



Spatiotemporal evolution and driving mechanism of synergistic carbon and pollution reduction

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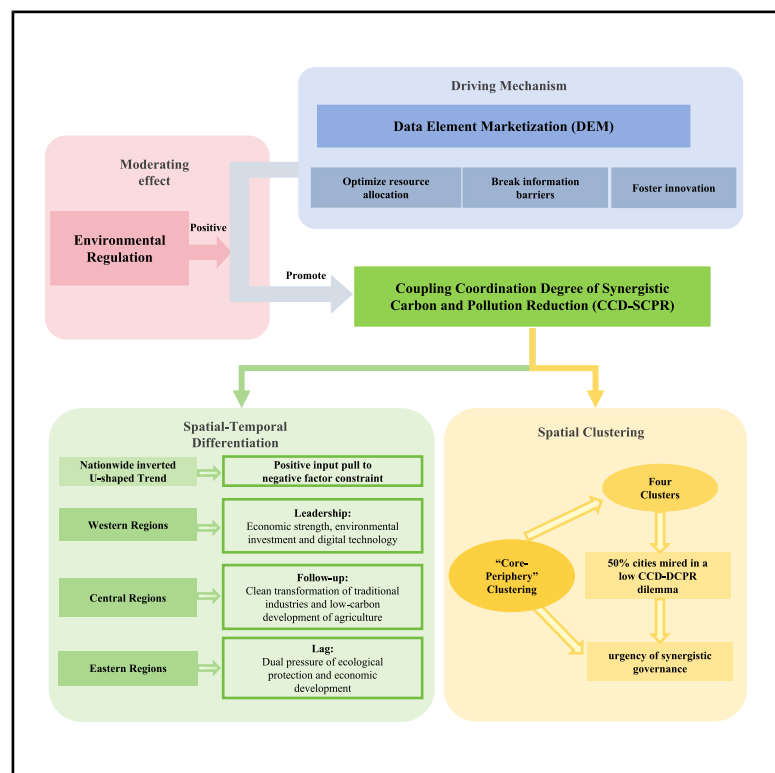
Citation for the original published paper (version of record):

Cai, Z., Ding, X., Yang, X. et al (2026). Spatiotemporal evolution and driving mechanism of synergistic carbon and pollution reduction. *iScience*, 29(3).
<http://dx.doi.org/10.1016/j.isci.2026.115084>

N.B. When citing this work, cite the original published paper.

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Graphical abstract



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In brief

Environmental science; Environmental policy; Pollution; Economics

Highlights

- CCD-SCPR follows an inverted U-shaped trajectory with regional disparities
- Half of Chinese cities remain trapped in low synergistic governance efficiency
- DEM significantly enhances synergistic carbon and pollution reduction
- Environmental regulation positively moderates the effect of DEM on CCD-SCPR



Article

Spatiotemporal evolution and driving mechanism of synergistic carbon and pollution reduction

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SUMMARY

Climate change and environmental pollution are key global challenges, with synergistic carbon-pollution reduction a global consensus. As the world's largest developing economy and carbon emitter, China's experience informs global synergistic governance. Spatiotemporal evolution and driving mechanisms of synergistic carbon and pollution reduction from 297 Chinese cities (2000–2023) are examined, applying the coupling coordination degree, k-means clustering, difference-in-differences, and moderating effect models. Findings show that the national coupling coordination degree of synergistic carbon and pollution reduction (CCD-SCPR) exhibits an inverted U-shaped dynamic evolution and gradient spatial differentiation. The “core-periphery” clustering pattern is found, with nearly half of the cities remaining in a dilemma of low CCD-SCPR, underscoring the urgency of synergistic governance. Data element marketization significantly improves CCD-SCPR by breaking information barriers, optimizing resource allocation, and empowering technological innovation. It forms a positive moderating effect with environmental regulation, yielding extra governance benefits. Proposals include differentiated strategies, innovative urban governance, optimized policy coordination, and deeper data element reforms.

INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) has highlighted that exceeding the 1.5°C global warming threshold would intensify extreme weather, cause ecological collapse, and precipitate food crises, directly undermining the achievement of the United Nations Sustainable Development Goals (SDGs). Fossil fuel dependence and industrial emissions are key contributors.¹ As the largest developing country, China, with an over 65% urbanization rate, faces a “dual lock-in dilemma” in environmental governance: rising marginal costs of air pollution control and strict carbon emission limits.² Spatially, significant disparities exist. Data from China's Ministry of Ecology and Environment in 2023 reveal that among 339 prefecture-level and above cities, the annual average Particulate Matter 2.5 (PM_{2.5}) concentration is 30 µg/m³. Notably, the Beijing-Tianjin-Hebei region and the Fenwei Plain report concentrations of 43 µg/m³, while the Yangtze River Delta region averages 32 µg/m³.³ As the leading global emitter of carbon, China's greenhouse gas emissions in 2023 totaled 12.6 billion tons of carbon dioxide (CO₂) equivalent, marking a 4.13% increase from 12.1 billion tons in 2022.⁴ Energy-intensive regions such as the North China Industrial Belt, continue to see CO₂ emission growth, while southeastern coastal cities have reduced carbon

intensity through industrial optimization. This spatial variation reveals tensions between carbon and pollution reduction efficiency and development rights allocation in collaborative governance.⁵ Despite the Chinese government's 2022 “Implementation Plan for Synergistic Enhancement of Carbon and Pollution Reduction,” traditional end-of-pipe approaches persist, hindering systemic efficiency. Improving integrated environmental and climate governance through system coupling remains a global challenge, the resolution of which is crucial for attaining multiple SDGs worldwide.

Existing research on synergistic carbon and pollution reduction primarily focuses on the driving mechanisms, response strategies, and effects of atmospheric pollutants and carbon emissions. In terms of synergistic pollution and carbon reduction, Ramanathan et al.⁶ found that large-scale decarbonization not only reduces carbon emissions but also decreases greenhouse gases such as ozone and methane. Zhu et al.⁷ analyzed the technologies for the synergistic reduction of pollutants and carbon in China's steel industry. Guo et al.⁸ highlighted that technological innovation in wastewater treatment facilitates greenhouse gas control. Regarding the synergistic effects and evaluations of environmental governance on carbon emission reduction, Okorn et al.⁹ monitored atmospheric pollutants and carbon emissions to verify emission reduction synergies. Bian et al.¹⁰ assessed



Tianjin's monthly synergistic development of pollution and carbon reduction using a synergy index. In terms of evaluations of their synergistic effects, Du and Li¹¹ evaluated enterprise-level synergistic effects of pollution and carbon reduction in China, exploring environmental regulation impacts. Studies have also explored synergistic effects in specific sectors such as industry,¹² construction,¹³ power,¹⁴ and agriculture.¹⁵ Theoretically, scholars have revealed the nonlinear relationship between pollutants and carbon emissions based on the Environmental Kuznets Curve (EKC) and decoupling theory.¹⁶ Methodologically, spatial econometric models¹⁷ and system dynamics simulations¹⁸ are widely used in synergy evaluations. In policy practice, the joint issuance of the "Implementation Plan for Synergistic Enhancement of Pollution and Carbon Reduction" by four departments, including the Ministry of Ecology and Environment, signifies a shift from single-objective to multi-objective governance.¹⁹ However, existing research still has limitations. First, there is a lack of detailed characterization of the spatial and temporal heterogeneity of synergistic governance at the urban scale, making it difficult to support differentiated policy design. Second, spatiotemporal analysis uses static cross-sectional data, making it challenging to capture dynamic evolution patterns.²⁰ Third, limited empirical analysis on the new initiative of synergistic enhancement of carbon and pollution reduction, with a focus on theoretical discussions, lacks the examination of interactions between pollution and carbon reduction and macro factors promoting high-quality economic development.

