (EPU) values. The dependent variable is carbon dioxide emissions (per capita/ton), serving as a proxy for overall environmental pollution within a country. Per capita Gross Domestic Product (GDP), population size, urbanization level, and industrialization level were sourced from the World Development Indicators (WDI). The index of economic policy uncertainty was measured using the method outlined by Baker [15] and others, involving analysis of over ten authoritative newspapers in each country. Higher values indicate greater economic policy uncertainty.

The Moran's Index is employed to examine the degree of spatial autocorrelation. Statistically significant positive values of the Moran's Index indicate spatial clustering, while negative values signify spatial dispersion among the sample countries. Using per capita carbon dioxide emissions data from 24 countries/regions, this paper computed the Moran's Index values for each year from 2003 to 2019, as presented in Table 1.

Table 1. Moran's Index Values from 2003 to 2019

year	Moran’s Index	Year	Moran’s Index
2003	0.4975**	2012	0.3874*
2004	0.4761**	2013	0.3889*
2005	0.4757**	2014	0.3868*
2006	0.4517**	2015	0.3874*
2007	0.4409**	2016	0.3899*
2008	0.4281*	2017	0.3885*
2009	0.4347**	2018	0.3989*
2010	0.4186*	2019	0.3960*
2011	0.3919*	--	-- [1]

[1] ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Null hypothesis: No spatial autocorrelation.

Table 1 shows a significant positive spatial autocorrelation in carbon emissions across countries. The Moran's I value is consistently positive and statistically significant at the 5% or 10% level. However, global Moran's I test only describes the overall average level of correlation. If there is positive spatial autocorrelation in some countries and negative spatial autocorrelation in others, these effects may offset each other, leading to a Moran's I value that tends towards 0, indicating non-spatial autocorrelation. To further examine spatial dependence, scatter plots of Moran's I values for the years 2003, 2005, 2009, 2012, 2016, and 2019 are presented in Figure 2.

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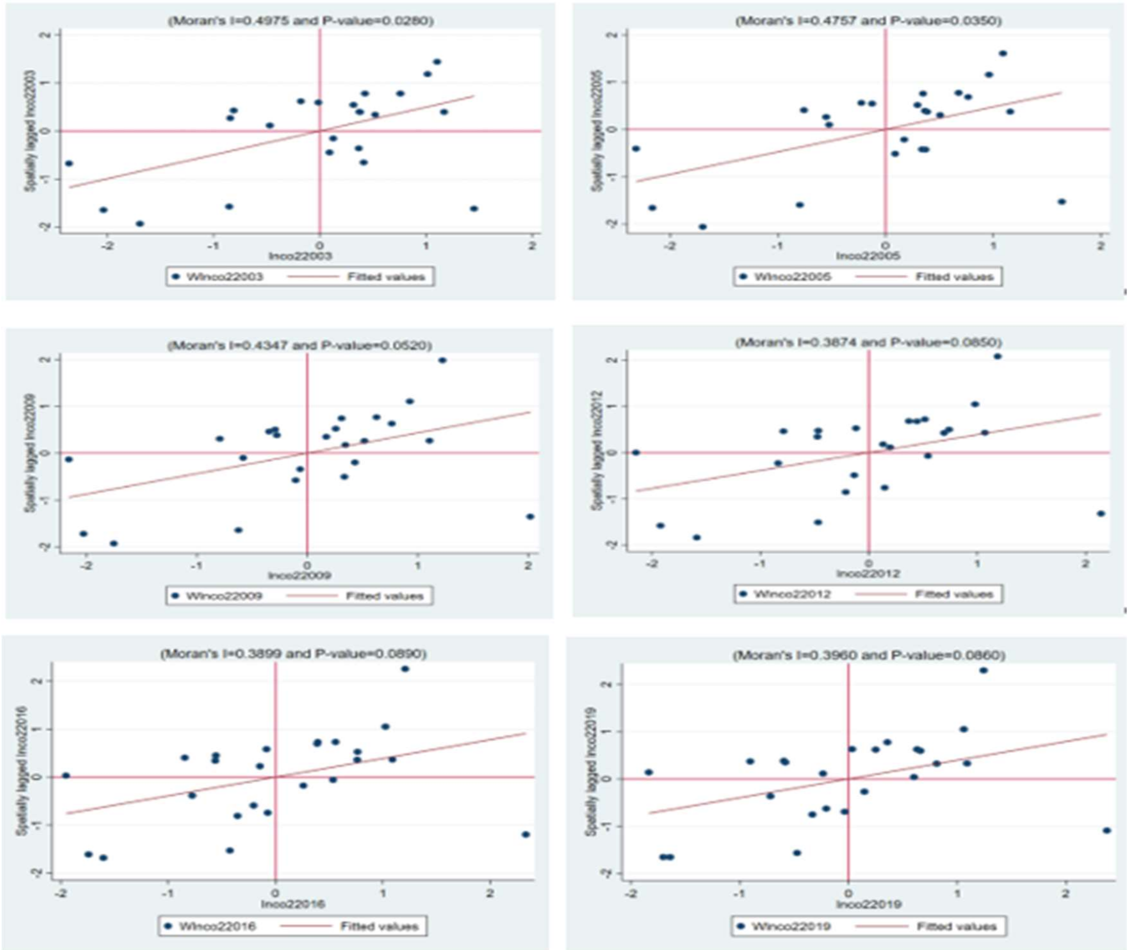

