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Spatial Spillover Effects of Supply Chain Digitalization on Synergies between Pollution Reduction and Carbon Mitigation: Evidence from China

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Abstract

Promoting synergistic governance of pollution reduction and carbon mitigation (PRCM) constitutes a core task for China's green transformation. As a major digital-driven initiative, the supply-chain digitization pilot policy (SCD) holds promise for advancing environmental governance, yet its spatial spillover effects on PRCM remain under-explored. Using panel data of 237 Chinese cities from 2011 to 2023, this study measures urban PRCM performance and adopts a spatial Durbin model (SDM) to explore SCD's direct and indirect impacts on PRCM, considering geographic and economic-geographic proximity. The results show PRCM has significant positive spatial autocorrelation; SCD significantly improves local PRCM and exerts positive spatial spillovers to neighboring cities under the economic-geography weight matrix; its promotion effect is most obvious in eastern and western cities, with significant spillovers across regions under the economic-geography matrix. These findings provide insights for cross-regional collaborative environmental governance in the digital era.

Keywords

Supply Chain Digitalization; Pollution-carbon Synergy; Spatial Durbin Model; Regional Heterogeneity; Spatial Spillover Effects.

1. Introduction

Over the past decade, the pressures caused by environmental pollution and climate change have increased, which have brought common and severe challenges to the economies of countries around the world. The International Energy Agency documented a historic high of 37.5 billion metric tons in global CO_2 emissions for 2023 [1], and the World Health Organization attributes around 7 million annual premature deaths across the globe to air pollution. These alarming statistics show that there is an urgent need to develop a comprehensive policy framework that integrates pollutant control and carbon emission reduction, rather than dealing with the two issues in isolation. It is under this urgent need that collaborative environmental governance-that is, the governance method of coordinating air quality improvement and greenhouse gas emission reduction-is increasingly valued in academic discussions and policy design [2]. Smart supply chain systems represent one compelling solution: digitalization unlocks opportunities to boost resource productivity, curb environmental externalities and advance cleaner production practices. However, although the intelligent supply chain has great potential in theory, empirical research on its ability to achieve collaborative pollution reduction and carbon mitigation (PRCM) and its intrinsic mechanism is still very limited, especially in the context of large-scale and policy-driven practical applications.

As the world's largest carbon emitter and facing serious air pollution for a long time, China has become a key region for the study of comprehensive environmental management strategies. In

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2023, China alone accounted for about 33.98% of global carbon dioxide emissions, and more than 80% of the PM2.5 concentration in its major cities exceeded the threshold set by the World Health Organization [3]. In response, the Chinese government has launched a series of national strategies aimed at harmonizing ecological protection with economic modernization. Among them, initiatives such as carbon trading market, green financial tools and industrial upgrading plans have attracted wide attention from the academic and policy circles [4–6]. However, the evidence of the effectiveness of these policies in achieving synergistic improvements in pollution and carbon emissions at the regional level remains scattered. China's "14th Five-Year Plan" clearly puts forward "high-quality development" and "green transformation", emphasizing the strategic importance of assessing whether and coordinating policy tools can produce tangible and quantifiable environmental synergies in actual implementation.

Against this policy background, the Supply Chain Innovation and Application Pilot Project (SCIAPP) has become a unique institutional experiment that integrates digital infrastructure, supply chain coordination and sustainable development goals. The project was launched by the government of the People's Republic of China in 2018. It aims to cultivate intelligent, resilient and environmentally friendly supply chain networks by deploying cutting-edge technologies such as big data analysis, blockchain and the Internet of Things. These technologies not only aim to optimize logistics and improve operational efficiency, but also to promote decarbonization and decontamination of industrial processes [7]. Existing studies regard SCIAPP as a proxy indicator of supply chain digitalization (SCD) and explore its role in improving green innovation capacity [8]; however, its environmental impact-especially in terms of pollution control and carbon emission reduction-still lacks in-depth research. Furthermore, as a core feature of networked supply chain systems, the potential spatial spillover effects of SCD have long been overlooked in traditional environmental policy evaluations. Given the inherent networked and cross-regional nature of supply chain systems, their environmental impacts extend beyond local boundaries, potentially leading to spatial overflow via industrial linkages, the spread of technology, and the movement of factors. The traditional econometric model fails to fully consider the dual dependence between geography and economy. Ignoring the spatial dimension may lead to bias in policy evaluation and misjudge the role of the mechanism.

To close these gaps in the research, this study follows the approach of previous studies and uses SCIAPP as the proxy variable for the SCD policy. First, this study measures PRCM at the urban scale, and empirically examines the spatial spillover effects of the SCD policy on PRCM across 237 Chinese cities using spatial econometric methods. Second, this study employs the Spatial Durbin Model (SDM) to evaluate the heterogeneous spatial spillover effects of the SCD policy under different geo-economic contexts and explores regional heterogeneity.

The remainder of this paper is structured as follows. Section 2 reviews existing literature. Section 3 describes the empirical methodology. Sections 4 present the empirical results. Section 5 concludes the study and provides policy recommendations.

2. Literature Review

2.1. SCD Policy

The SCD policy is a national strategy implemented by China to meet the challenges of global supply chain restructuring and promote the modernization of the industrial chain. The policy was launched in 2018 through the pilot notice issued by eight ministries, including the Ministry of Commerce, to promote the reform and upgrading of the supply chain through digitalization, intelligence and standardization, so as to enhance economic resilience and safety [9]. The policy focuses on building an integrated and collaborative modern supply chain system [10], giving priority to cultivating leading enterprises in manufacturing and distribution industries to

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establish a replicable model [11]. This initiative not only reflects the country's strategic focus on the supply chain as a key form of industrial organization, but also reflects its high importance on balancing the efficiency and safety of the supply chain under the new dual-cycle development pattern.

The existing research mainly focuses on assessing the effectiveness of policies and operating mechanisms. Most empirical studies show that the policy has significantly promoted the digital transformation of enterprises and the efficiency of supply chain coordination [12–14], and enhanced the competitiveness of the industrial chain through the spillover effect of technological innovation and network integration [15]. Some literature also emphasizes the positive impact of the policy on regional economic growth and logistics cost reduction [16]. However, some scholars point out that there are heterogeneous effects on policy implementation, emphasizing that there are significant differences between different industries, regions and enterprise sizes [9]. In addition, some studies point out that investment mismatch may occur in the process of policy implementation [17]. In recent years, research has begun to pay attention to the spillover effect of the policy in the fields of new energy supply chain [18] and pollution emissions [19], thus enriching the dimension of policy evaluation.