Global evidence indicates that the circulation and sharing of data elements can enhance environmental governance efficiency. For instance, cities such as New York and London have utilized green bonds and emission trading mechanisms to demonstrate the guiding role of data markets in environmental protection.^{21,22} China's Emissions Trading System (ETS) has shown initial success in resource allocation and emission reduction cost control. However, significant disparities exist in regional carbon market efficiencies, with economically developed areas exhibiting more pronounced synergistic effects.²³ Command-and-control policies, such as the "Ten Measures for Air," have directly reduced pollutant emissions but rely on administrative means, limiting digital technologies' potential in environmental governance.²⁴ The relationship between data element marketization (DEM) and coordinated reductions in carbon emissions and air pollutants remains unclear.²⁵ Current research suggests that data elements can drive synergistic carbon and pollution reduction.²⁶ Firstly, data elements' high liquidity can break information barriers in traditional factor markets, facilitating precise matching of green talents, technologies, and funds, thus promoting synergistic reductions.²⁷ Second, establishing data trading platforms using technologies such as blockchain enhances transparency in carbon trading and reduces environmental information disclosure costs, alleviating financing constraints for corporate green innovation.²⁸ Thirdly, the "multiplier effect" of data elements can optimize industrial structures. For example, digital technologies promote the coordinated agglomeration of manufacturing and service industries, indirectly reducing per-unit output emissions of CO₂ and air pollutants.²⁹ Research on the enabling mechanisms of data elements lags behind practical applications. Although the National Envi-

ronmental Monitoring Center has achieved real-time public disclosure of air quality data, data-driven policy optimization paths remain to be explored. Existing studies often focus on single issues of carbon emissions or air pollution, with limited exploration of synergistic reduction.³⁰ Research perspectives are often confined to technology and market aspects, typically concentrating on specific industries or regions, lacking in-depth analysis of multiple subjects' collaborative roles.³¹ Moreover, theoretical research on how data elements influence the behaviors and decisions of different entities to achieve synergistic carbon and pollution reduction is insufficient, and comprehensive evaluations of existing policies' effectiveness in promoting data-driven synergistic reductions are lacking.³²

Crucially, existing research frequently adopts a singular perspective, focusing either on pollutants or CO₂, with a paucity of quantitative analyses on the spatiotemporal heterogeneity and evolution of synergistic governance. This gap extends to the collaborative roles of diverse stakeholders and an overreliance on traditional economic factors while overlooking emerging digital drivers, such as data circulation.^{33,34} Theoretically, synergistic effects exhibit significant spatial dependence and temporal dynamics, with nonlinear relationships influenced by developmental stages.³⁵ Spatial econometric models verify positive spillovers in coordinated governance,³⁶ and empirical patterns, such as gradient evolution in the Yangtze River Delta versus "core-periphery" differentiation in Beijing-Tianjin-Hebei due to energy lock-in,³⁷ highlight complex spatiality. International comparisons further reveal efficacy decay in developing cities.³⁸ However, measurements often remain static, failing to uncover clustering patterns and dynamic paths.² Based on this, Hypothesis 1 is proposed.

H1: The coupling coordination degree of synergistic carbon and pollution reduction among cities exhibits spatiotemporal differentiation characteristics, allowing for classification into different types based on features.

Furthermore, DEM is posited to reshape governance by correcting market failures rooted in information asymmetry.³⁹ By transforming implicit environmental knowledge into tradable digital assets, DEM can reduce transaction costs,⁴⁰ trigger synergistic effects through breaking departmental silos,⁴¹ enabling precise source management via big data,⁴² and fostering "digital twin" markets via blockchain.⁴³ However, its efficacy may be uneven, advantaging regions with advanced digital infrastructure.⁴⁴ Based on this, Hypothesis 2 is proposed.