Figure 2. Moran index in every year

The statistical significance of Moran's I values indicates that conventional econometric methods without accounting for spatial dependence might lead to estimation errors. Moreover, in conjunction with the spatial distribution of carbon dioxide emissions depicted in Figure 3, it can be concluded that countries with similar carbon dioxide emission levels tend to cluster, especially those with closely aligned values become neighbors.

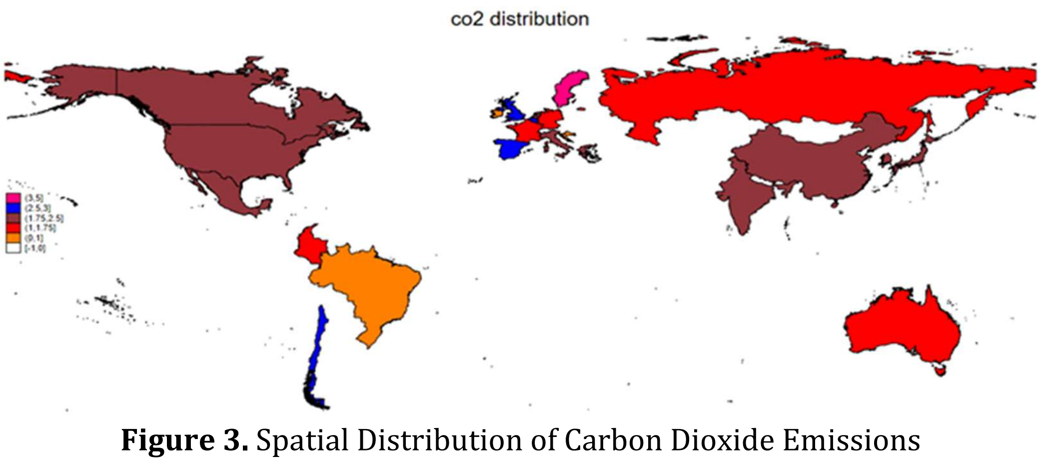

Figure 3. Spatial Distribution of Carbon Dioxide Emissions

Next, we need to conduct panel unit root and cointegration tests for the model. First, this paper performs cross-sectional dependence tests (CD test) on the variables to further examine whether there is spatial dependence among countries. The CD test does not require specifying

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a spatial weight matrix, and the results are presented in Table 2. All variables reject the null hypothesis, indicating the significance of considering spatial dependence among countries in this context. Therefore, establishing a spatial panel data model is necessary.

Table 2. Cross-Sectional Dependence Test Results

	lnco2	lngdp	lnepu	lnpop	lnindus	lnurban
CDtest	8.512***	38.955***	34.031***	29.103***	26.729***	34.850*** [1]

[1] The CD test tests the null hypothesis of cross-sectional independence. *** indicates significance at the 1% level.