2.2. PRCM

PRCM is a key strategic concept to address the dual challenges of climate change and environmental pollution. It emphasizes the reduction of pollutant emissions while controlling greenhouse gas emissions to enhance the comprehensiveness and systematicity of environmental governance [20]. This concept originates from China's "dual carbon" target framework, which aims to maximize environmental and climate benefits through mechanism linkage, technical coordination and policy integration [21]. Scholars have developed a variety of methods for evaluating synergies, including single-indicator methods-such as pollutant emissions per unit of carbon emissions or synergy efficiency indices [15]. Although these methods are easy to understand, they are difficult to fully capture the complex mechanism of multi-factor synergy. In order to further systematically quantify the synergy effect, the researchers also proposed the index system method [22], combined with the coordination degree model [23], and the synergy efficiency model based on Data Envelopment Analysis (DEA) [24].

Among such methods, the DEA method is widely used because of its ability to handle multiple inputs, multiple expected outputs and non-expected outputs at the same time, especially for assessing the synergistic efficiency at the regional or industry level. This method does not need to set the functional form in advance, which effectively avoids subjective bias and ensures the objectivity of the evaluation results. For example, Wang et al. [25] built an SBM-DEA model that included carbon emissions and a variety of pollutants as bad outputs.

In order to analyze the performance of collaborative governance more dynamically, Li and Chen [26] combined the global machine learning index with data envelope analysis (DEA) to capture efficiency changes and technological evolution trends. Regarding the selection of indicators, common bad emissions include carbon dioxide, PM2.5, sulfur dioxide and nitrogen oxides. Some studies have also incorporated other types of pollutants such as volatile organic compounds and industrial wastewater to comprehensively characterize the synergistic control effect.

2.3. SCD Policy and PRCM

The relationship between SCD and PRCM has attracted more and more academic attention, but empirical and theoretical debates continue. The existing literature still disagrees on whether the digital-driven supply chain transformation can ultimately improve the effectiveness of environmental governance. Some studies believe that through technology integration and

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process reinnoduction, SCD can improve efficiency, optimize resources and reduce emissions [27]. Other studies are concerned about the possible rebound effects, such as the increase in energy consumption caused by digital infrastructure and the spillover of pollution to less regulated areas [28]. The third type of literature emphasizes the nonlinearity and situational dependence of its influence paths, which are affected by regulating factors such as regional industrial structure, technological maturity and policy implementation intensity [2].

In short, although the current research has laid the initial foundation for understanding the connection between SCD and PRCM, there are still some limitations: First of all, most studies focus on enterprise-level analysis, while urban-level research is relatively lacking. Secondly, the existing research mainly emphasizes the economic benefits of SCD, and has made a limited discussion on the mechanism of environmental synergy benefits and regional spatial characteristics. Third, the existing research lacks a systematic analysis of the potential spatial spillover effect of SCD, which hinders a comprehensive assessment of its overall environmental impact. Based on this, the following are the paper's possible contributions: First, we collect prefecture-level city data to construct SCD and PRCM indicators, revealing their distribution and evolution at the urban scale. Secondly, we use the spatial econometrics method to identify the direct and indirect impact of SCD on PRCM, so as to test its spatial overflow mechanism. Third, we conduct a regional heterogeneity analysis to reveal the differentiated impacts of SCD on cities across different regions, providing a basis for formulating coordinated digitalization and greening policies tailored to local conditions.

3. Methodology

3.1. Spatial Econometric Model

Due to potential spatial correlations among cities' PRCMs, implementing SCD policy in city i affects not only its own PRCM but also those of neighboring cities. Derived from the spatial correlation framework suggested by Elhorst [29], empirical studies in spatial econometrics typically employ spatial autoregressive models (SAR), spatial error models (SEM), and spatial Durbin models (SDM). Consequently, the study develops the following three fundamental spatial econometric models:

$$PRCM_{it} = \alpha_0 + \rho WPRCM_{it} + \alpha_1 SCD_{it} + \sum_{n=2}^{8} \alpha_n X_{nit} + \varepsilon_{it} \quad (1)$$

$$PRCM_{it} = \alpha_0 + \alpha_1 SCD_{it} + \sum_{n=2}^{8} \alpha_n X_{nit} + \lambda W\varepsilon_{it} + \mu_{it} \quad (2)$$

$$PRCM_{it} = \alpha_0 + \rho WPRCM_{it} + \alpha_1 SCD_{it} + \beta_1 WSCD_{it} + \sum_{n=2}^{8} \alpha_n X_{nit} + \sum_{n=2}^{8} \beta_n WX_{nit} + \varepsilon_{it} \quad (3)$$

where i represents city, t represents year, and $PRCM_{it}$ represents the dependent variable, represented by the logarithmic value of the interaction term between the comprehensive urban environmental pollution index and carbon emissions of city i in year t. The variable SCD_{it} is a dummy variable that represents the construction of SCD. Specifically, $SCD_{it} = policy_{it} \times post_{it}$, where $policy_{it}$ indicates whether city i is a SCD, it takes the value of 1 if it is and 0 otherwise. $post_{it}$ indicates whether SCD was implemented in year t, it takes the value of 1 if it was and 0 otherwise. ρ is the spatial autoregressive coefficient, representing the spatial spillover effect of PRCM. α_1 is the estimated coefficient of the core independent variable, measuring the impact of SCD on a city's PRCM; X denotes control variables; α_n represents the estimated coefficient for

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control variables. β_1 is the spatial regression coefficient, used to calculate the spatial spillover effect of SCD on other cities' PRCM; β_n is the spatial impact coefficient for control variables. ε_{it} represents the random disturbance term, and W is the spatial weight matrix.

3.2. Setting of the Spatial Weight Matrix

The use of spatial weight matrices to describe the spatial distribution patterns of observations across various regions is a key distinction between spatial econometrics and classical econometrics. Drawing on existing research, develops these three spatial weight matrices:

Geographic inverse distance weight matrix (W1). Given data gaps in some cities, adjacency matrices struggle to accurately capture spatial relationships between regions. Consequently, this research employs a geographic inverse distance weight matrix, designating the inverse distance between two cities as the weight factor. The specific form of this matrix is outlined below:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{4}$$

Economic-geographic distance weighting matrix (W2). This matrix integrates geographic and economic factors, combining spatial economic distance and geographic distance dimensions. Its weights depend on the reciprocal of the product of the per capita GDP disparity between two regions and their geographic distance. The specific expression is as follows:

$$w_{ij} = \begin{cases} \frac{1}{\left|dgdp_i - dgdp_j\right| d_{ij}}, i \neq j \\ 0, i = j \end{cases} \tag{5}$$

Adjacency matrix (W3). In cases where two cities lie next to each other, the assigned weight value is 1. In cases where two cities are not neighboring, the assigned weight value stands at 0. Its expression is:

$$w_{ij} = \begin{cases} 1, i \text{ is adiacent to } j \\ 0, i \text{ is not adiacent to } j \text{ or } i = j \end{cases} \tag{6}$$