H2: Data element marketization will promote the urban synergistic effect of carbon and pollution reduction.

The interaction between DEM and institutional forces is pivotal. Environmental regulation, as a tool to correct negative externalities, can dynamically couple with DEM. According to the extended Porter hypothesis, regulation can drive corporate digital transformation, generating demand for and guiding the allocation of data elements toward green innovation.⁴⁵ DEM's scale, structure, and technology effects are optimized under such regulation, promoting low-carbon transitions and cross-industry data sharing.⁴⁶ Their positive interaction suggests that environmental regulation can steer data empowerment toward enhanced environmental welfare, upgrading outcomes from singular to synergistic dimensions within externality and

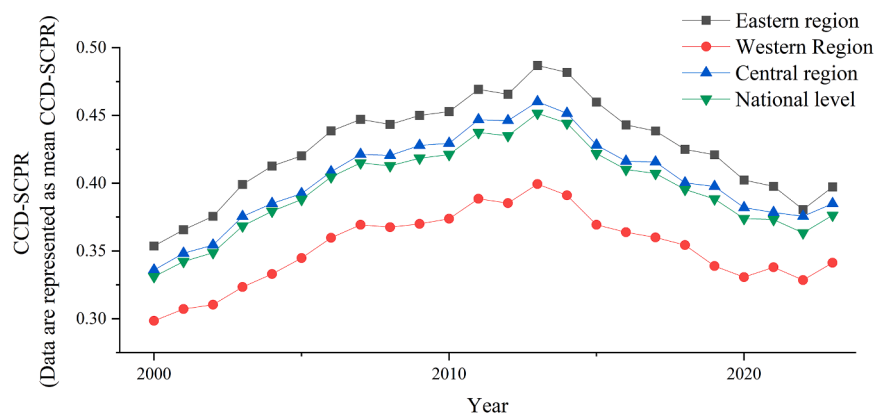


Figure 1. Regional and national CCD-SCPR values

The figure shows mean CCD-SCPR values in eastern, central, and western regions and the whole country from 2000 to 2023.

collaborative governance theories.⁴⁷ Based on this, Hypothesis 3 is proposed.

H3: Environmental regulation will play a positive moderating role in the synergistic carbon and pollution reduction effect of data element marketization.

This study employs panel data from 297 Chinese cities (2000–2023) to systematically examine the spatiotemporal evolution, driving mechanisms, and policy interactions of synergistic carbon and pollution reduction. Methodologically, this study applies the coupling coordination degree, k-means clustering, difference-in-differences (DIDs), and moderating effect models. Its marginal contributions are as follows: First, it refines the dynamic evolution and spatial differentiation of synergistic governance at the urban scale, identifying core drivers and constraints across stages by measuring the coupling coordination degree of synergistic carbon and pollution reduction (CCD-SCPR) of 297 cities. Second, it develops a framework linking DEM and synergistic governance, enriching interdisciplinary research on digital economy and environmental governance, and offering a different theoretical perspective. Finally, it verifies the complementary

synergy between environmental regulation and data elements, reveals the synergetic loop of institutional guarantee and technological empowerment, and provides empirical support for policy synergy design. This study aims to offer a Chinese model for global synergistic carbon-pollution reduction, insights for developing countries to resolve economic-environmental dilemmas, and references for cutting-edge issues such as AI empowering environmental rights markets.