Secondly, this paper conducts panel unit root tests using the LLC, IPS, and HT methods. Table 1 demonstrates that after first differencing, all variables in This paper are stationary at the 1% significance level, except for the population variable, which is significant at the 10% level in the IPS test.

Table 3. Panel Unit Root Tests First-order Difference

	LLC	IPS	HT
lnco2	-1.0199***	-2.7450***	-0.0548***
lnepu	-1.3315***	-3.1900***	-0.1167***
lngdp	-0.5434***	-2.0160***	0.4404***
lnpop	-0.2299***	-1.7990*	0.7045***
lnindus	-1.0558***	-2.8630***	-0.0433***
lnurban	-1.3655***	-3.2790***	-0.1286*** [1]

[1] ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The third step involved conducting panel cointegration tests using the Pedroni cointegration test. The results of the panel cointegration test rejected the null hypothesis, indicating that there is no cointegrating relationship between the explanatory variables and the dependent variable. However, a long-term relationship exists among the explanatory variables and the dependent variable.

Table 4. Panel Cointegration Test Results

	Statistic	p-value
Modified Phillips-Perron t	4.3859***	0.0000
Phillips-Perron t	-4.9302***	0.0000
Augmented Dickey-Fuller t	-3.9834***	0.0000 [1]

[1] ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.2. Results

Table 5 provides the estimated results of the panel data regression using various models, including the pooled OLS, spatial fixed-effects, time fixed-effects, and a double fixed-effects model that incorporates both spatial and time fixed effects. The coefficients in these models represent the relationships between the variables and the dependent variable, carbon emissions.

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Table 5. The estimation results of the non-spatial panel data models.

	Pooled OLS	Spatial fixed effect	Time fixed effect	Two-way Fixed Effects
lngdp	-0.0466 (-0.09)	4.9070*** (15.88)	-0.1092 (-0.20)	0.0481 (0.08)
lngdp2	0.0405 (1.47)	-0.2100*** (-12.83)	0.0434 (1.55)	0.0338 (1.14)
lnepu	-0.0268 (-0.49)	-0.0557*** (-4.35)	0.0194 (0.28)	0 .0656 (0.85)
lnpop	0.0326* (1.62)	-0.3275** (-2.31)	0.0317 (1.54)	0.0199 (0.91)
lnurban	0.0925 (0.53)	-3.0271*** (-12.07)	0.1142 (0.64)	0.0602 (0.32)
lnindus	0.8502*** (7.80)	0.0454 (0.64)	0 .8236*** (7.35)	0.8466*** (7.17)
intercept	-5.2762** (-2.23)	-6.9692** (-2.26)	-5.1595** (-2.15)	-5.504514** 1 (-2.17)

1 ***, **, and * denote significance levels at 1%, 5%, and 10%, respectively. Standard errors are shown in parentheses.

The likelihood ratio (LR) test is conducted in This paper to compare mixed effects with spatial fixed effects and time fixed effects. The LR test indicates that the maximum value of the likelihood function does not significantly decrease under the constraint of the parameters. The results of the LR tests for mixed effects vs. time fixed effects are shown in Table 6, and for mixed effects vs. spatial fixed effects are presented in Table 7. In the comparison between mixed effects and time fixed effects, the null hypothesis H0 is not rejected, indicating that mixed effects are preferred over time fixed effects. However, in the comparison between mixed effects and spatial fixed effects, the null hypothesis H0 is rejected, favoring the constrained model with spatial fixed effects. The LR test rejects the null hypothesis of spatial fixed effects. However, the null hypothesis of the unimportance of time fixed effects is not rejected. These results affirm the necessity of selecting a panel data model with spatial fixed effects for the subsequent analysis.

Table 6. LR Test for Mixed Effects vs. Time Fixed Effects

Likelihood-ratio test			LR chi2(15) = -0.29
Model	df	AIC	BIC
M_OLS	7	557.1961	585.2750
M_time_FE	22	587.4835	675.7314

Next, the paper needs to consider the selection of spatial econometric models. Initially, this paper estimates the fixed effects and random effects of the spatial Durbin model to validate the reliability of the conclusions obtained in the ordinary panel data model. Hausman test is employed to compare fixed and random effects. The results indicate that in terms of coefficient estimation, the results of the fixed effects model and random effects model are highly consistent in terms of signs. The results in Table 8 show the rejection of the random effects model. The fixed effects model can be chosen, which is consistent with the findings obtained in the ordinary panel data model.