3.3. Variable Selection

3.3.1. Explained Variable: PRCM

The logarithmic value of the interaction term between the environmental pollution index (EPI) and carbon emissions (CE) represents the dependent variable in this study, which is the synergy of pollution reduction and carbon mitigation (PRCM). The improved entropy-weighted TOPSIS technique is used to calculate the EPI based on three indicators: total wastewater emissions, SO_2 emissions, and smoke emissions [30]. Note that higher values of PRCM correspond to worse performance of pollution-carbon synergy. A significantly negative regression coefficient thus indicates that the policy improves the synergistic governance performance.

$$PRCM_{i,t} = Ln\left(EPI_{i,t} \times CE_{i,t}\right) \tag{7}$$

3.3.2. Core Explanatory Variable: SCD

This paper defines the interaction term between the policy timing variable (post) and policy dummy variable (policy) as the core explanatory variable (SCD), with the aim of quantifying the

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dynamic policy effects. Cities selected as pilots constitute the treatment group where policy = 1, and the remaining cities serve as the control group with policy = 0. Given that this pilot policy was implemented in 2018, post takes the value of 1 for 2018 and subsequent years, and 0 for all years before 2018. Fig. 1 maps the geographic distribution of SCD pilot cities.

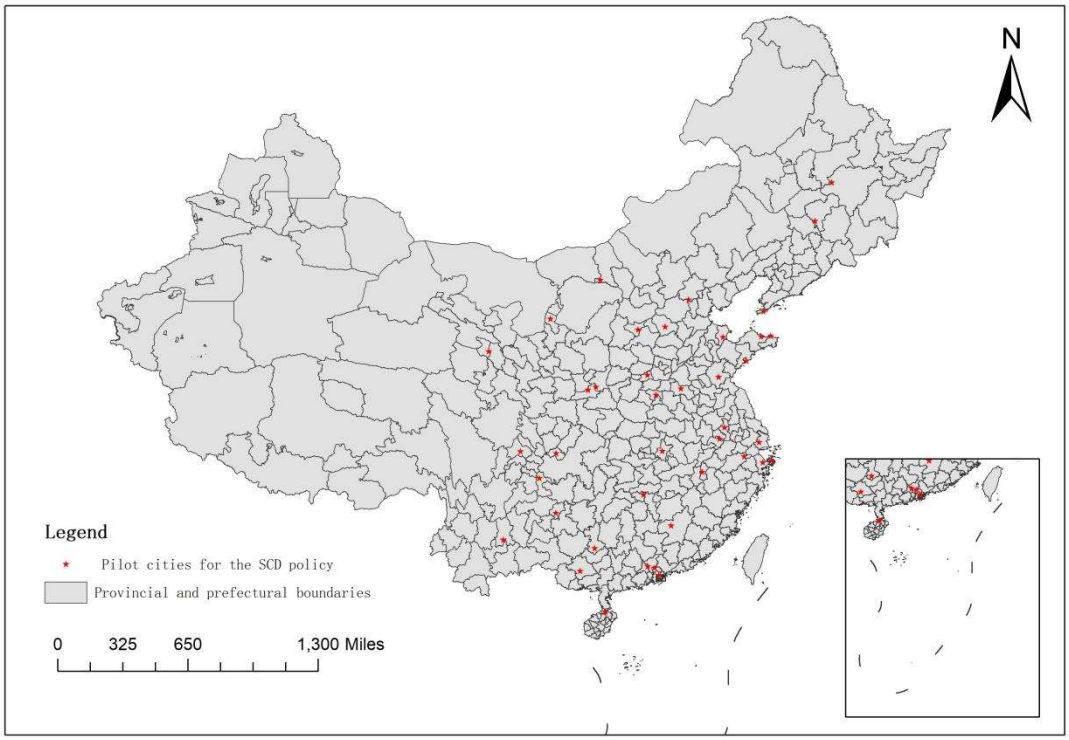


Fig. 1 Map of the distribution of SCD pilot cities

3.3.3. Control Variables

In order to alleviate the bias of missing variables caused by potential unobserved factors, this paper draws on the research of Hu et al. [31] and Xian et al. [32], and introduces a series of control variables into the measurement model. The definition of variables is set as follows: (1) Population Density (PD): the natural logarithm of the population per square kilometer of each city; (2) Economic Development Level (EDL): the natural logarithm of urban per capita GDP; (3) Government Intervention (GI): the ratio of local fiscal expenditure to GDP; (4) Environmental Protection Expenditure Level (EPEL): the proportion of urban environmental protection expenditure to the total municipal public expenditure; (5) Industrialization Level (IL): the ratio of industrial added value to GDP; (6) Industrial Structure (IS): the ratio of the output value of the secondary industry to the total output value; (7) Foreign Direct Investment (FDI): the ratio of foreign direct investment to urban GDP.

3.4. Data Description

The sample of this paper consists of panel data for 237 prefecture-level and above Chinese cities spanning 2011 to 2023. The dataset is compiled from multiple statistical publications, including the China City Statistical Yearbook, China Urban Construction Statistical Yearbook, China Energy Statistical Yearbook, and provincial yearbooks. Urban carbon emission calculation adopts the relevant conversion factors outlined in the IPCC Guidelines for National Greenhouse Gas Inventories (2006). The industrial wastewater discharge from 2020 to 2023 is extrapolated using the three-year average annual growth rate. We apply the interpolation technique to handle minor missing data, and remove cities with substantial missing values from the final sample. Descriptive statistics for all variables are summarized in Table 1.

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Table 1. Descriptive statistics

Variables	N	mean	sd	min	max
PRCM	3081	11.764	1.725	4.440	17.004
PRCM1	3081	19.851	1.156	15.244	23.287
SCD	3081	0.078	0.268	0.000	1.000
PD	3081	5.562	0.900	1.806	8.396
EDL	3081	10.866	0.546	9.219	12.237
GI	3081	0.186	0.077	0.044	0.675
EPEL	3081	0.036	0.039	0.000	0.645
IL	3081	0.381	0.120	0.014	1.119
IS	3081	0.451	0.102	0.116	0.821
FDI	3081	0.016	0.017	0.000	0.173

4. Results and Discussion

4.1. Spatial Distribution of PRCM

The study employed exploratory spatial data analysis to examine the spatial distribution patterns of PRCM in 2023, with results presented in Fig. 2. The figure visually illustrates the gradient variation in PRCM levels across cities through a five-level color scale ranging from green to red (corresponding to increasing numerical values). The figure indicates that the eight cities with the highest PRCM values are Tangshan, Baotou, Shanghai, Suzhou, Zhangzhou, Binzhou, Chongqing, and Xining, all exceeding 14.2. Cities with high PRCM levels are mainly concentrated in Inner Mongolia, Shanxi, Shandong, Jiangxi, Zhejiang, Guangdong, Fujian and other provinces, showing obvious spatial cluster characteristics of PRCM.