RESULTS AND DISCUSSION

Spatiotemporal characteristics of the coupling coordination degree of synergistic carbon and pollution reduction

China's CCD-SCPR exhibited a pronounced inverted U-shaped evolution over this period, characterized by a prolonged stagnation in the borderline dysregulation and forced coordination stages without reaching a stable, coordinated development range (Figure 1 and Table 1). The year 2013 stands out as a critical inflection point, marking a shift from a steady rise before 2013 to a subsequent gradual decline. Though the overall growth from 2000 to 2023 was limited, it objectively reflects the gradual enhancement of China's synergistic coordination capacity among economic growth, social development, and ecological protection systems. The growth before 2013 benefited from synergistic efforts in energy structure optimization in the mid-to-late industrialization stage, large-scale investment in end-of-pipe treatment facilities, and early environmental regulatory policies.⁴⁸ Pollution control policies before the implementation of the "Ten Atmospheric Articles" initially synergized with carbon reduction; measures such as coal-fired unit retrofits and scattered coal management reduced both traditional pollutant emissions and carbon emissions. Meanwhile, optimized energy consumption structure and increased share of environmental protection investment, as core drivers, shifted synergistic governance from passive response to active prevention.⁴⁹ The decline after 2013 is mainly due to the marginal narrowing of the synergistic benefits of traditional environmental governance policies, the insufficient potential of structural transformation measures in transportation, industry, and other fields, and the long-term emphasis of environmental policies on the short-term treatment of pollutants such as sulfur dioxide and nitrogen oxides. The structural adjustment cycles required for carbon reduction, such as deep industrial transformation and decarbonization of the energy system, are longer and more costly, resulting in a contrast between the continuous increase in carbon dioxide emissions and the effectiveness of pollutant reduction. Coupled

Table 1. Development stages and levels classifications of the coupling coordination degree

Coordination stage	Coupling coordination degree	Coupling coordination level
Dysfunctional recession	$0 < D \leq 0.1$	Extreme dysregulation
Dysfunctional recession	$0.1 < D \leq 0.2$	Severe dysregulation
Borderline dysregulation	$0.2 < D \leq 0.3$	Moderate dysregulation
Borderline dysregulation	$0.3 < D \leq 0.4$	Mild dysregulation
Forced coordination	$0.4 < D \leq 0.5$	Borderline dysregulation
Forced coordination	$0.5 < D \leq 0.6$	Forced coordination
Basic coordination	$0.6 < D \leq 0.7$	Primary coordination
Basic coordination	$0.7 < D \leq 0.8$	Intermediate coordination
Highly coordination	$0.8 < D \leq 0.9$	Good coordination
Highly coordination	$0.9 < D \leq 1$	Highly coordination

This table defines five coordination stages and ten levels of coupling coordination degree (CCD), based on D-value thresholds ranging from 0 to 1. Each stage comprises two levels, from extreme dysregulation to high coordination.