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Table 7. LR Test for Mixed Effects vs. Spatial Fixed Effects

Likelihood-ratio test			LR chi2(22) = 1449.29
Model	df	AIC	BIC
M_OLS	7	557.1961	585.2750
M_Spatial_FE	29	-848.0954	-731.7686

After confirming the necessity of using a spatial econometric model with fixed effects, it is important to test whether the SDM (Spatial Durbin Model) can be simplified into the SEM (Spatial Error Model). The LR (Likelihood Ratio) test results, as shown in Table 9, reject the hypothesis that the spatial Durbin model can be simplified into a Spatial Error Model. Similarly, the LR test results reject the null hypothesis that the spatial Durbin model can be simplified into a Spatial Lag Model. Therefore, This paper on the spatial dependence of EPU (Economic Policy Uncertainty) on carbon emissions should utilize the SDM model.

Table 8. The Hausman test results in the spatial Durbin model

	Spatial fixed effect	Spatial random effects
lnepu	-0.0557	-0.0587
lnpop	-0.3275	-0.1099
lngdp	4.9070	4.7487
Lngdp2	-0.2100	-0.2061
lnindus	0.0454	0.1328
lnurban	-3.0271	-2.6721
Hausman test	38.53***	

Economic Policy Uncertainty (EPU) has a negative impact on per capita carbon dioxide emissions in this country, meaning that EPU reduces carbon emissions. This conclusion appears to contradict conventional wisdom. The higher levels of EPU affect the external operating environment of economic entities, which in turn influences their business decisions and, consequently, the overall carbon emissions of a region. These influences tend to be negative. However, empirical results using the autoregressive distributed lag model suggest that, in the short term, EPU decreases carbon emissions, thereby improving environmental quality. However, in the long term, EPU leads to an increase in carbon emissions, indicating that EPU causes environmental degradation.

Table 9. LR test results for spatial model selection

	SAR	SEM
LR chi2(6)	99.33	52.85
P values	0.0000	0.0000

Furthermore, there exists a strong spatial dependence in carbon emissions and their influencing factors. An increase in carbon emissions in neighboring countries leads to an increase in carbon dioxide emissions in the focal country. The coefficient for per capita GDP is positive, while the squared term is negative. These results support the inverted U-shaped relationship between carbon emissions and per capita income. The significant negative coefficient of industrial structure implies that a higher proportion of industrial value-added in the Gross Domestic Product (GDP) reduces carbon emissions. These findings contradict traditional beliefs, as industrial development is conventionally associated with energy consumption, suggesting that higher industrialization would lead to increased energy

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consumption and higher carbon emissions. However, the model results show a significantly negative coefficient, possibly influenced by the sample used in the model.

In the sample of 24 countries studying economic policy uncertainty, developed countries account for 75% of the sample. Additionally, other developing countries such as China, India, Colombia, Chile, Mexico, and Brazil are either economic giants or close to the level of developed countries. For these relatively advanced countries, traditional industrial structures are gradually being improved, transitioning from high-energy-consuming industrial structures to high-end industrial structures primarily based on advanced technologies. This shift might be the main reason for the significantly negative coefficient of industrial structure in the model. At the 1% significance level, the coefficient for urbanization is significantly negative. Under all other conditions being equal, a higher degree of urbanization is associated with lower carbon emissions. The coefficient for population size is negative but not statistically significant, indicating that a country's population size does not affect per capita carbon emissions. It is commonly assumed that a larger population directly or indirectly leads to more energy consumption, thereby increasing per capita carbon emissions. Therefore, the coefficient should be significantly positive. One possible explanation is that population size is related to some form of agglomeration, which can enhance production efficiency, thereby reducing per capita carbon emissions. These effects offset each other, potentially resulting in the observed outcome.