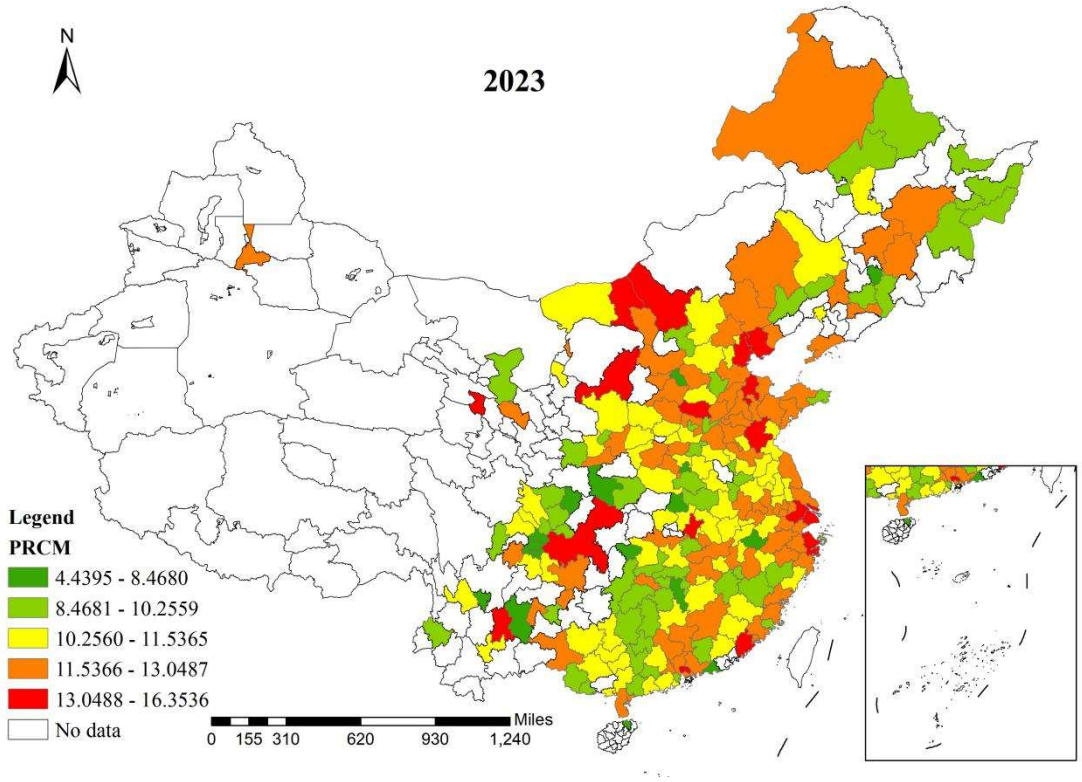


Fig. 2 Spatial distribution of PRCM in 2023

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4.2. Spatial Correlation Test of PRCM

Table 2 shows the test results of spatial self-correlation. Under the two weight matrices (W1 and W2), from 2011 to 2023, the Moran I value of PRCM in each city was significantly higher than zero, successfully passing the 1% significance threshold. This indicates that PRCM shows obvious positive spatial self-correlation, which is manifested as a high-high or low-low spatial aggregation pattern. Fig. 3 and Fig. 4 use the Moran scatter diagram respectively to further show the local space correlation patterns under two matrices in 2011 and 2023. The actual PRCM value is displayed on the horizontal axis, while the vertical axis represents the spatial lag term. It is evident that in both weighting matrices, the majority of urban sample locations are situated in the first and third quadrants, indicative of distinct positive spatial clustering characteristics.

Table 2. Global Moran's I index of PRCM

Year	W1		W2	
	I	p-value	I	p-value
2011	0.057	0.000	0.288	0.000
2012	0.068	0.000	0.303	0.000
2013	0.069	0.000	0.309	0.000
2014	0.073	0.000	0.322	0.000
2015	0.074	0.000	0.328	0.000
2016	0.072	0.000	0.308	0.000
2017	0.059	0.000	0.220	0.000
2018	0.059	0.000	0.217	0.000
2019	0.052	0.000	0.188	0.000
2020	0.090	0.000	0.229	0.000
2021	0.059	0.000	0.199	0.000
2022	0.058	0.000	0.176	0.000
2023	0.051	0.000	0.152	0.000