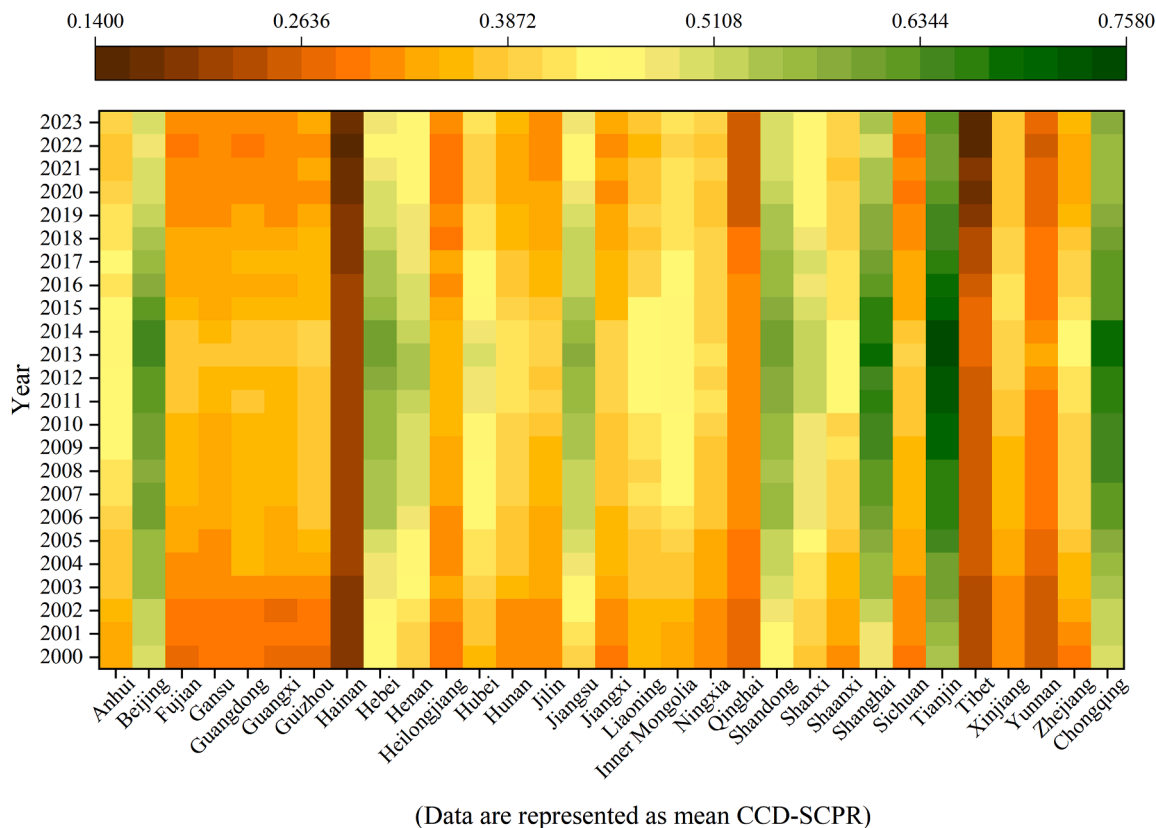


Figure 2. Provincial CCD-SCPR values

The figure shows mean CCD-SCPR values by province and municipality from 2000 to 2023.

with uneven regional development and insufficient research and development support, CCD-SCPR has ultimately shown a downward trend, highlighting the deep-seated challenges that China's collaborative governance of carbon reduction and pollution reduction still faces, such as insufficient policy coordination and lagging structural transformation.

Regionally, it verifies that China's CCD-SCPR exhibits significant spatial differentiation characteristics (Figure 1), confirming Hypothesis 1. The eastern region has long led the nation in CCD-SCPR, followed by the central and western regions. Overall, the eastern and central regions have consistently remained above the national average, with inter-regional gaps showing a trend of stabilization with slight narrowing but remaining significant. This spatial pattern stems from heterogeneities in regional development foundations, policy supply intensity, and factor allocation efficiency.⁵⁰ Leveraging its strong economic strength, intensive environmental protection investment, and advanced digital technology empowerment, the eastern region has built a multi-dimensional governance system of "policy synergy-technological innovation-market drive." Its industrial structure upgrading, clean energy substitution, and precise implementation of environmental regulations, such as regional joint prevention and control mechanisms, have collectively improved synergistic governance efficiency. The central region, guided by green transformation in industrial transfer, has formed synergistic effects in the clean transformation of traditional industries and

low-carbon agricultural development, placing it at the upper-middle level nationwide. In contrast, constrained by low economic development, weak digital infrastructure, and a resource-dependent industrial structure, the western region has relatively low environmental protection investment and technology conversion efficiency; some areas also face dual pressures of ecological protection and economic development, resulting in insufficient foundational conditions for synergistic carbon reduction and pollution abatement, with CCD-SCPR long remaining below the national average.⁵¹ Such spatial differentiation reflects the objective reality of unbalanced regional development in China, providing empirical support for formulating differentiated governance policies.