The factors of the spatial Durbin former do not immediatly report the side effects of every explaining variable on the dependent variable. Table 11 presents the direct, indirect, and total effects of EPU on carbon emissions. In This paper, the direct effect represents the impact of EPU in a specific country/region on carbon emissions. The indirect effect represents the impact on the carbon emissions of this country due to changes in EPU in other countries/regions. The total effect is simply the sum of the direct and indirect effects.

Table 10. The estimated results of the spatial Durbin model

	coefficient	z value	coefficient	z value
	Fixed Effect		Random Effect	
ρ	0.3909***	10.42	0.3776***	9.89
lnepu	-0.0351***	-3.14	-0.0323***	-2.87
lnpop	-0.0058	-0.04	0.0394	0.51
lngdp	3.5234***	12.56	3.5777***	12.66
lngdp2	-0.1348***	-8.99	-0.1389***	-9.30
lnindus	-0.1465***	-2.36	-0.1175**	-1.96
lnurban	-1.9134***	-8.22	-1.8585***	-8.27
W*lnepu	-0.0200	-1.45	-0.0257*	-1.85
W*lnpop	0.1871	1.08	0.0098	0.10
W*lngdp	-0.9893**	-2.43	-0.9342**	-2.31
W*lngdp2	0.0216	1.03	0.0218	1.05
W*lnindus	0.18278***	2.76	0.1519**	2.38
W*lnurban	-0.1893	-0.59	-0.1281	-0.42
R^2	0.6258		0.6278 [1]	

[1] ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The direct and indirect effects of Economic Policy Uncertainty (EPU) on carbon emissions are both negative, with the indirect effect being larger than the direct effect. Countries with higher EPU exert a positive impact on environmental quality, meaning that EPU reduces carbon emissions, thereby improving environmental quality. There are two potential reasons behind

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this result. Firstly, higher EPU might reduce energy consumption, investments at the company level, company profits and cash flows, as well as the impact on tourism and GDP growth. These reductions subsequently lead to a decrease in carbon emissions. Secondly, higher EPU could influence the decisions of economic entities, further reducing carbon emissions. In the long term, however, EPU increases carbon emissions, indicating that EPU leads to environmental degradation. This finding could be due to two possible reasons. On one hand, EPU might hinder research and development, innovation, and the consumption of renewable energy sources, thereby exacerbating carbon emissions. Political tensions among major world powers force countries to cut spending on research and development, innovation, and renewable energy investments. For instance, recently, the United States reduced research and development expenditure by 21%, leading to an increase in carbon emissions. On the other hand, EPU also encourages manufacturers to put to use experienced and environmentally unfriendly methods of production, leading to a significant increase in carbon emissions.

4. Discussion

Additionally, this paper results reveal interesting insights that offer directional perspectives for future research on carbon emissions. On one hand, carbon emissions are not only influenced by changes in factors but also because these influencing factors can transmit feedback effects through neighboring countries back to the focal country itself. Table 11 shows that the direct effects on factors influencing carbon emissions differ from their coefficient estimates. The direct effect of GDP is 3.636, with a coefficient estimate of 3.523, resulting in a feedback effect of 0.1130. The direct effect of EPU is -0.0414, with a coefficient estimate of -0.0351, leading to a feedback effect of -0.0063. The direct effect of industrial structure is -0.1201, with a coefficient estimate of -0.1465, resulting in a feedback effect of 0.0264. The direct effect of urbanization level is -2.111, with a coefficient estimate of -1.913, leading to a feedback effect of -0.198. On the other hand, the indirect effects of other influencing factors produce intriguing results. For per capita GDP, the spillover effect is 0.587, suggesting that the economic growth of all neighbuoring states adds, and the carbon footprint of the focal state also increase. Similar results are found in industrial structure, where the spillover effect is 0.178. If neighboring countries experience an increase in their industrial structure, the corresponding country's carbon emissions also increase, although the magnitude of this increase is smaller compared to the increase in per capita GDP. Furthermore, the spillover effect can overcome the negative direct impact of industrial structure, indicating an overall positive effect (0.058). Regarding the size of population , the cumulative overflow effect is 0.255, indicating that an increase in population size in all neighboring regions leads to an increase in the carbon emissions of the local country. The estimated indirect spillover effect is significantly correlated with the level of urbanization negative (-1.325), and the direct effect is also negative (-2.111), resulting in a significant negative total effect (-3.436). The indirect effect coefficient implies that being surrounded by highly urbanized countries has a negative impact on environmental quality. By comparing the coefficients of direct and indirect effects, it becomes apparent that the indirect effects of EPU, population size, and industrial structure are larger than their direct effects, while the direct effects of per capita GDP and urbanization level are greater than their indirect effects. These results emphasize the importance of considering spatial dependence when evaluating determinants of carbon emissions. Without accounting for these effects, carbon emission governance would only consider the internal impacts of policies, neglecting external influences (indirect effects).