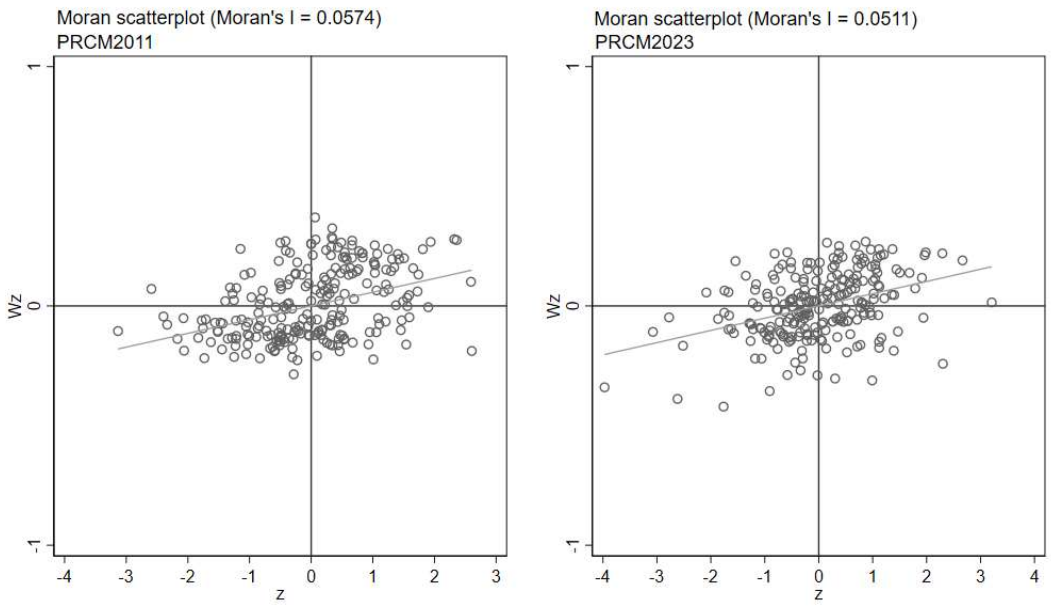


Fig. 3 Moran Scatter Plots in 2011 and 2023 under W1

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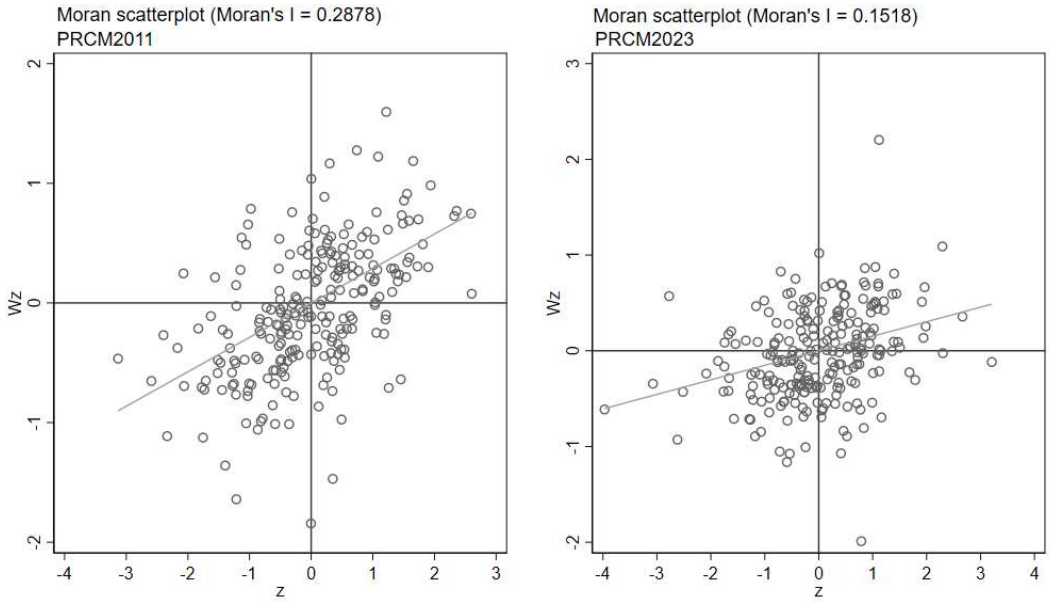


Fig. 4 Moran Scatter Plots in 2011 and 2023 under W2

4.3. Regression Results of the Total Sample

Table 3. Test of the spatial econometric model

Test statistics	W1	W2
LMLAG	2964.413 (0.000)	388.033 (0.000)
Robust-LMLAG	12.819 (0.000)	127.993 (0.000)
LMERROR	4007.999 (0.000)	284.014 (0.000)
Robust-LMERROR	1056.405 (0.000)	23.974 (0.000)
LR spatial lag	63.810 (0.000)	54.760 (0.000)
LR spatial error	62.440 (0.000)	66.730 (0.000)
Wald spatial lag	64.330 (0.000)	55.090 (0.000)
Wald spatial error	61.590 (0.000)	67.110 (0.000)

Note: P-value in parentheses.

Spatial econometric models mainly use three key models to characterize the autocorrelation and distinction of spatial impacts: SAR, SEM, and SDM. As indicated in Table 3, the Lagrange multiplier (LM) test was employed for preliminary diagnosis of spatial correlation in the models. Results indicate that under both W1 and W2 spatial weight matrices, the LMLAG and LMERROR statistics are highly significant at the 1% level. This robustly refutes the null hypothesis regarding the absence of spatial correlation, thereby affirming the substantial spatial interdependence between the variables. Similarly, the Robust Lagrange Multiplier (Robust-LM) test further identified the dominant form of spatial effects: under the W1 matrix, Robust-LMERROR was significant while Robust-LMLAG was insignificant, indicating that

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spatial error effects predominated; under the W2 matrix, both robust tests were significant, with the Robust-LMLAG statistic being larger, suggesting that spatial lag effects were more prominent. This difference highlights the importance of spatial matrix setting in model recognition.

To further assess model applicability and to ascertain whether SDM might be reduced to SAR or SEM, likelihood ratio (LR) tests and Wald tests were utilized. Results show that under both weighting matrices, the p-values for the LR test and Wald test are both 0.000. At the significance level of 1%, both tests strongly rejected the original assumption that SDM could be simplified into a simpler model. This shows that the SDM model contains both the spatial lag of dependent variables and independent variables, which has stronger modeling advantages and statistical applicability. Therefore, the subsequent analysis of this article will focus on the more general SDM model.

First, utilizing W1 and W2, a comparison analysis was carried out based on the SDM regression findings (see Table 4). Under different spatial weighting matrix settings, SCD, the primary explanatory factor, shows a statistically notable adverse direct impact on the area's PRCM at a 1% significance level, evidenced by coefficients of -0.368 and -0.264, respectively. This finding shows that the SCD policy has significantly improved the performance of local PRCM, while the promotion effect is relatively weak under the economic-geographic weight matrix (W2). However, the spatial spillover effect of SCD is significantly different between the two matrices. Under W1, the spillover coefficient (W*SCD) is -0.010 and statistically not significant, indicating that SCD does not produce an obvious spatial overflow effect from the perspective of geographical proximity. In the W2 stage, the coefficient showed a significant negative value (-0.791) at the critical value of 1%, indicating that after considering economic factors, the pilot policy had an obvious negative spillover effect on the PRCM of the relevant cities, reflecting a "regional competition" or "syphon" effect. Under both types of matrices, the spatial lag coefficient shows significant statistical significance at the 1% level, which further confirms the spatial dependence of PRCM. However, there are differences in the intensity of dependence and transmission mechanism between different matrices: the geographical proximity effect is more significant, while the spatial dependence under economic association is relatively weak.

Although Table 4 confirms the spatial relationship between PRCM and the local promotion effect of SCD, it is still difficult to directly identify the complex impact mechanism of SCD on local and peripheral PRCM. Therefore, in order to systematically analyze the marginal impact of each variable on local and surrounding areas, this study further adopts the effect decomposition method proposed by Pace and LeSage [33] to decompose the overall effect into direct effects and indirect effects.

The effect decomposition results in Table 5 show that there are differences in the estimated values of SCD under different spatial matrices. Under the W1 and W2 matrices, the direct impact is significantly negative at the threshold of 1%, indicating that the policy has greatly improved the local PRCM. This result is likely to stem from the fact that digital technology is reshaping the entire supply chain process. By improving energy efficiency, optimizing logistics routes, and strengthening emission monitoring, these technologies have achieved source pollution control and management. More importantly, there are significant differences in its spatial spillover effect in different matrices: In the pure geographical matrix, the spillover effect is not significant; while in the economic-geographical matrix, the indirect effect is obviously negative (-0.967) at the threshold of 1%, indicating that the positive impact of the policy mainly spreads to the surrounding areas through economic linkage channels. This promotes a benign development model characterized by "local drive and regional coordination". The overall effect (-1.248) is significantly negative, further confirming its positive net effect throughout the region.