Eastern provinces are mainly in forced coordination, while most central and western regions remain in borderline dysregulation, with significant gaps in inter-regional synergistic governance levels (Figure 2 and Table 1). Specifically, core eastern regions such as Beijing, Shanghai, and Zhejiang have reached the forced coordination stage, benefiting from the synergy between industrial green transformation and multi-dimensional environmental regulations, laying a solid foundation by curbing high-energy-consuming industries and fostering low-carbon emerging sectors, improving governance efficiency through integrating market-oriented tools with administrative measures, breaking bottlenecks via technological innovation and digital empowerment, and achieving cross-regional synergy through the

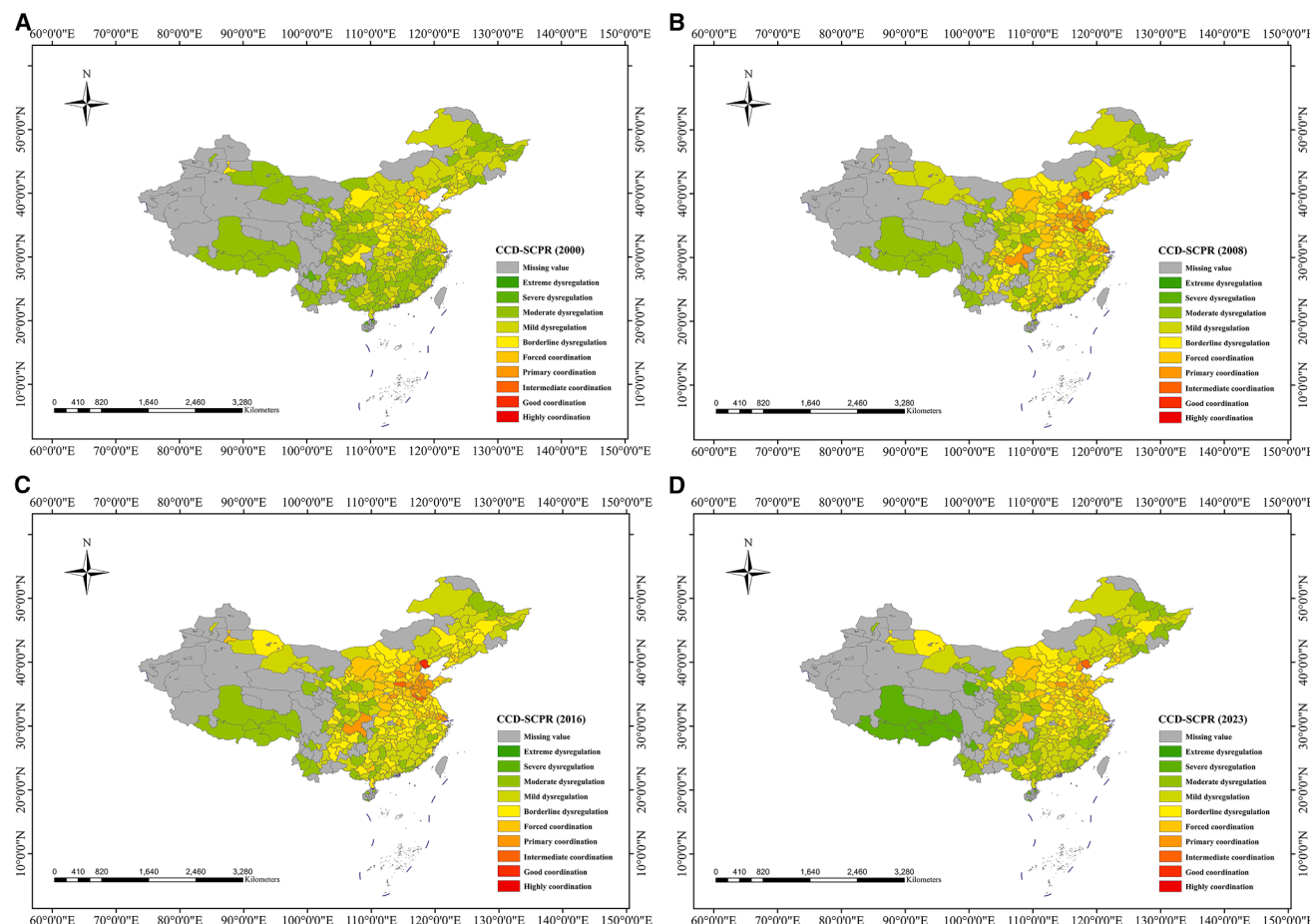


Figure 3. Spatial distribution of CCD-SCPR

The figure shows CCD-SCPR values of 297 cities in China for four representative years. Map source: GS(2024)0650.