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Table 11. The direct effect, indirect effect, and total effect

	Direct Effect		Indirect Effect		Total Effect	
	coefficient	z value	coefficient	z value	coefficient	z value
lnepu	-0.0414***	-3.44	-0.0479***	-2.43	-0.0893***	-3.40
lnpop	0.0255	0.18	0.2546	1.06	0.2801	0.89
lngdp	3.6365***	12.79	0.5869	1.11	4.2234***	6.20
Lngdp2	-0.1429***	-9.58	-0.0461*	-1.67	-0.1890***	-5.31
lnindus	-0.1201*	-1.72	0.1782**	1.70	0.0581	0.37
lnurban	-2.1112***	-9.27	-1.3253***	-2.98	-3.4365***	-6.42 [1]

[1] ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusion

This paper, based on the STIRPAT theory, investigates the spatial dependence of the impact of Economic Policy Uncertainty (EPU) on carbon emissions. Spatial autocorrelation tests using the Moran's Index were conducted, and a Moran's Index scatter plot was generated to assess spatial dependence. Panel data models with spatial fixed effects and the spatial Durbin model were employed to explore the spatial dependence of EPU's impact on carbon emissions. The key conclusions drawn from This paper are as follows: Firstly, EPU exhibits strong spatial dependence concerning its impact on carbon emissions. Secondly, the influence of economic policy uncertainty on carbon emissions is significantly negative, higher EPU leads to a decrease in carbon dioxide emissions. In the short term, many countries might increase their EPU at the expense of controlling carbon emissions. However, in the long term, stabilizing economic policies remain essential for reducing carbon emissions. Thirdly, the indirect effects of EPU on carbon emissions are greater than the direct effects. Countries with higher EPU values have a positive impact on environmental quality, in other words, EPU reduces carbon emissions, thereby improving environmental quality.

Based on the empirical analysis of the spatial dependence of the impact of Economic Policy Uncertainty (EPU) on carbon emissions, this paper proposes several policy recommendations: (1) Consider the Influence of Neighboring Countries: Both the spatial dependence of the dependent and independent variables have significant effects, either positive or negative, on both local and neighboring countries from a regional and national perspective. Decision-makers and international organizations should not only focus on national interests but also consider their impact on neighboring countries. They should pay special attention to the spatial dependence effects brought about by higher levels of economic integration with other regions of the world. (2) Strengthen International Environmental Cooperation: With the deepening of economic globalization, countries are increasingly interconnected in terms of economic, political, and environmental policies. Strengthening international cooperation is crucial for energy conservation and emissions reduction. Additionally, central governments should enact legislation and administrative measures to raise awareness about energy conservation. (3) Stabilize Economic Policies and Promote Clean Energy Use: In the short term, EPU might decrease carbon emissions, but in the long term, it could lead to an increase in carbon emissions. While some countries might consider increasing EPU as a means to control carbon emissions, stable economic policies remain essential in the long run. If countries aim to simultaneously reduce environmental pollution and EPU, they should introduce innovative and renewable energy sources. Governments should encourage the use of clean energy by providing tax exemptions and increasing research and development budgets for clean energy technologies that also promote employment. (4) Tailor Differentiated Environmental Policies: There are significant differences in economic and social development among countries. Therefore, environmental policies should be tailored to these differences. For instance, developing

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countries are still in the process of industrialization and have a strong incentive to introduce heavy industries, especially those that promote rapid GDP growth. However, due to the fragility of their environments, strict measures should be taken to limit high-pollution industries in these countries.

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