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Table 4. Regression results of the total sample

Variables	W1			W2		
	SAR	SEM	SDM	SAR	SEM	SDM
SCD	-0.385*** (-6.54)	-0.375*** (-6.43)	-0.368*** (-6.15)	-0.348*** (-5.87)	-0.341*** (-5.63)	-0.262*** (-4.29)
EDL	0.580*** (5.92)	0.647*** (6.25)	0.771*** (6.62)	0.574*** (5.83)	0.591*** (5.79)	0.428*** (3.82)
PD	-0.861** (-2.41)	-1.002 (-2.67)	-1.469*** (-3.56)	-0.759** (-2.12)	-0.796** (-2.12)	-0.695 (-1.60)
GI	-0.189** (-0.43)	-0.285 (-0.63)	-0.429 (-0.90)	-0.163 (-0.37)	-0.129 (-0.28)	0.072 (0.15)
FDI	2.118* (1.93)	2.473** (2.22)	3.128*** (2.78)	1.925* (1.75)	2.096* (1.88)	1.593 (1.42)
IL	1.274*** (5.35)	1.167*** (4.587)	1.098*** (4.60)	1.342*** (5.62)	1.301*** (5.45)	1.377*** (5.80)
EPEL	0.115 (0.25)	0.194 (0.43)	0.480 (1.05)	-0.017 (-0.04)	0.025 (0.05)	-0.163 (-0.36)
IS	-0.394 (-1.04)	-0.376 (-0.97)	0.062 (0.18)	-0.354 (-0.94)	-0.354 (-0.92)	-0.192 (-0.49)
W*SCD			-0.010 (-.0.01)			-0.791*** (-5.31)
W*EDL			-0.769 (-0.95)			0.632*** (2.68)
W*PD			6.453** (2.36)			-0.654 (-0.78)
W*GI			-1.470 (-0.33)			-1.535 (-1.43)
W*FDI			-32.663*** (-2.76)			-5.032 (-1.64)
W*IL			16.608*** (5.60)			1.459** (2.34)
W*EPEL			-14.522*** (-2.89)			-2.121 (-1.57)
W*IS			-14.186 (-3.57)			-0.675 (-0.71)
rho	0.684*** (9.22)		0.623*** (7.20)	0.192*** (6.17)		0.149*** (4.65)
lambda		0.697*** (9.62)			0.163*** (5.06)	

Note: *** p<0.01, ** p<0.05, * p<0.1, z-statistics in parentheses. The same below.

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Table 5. Effect decomposition of the total sample

Variables	W1			W2		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
SCD	-0.371*** (-5.80)	-0.750 (-0.22)	-1.120 (-0.32)	-0.281*** (-4.66)	-0.967*** (-5.88)	-1.248*** (-7.79)
EDL	0.756*** (7.76)	-0.788 (-0.31)	-0.032 (-0.01)	0.433*** (4.61)	0.815*** (3.03)	1.248*** (4.80)
PD	-1.380*** (-3.24)	15.791* (1.69)	14.411 (1.56)	-0.681 (-1.51)	-0.870 (-0.84)	-1.551* (-1.72)
GI	-0.426 (-0.85)	-5.785 (-0.41)	-6.211 (-0.44)	0.047 (0.09)	-1.807 (-1.36)	-1.760 (-1.41)
FDI	2.584** (2.01)	-87.407** (-2.26)	-84.823** (3.84)	1.265 (0.97)	-5.620* (-1.74)	-4.355 (-1.29)
IL	1.303*** (5.56)	49.566*** (3.76)	50.869 (0.84)	1.432*** (6.28)	2.018*** (2.99)	3.450*** (4.66)
EPEL	0.335 (0.77)	-39.533** (-2.44)	-39.128** (-2.42)	-0.212 (-0.48)	-2.522 (-1.51)	-2.734 (-1.57)
IS	-0.884** (-2.38)	-41.581*** (-3.05)	-42.465*** (-3.10)	-0.249 (-0.69)	-0.851 (-0.79)	-1.100 (-0.99)

4.4. Regression Results of Regional Samples

In view of the significant differences in the digital supply chain infrastructure and development stage of Chinese cities [34], the SCD policy's impact on PRCM may show obvious regional heterogeneity. In order to study this phenomenon, the study divides the sample into three main regions: east, middle and west, and uses SDM with W1 and W2 weight matrices to estimate. Table 6 shows the regression results. The study found that the impact of SCD on PRCM varies significantly in different regions, and this conclusion is still sound under different weighted matrices. In W1 and W2, SCD was significantly lower than 5% or higher in both eastern and western regions, indicating that the policy significantly increased PRCM in these regions. However, the estimate of the central region is still not significant, reflecting that the region still faces the challenges of transformation in the integration of digitalization and greening. Regarding the spatial spillover effect, the W2 matrix shows that SCD shows significant negative spatial interaction coefficients in the eastern, central and western regions, indicating that the policy generates a synergistic promotion effect between regions through economic linkage channels. Regarding spatial dependence, except for the failure of the spatial lag coefficient in the western region under the W2 matrix to pass the significance test, the eastern and central regions showed significant positive spatial self-correlation in both matrices. This shows that PRCM shows obvious spatial spillover characteristics in most areas.

Table 7 further shows the results of effect decomposition. The results show that there are significant differences in the direct, indirect and overall effects of SCD in the eastern, central and western regions. In addition, the W2 matrix is more effective than the W1 matrix in identifying the spatial overflow mechanism. Under the W1 and W2 matrices, the SCD in the eastern and western regions are significantly negative, indicating that the SCD policy has effectively enhanced the local synergy in PRCM. The central region has never shown significant impact, reflecting that the region still has persistent institutional or structural obstacles to coordinated digitalization and green transformation. Regarding the indirect effect, all regions have shown significant negative spillover effects under the W2 matrix, indicating that the policy enhances regional synergy through economic linkages. In contrast, only the western region showed a significant impact under the W1 matrix. Combined with the overall negative effect

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across all regions in the economic matrix, this suggests that SCD policy spillovers rely more on economic connections than geographic proximity.

Table 6. Regional regression results

Variables	W1			W2		
	East	Central	West	East	Central	West
SCD	-0.638***	-0.036	-0.489***	-0.446***	-0.024	-0.323**
	(-8.08)	(-0.32)	(-3.21)	(-4.57)	(-0.24)	(-2.38)
EDL	0.502***	1.373***	0.454*	0.805***	1.051***	-0.573**
	(2.90)	(7.56)	(1.73)	(4.89)	(6.02)	(-2.03)
PD	-1.397***	-2.720***	-0.829	-0.835	-1.791**	-1.004
	(-2.89)	(-3.30)	(-0.94)	(-1.64)	(-2.02)	(-0.93)
GI	0.548	-0.154	-1.962**	-0.416	0.555	-1.401
	(0.58)	(-0.20)	(-2.30)	(-0.44)	(0.68)	(-1.55)
FDI	3.098**	2.280	-1.827	1.531	3.568	7.637*
	(2.50)	(0.98)	(-0.42)	(1.21)	(1.61)	(1.70)
IL	0.299	1.305***	0.906**	0.789*	1.548***	1.184***
	(0.67)	(2.98)	(2.16)	(1.75)	(3.51)	(2.92)
EPEL	0.317	1.134*	-0.398	0.361	0.602	-1.192
	(0.51)	(1.85)	(-0.21)	(0.58)	(0.99)	(-0.60)
IS	0.753	-1.599**	-0.171	0.800	-2.760***	1.237*
	(0.98)	(-2.20)	(-0.25)	(1.04)	(-4.05)	(1.68)
W*SCD	-0.446	-0.097	-3.320***	-0.438**	-0.437**	-1.145***
	(-0.58)	(-0.09)	(-2.69)	(-2.02)	(-2.00)	(-3.68)
W*EDL	4.655***	-0.314	-3.976***	0.425	-0.261	0.316
	(5.00)	(-0.30)	(-2.95)	(1.34)	(-0.63)	(0.53)
W*PD	1.475	7.238	6.229*	-0.992	-1.307	1.507
	(0.79)	(1.53)	(1.68)	(-1.11)	(-0.63)	(0.76)
W*GI	-5.638	5.051	-17.500***	-0.513	1.818	-2.886
	(-1.25)	(1.28)	(-2.91)	(-0.28)	(1.35)	(-1.32)
W*FDI	2.496	-7.687	-99.382***	-2.928	-2.873	8.627
	(0.31)	(-0.71)	(-3.10)	(-0.85)	(-0.62)	(0.76)
W*IL	3.224	6.034***	11.829***	-0.887	5.200***	2.702**
	(0.96)	(2.61)	(4.05)	(-1.03)	(5.03)	(2.55)
W*EPEL	-20.478***	2.594	5.954	0.702	-2.307	-14.061***
	(-4.05)	(0.66)	(0.45)	(0.42)	(-1.44)	(-3.50)
W*IS	-22.529***	-19.791***	-0.697	-1.103	0.017	-5.840***
	(-5.00)	(-5.46)	(-0.12)	(-0.78)	(0.01)	(-3.19)
rho	0.339***	0.504***	-0.671***	0.251***	0.177***	-0.075
	(3.11)	(5.46)	(-3.56)	(5.89)	(3.76)	(-1.25)

Table 7. Effect decomposition

	Variables	W1			W2		
		East	Central	West	East	Central	West
Direct effect	SCD	-0.647***	-0.038	-0.435***	-0.477**	-0.038	-0.308**
		(-8.19)	(-0.30)	(-3.01)	(-5.16)*	(-0.38)	(-2.24)
Indirect effect	SCD	-1.072	-0.270	-1.840***	-0.724***	-0.539**	-1.062***
		(-0.97)	(-0.12)	(2.17)	(-2.77)	(-2.18)	(-3.88)
Total effect	SCD	-1.718	-0.308	-2.276***	-1.201***	-0.577**	-1.370***
		(-1.56)	(-0.14)	(-3.01)	(-5.17)	(-2.12)	(-5.21)
	Controls	YES	YES	YES	YES	YES	YES

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4.5. Robustness Test

The above analysis indicates that SCD not only impacts local cities but also exerts effects on neighboring regions through spatial spillover effects, thereby influencing PRCM. This study re-estimates the association in two methods to validate the robustness of this conclusion: first, W3 is substituted for the original spatial matrix, and then the regression analysis is repeated using the SDM. Second, employing an alternative method to calculate the city PRCM (PRCM1 in Table 1), which measures the logarithm of the interaction term between a city's PM2.5 concentration and its carbon emissions [35].

4.5.1. Replace the Weight Matrix

SCD's core impact on PRCM aligns closely with previous conclusions, according to the robustness test results based on the W3 (see Table 8). The policy greatly improves local PRCM, as seen by its significantly negative direct effect at the 1% level. The total effect is also significantly negative, further validating the policy's overall net positive impact. The spatial lag coefficient is significantly positive, which further confirms the spatial dependence of PRCM. In summary, the estimation results under the W3 provide robust evidence for the solid robustness of the earlier research findings.

Table 8. Regression results under W3

Variables	Main	Wx	Spatial	Direct	Indirect	Total
SCD	-0.373***	-0.020		-0.375***	-0.069	-0.443***
	(-6.28)	(-0.17)		(-6.25)	(-0.61)	(-3.31)
EDL	0.856***	-0.442***		0.836***	-0.353**	0.483***
	(7.57)	(-3.34)		(8.78)	(-2.50)	(3.19)
PD	-1.605***	2.048***		-1.523***	1.982***	0.459
	(-3.89)	(3.12)		(-3.53)	(2.65)	(0.67)
GI	-0.895*	0.792		-0.855*	0.699	-0.156
	(-1.86)	(1.11)		(-1.70)	(0.87)	(-0.19)
FDI	2.760**	-7.055***		2.367*	-7.227***	-4.860**
	(2.43)	(-3.15)		(1.81)	(-3.32)	(-2.06)
IL	1.159***	1.363***		1.217***	1.640***	2.857***
	(4.80)	(3.15)		(5.27)	(3.88)	(5.82)
EPEL	-0.053	-0.099		-0.050	-0.125	-0.175
	(-0.11)	(-0.14)		(-0.11)	(-0.16)	(-0.20)
IS	-0.588	-1.056		-0.661*	-1.220*	-1.881***
	(-1.45)	(-1.60)		(-1.81)	(-1.80)	(-2.59)
rho			0.115***			
			(4.96)			

4.5.2. Replace the Explained Variable

Robustity tests after replacing the dependent variable (see Tables 9 and 10) further confirm the dependability of the earlier research findings. Under both W1 and W2 matrices, the direct effect of SCD is significantly negative at the 1% level, suggesting that the policy has a steady and beneficial impact on improving PRCM. Moreover, the policy's positive geographical spillover effects in the economic linkage dimension. are further validated by the fact that both its indirect effect and total effect are notably negative in W2. In summary, after altering the measurement approach for the dependent variable, all core estimation results remain consistent, demonstrating robust validity for the study's conclusions.

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Table 9. Regression results by replace the explained variable

Variables	W1			W2		
	Main	Wx	Spatial	Main	Wx	Spatial
SCD	-0.335*** (-8.67)	0.755 (0.87)		-0.287*** (-7.29)	-0.257*** (-2.65)	
EDL	0.593*** (7.89)	-1.032** (-1.99)		0.367*** (5.08)	0.286* (1.88)	
PD	-0.704*** (-2.65)	3.875** (2.20)		-0.167 (-0.60)	-0.770 (-1.43)	
GI	0.505 (1.63)	-7.731*** (-2.71)		0.573* (1.84)	-2.010*** (-2.91)	
FDI	1.648** (2.27)	-13.852* (-1.82)		0.865 (1.20)	-0.392 (-0.20)	
IL	0.608*** (3.95)	6.705*** (3.50)		0.680*** (4.44)	0.336 (0.83)	
EPEL	0.100 (0.34)	4.722 (1.47)		-0.051 (-0.17)	-0.500 (-0.58)	
IS	-0.282 (-1.09)	-12.160*** (-4.71)		-0.231 (-0.91)	-1.679*** (-2.72)	
rho			0.752*** (12.36)			0.223*** (7.60)

Table 10. Effect decomposition by replace the explained variable

Variables	W1			W2		
	Direct	Indirect	Total	Direct	Indirect	Total
SCD	-0.326*** (-7.38)	2.150 (0.61)	1.824 (0.52)	-0.298*** (-7.70)	-0.409*** (-3.61)	-0.707*** (-6.30)
EDL	0.575*** (9.24)	-2.482 (-0.96)	-1.907 (-0.74)	0.373*** (6.19)	0.469** (2.51)	0.842*** (4.58)
PD	-0.623** (-2.30)	14.889 (1.55)	14.266 (1.49)	-0.175 (-0.61)	-1.006 (-1.41)	-1.181* (-1.85)
GI	0.38 (1.23)	-32.523** (-1.99)	-32.136** (-1.97)	0.513 (1.62)	-2.394*** (-2.60)	-1.881** (-2.13)
FDI	1.279 (1.54)	-56.212 (-1.51)	-54.933 (-1.47)	0.718 (0.85)	-0.319 (-0.14)	0.398 (0.17)
IL	0.751*** (4.88)	31.946*** (3.02)	32.697*** (3.07)	0.709*** (4.79)	0.677 (1.44)	1.386*** (2.67)
EPEL	0.190 (0.67)	20.906 (1.38)	21.095 (1.39)	-0.069 (-0.24)	-0.672 (-0.58)	-0.741 (-0.60)
IS	-0.533** (-2.15)	-54.003*** (-3.33)	-54.536*** (-3.34)	-0.319 (-1.36)	-2.203*** (-2.94)	-2.522*** (-3.22)

5. Conclusion, Policy Implications and Limitations

5.1. Conclusion

The spatial effects and operational mechanisms of SCD policy on PRCM in Chinese cities are empirically investigated in this study using a spatial Durbin model. The primary findings are as follows:

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First, Chinese cities show significant positive spatial correlation at the level of PM2.5 concentration, showing obvious "high-high" and "low-low" cluster patterns. When economic linkages are taken into account, spatial dependencies become more complex, highlighting the necessity and potential of regional collaborative governance.

Second, SCD policy's impact on PRCM has a complex spatial dimension. Through the linkage channel of economic geography, it not only greatly improves the PRCM efficiency of local cities, but more importantly, it has a significant positive spillover effect on surrounding cities. This shows that the impact of the SCD policy goes beyond administrative boundaries and promotes a synergistic promotion model between closely connected economic regions, and geographical proximity alone is not enough to trigger significant spillover effects.

Third, SCD policy effects show obvious regional heterogeneity. Although their direct promotion is relatively limited in the central region, it is very obvious in the eastern and western regions. Under the economic geography matrix, all regions show significant positive spatial spillover effects. This further confirms the universality of spillover mechanisms based on economic networks, indicating that policy dividends can be shared more widely through regional economic integration.

5.2. Policy Implications

First, given that pollution and carbon emissions in cities such as Tangshan, Baotou, Shanghai, Suzhou, Zhangzhou, Binzhou, Chongqing, and Xining remain persistently high, forming continuous pollution problem areas, these areas should be designated as key areas for the country to coordinate emission reduction and carbon control. At the national level, policy support and supervision in these areas should be strengthened to promote the green transformation of their industrial structure and the clean transition of their energy structure, so as to prevent negative impacts on surrounding areas.

Second, we should focus on the construction of a digital governance network centered on economic links. Policy formulation should go beyond individual cities and promote the unification of digital supply chain standards and joint data sharing platforms within major urban clusters or economic belts. Actively cultivate cross-regional green digital supply chain alliances, guide leading enterprises to promote green technology and share best practices in these networks, so as to turn economic links into practical environmental synergies.

Third, accurately optimize the regional implementation priorities of the SCD policy. In the eastern region, where the policy has a significant impact, we should promote the deepening of digital applications and explore cutting-edge scenarios such as intelligent energy management and product life cycle carbon footprint tracking. In the central areas where the impact is relatively lagging behind, the policy should pay attention to the shortcomings of digital infrastructure and optimize the business environment to create conditions for the effective implementation of SCD policies. Priority should be given to promoting the integration of digitalization and green upgrading of characteristic industries in the western region.

5.3. Limitations

There are four main limitations of this study. First, regarding the research design, the sample focuses on 237 cities in China from 2011 to 2023. Although this provides a broad urban perspective, the aggregation of urban-level data may mask the heterogeneity of enterprises in digital applications and environmental performance, thus limiting the revelation of micro-level mechanisms. Second, the pollution-carbon cooperative control measurement constructed through the interaction between the environmental pollutant index and carbon emissions may not fully reflect the multi-dimensional and dynamic characteristics of pollution and carbon synergy, especially the differentiated treatment of different types of pollutants. Third, regarding the time horizon, although the research period covers 13 years, the pilot policy was

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introduced in 2018, resulting in a relatively short post-policy window (2018–2023), making it difficult to observe long-term dynamic effects and potential lagged spillover effects. Fourth, although the spatial weight matrix has been carefully set, it may not be able to fully cover all aspects of intercity economic links, such as digital infrastructure networks or supply chain links that go beyond geographical and GDP proximity.

There are two main directions for future research. First, the method can be improved and the scope of the investigation can be expanded. This may include integrating data at the enterprise or factory level to reveal the micro-mechanism of digital spillage, or conducting transnational comparative studies to assess the external validity of the research results outside the background of the Chinese system. By building a more comprehensive multi-dimensional PRCM index and using objective high-frequency satellite environmental data, the measurement ability of core variables can be enhanced. Second, researchers can further explore the underlying mechanisms and their systemic implications. They can study more complex paths, including chain mediation or controlled mediation models, to explore the interaction between SCD policies and other environmental policies (such as carbon trading mechanisms and low-carbon urban pilot projects).

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Data Availability

Data will be made available on request.

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