- (A) CCD-SCPR values in 2000.
(B) CCD-SCPR values in 2008.
(C) CCD-SCPR values in 2016.
(D) CCD-SCPR values in 2023.

Beijing-Tianjin-Hebei and Yangtze River Delta integration strategies, which provide important references for enhancing national CCD-SCPR.⁵² As a benchmark city for synergistic governance in central and western China, Chongqing has an average CCD-SCPR of 0.6, remaining stably in forced coordination and basic coordination stages for a long time, a sharp contrast to most central and western cities, attributed to the synergy between the clean transformation of traditional industries in the Chengdu-Chongqing Twin City Economic Circle and ecological protection policies of the Yangtze River Economic Belt. Hainan, Tibet, Qinghai, Yunnan and other regions have long been in dysfunctional recession or borderline dysregulation, significantly below the national average, with common constraints including low industrial levels, backward environmental infrastructure, and insufficient technical and talent support; individual issues include Hainan's conflict between urbanization and ecological protection, Tibet's constraints from plateau vulnerability and high infrastructure costs, Qinghai's contradiction between clean energy advantages and inadequate synergy mechanisms, and

Yunnan's challenges from energy mismatch and industrial transfer regulatory pressures. Therefore, central and western provinces should be based on their respective resource endowments and development orientations, and gradually improve synergistic pollution and carbon reduction efficiency by strengthening infrastructure, enhancing technological innovation capabilities, improving policy synergy mechanisms, and exploring distinctive green development paths.⁵³

It presents an evolutionary trend characterized by "overall upward movement, phased fluctuations, and hierarchical differentiation." In terms of stage classification, the number of cities in borderline dysregulation is the largest, reaching 112 (accounting for 37.7%), followed by those in forced coordination (81 cities, 27.3%), cities in mild dysregulation and primary coordination stages are 58 and 46 respectively, accounting for 19.5% and 15.5% (Figures 3A–3D and Table 1). This distribution structure reflects that China's synergistic development of carbon and pollution reduction is generally in a transitional phase from dysregulation to coordination, with most cities yet to achieve a

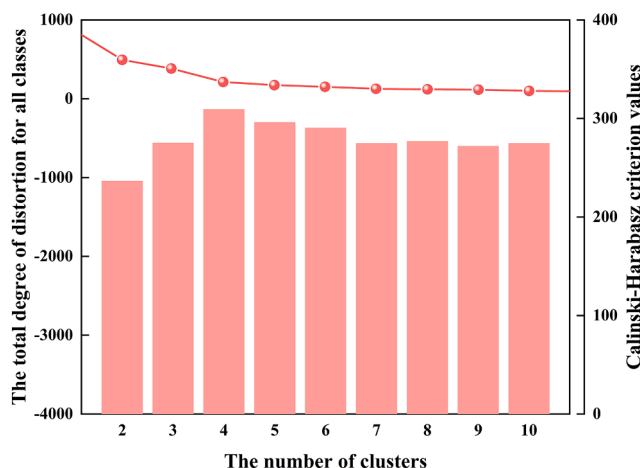


Figure 4. The optimal number of clusters

The figure indicates the number of clusters for CCD-SCPR from 2 to 10. Both metrics peak at four, indicating four clusters as the optimal solution.

stable coupling coordination state. In the high-level cities, industrial hubs, and economic central cities constitute the core force. Besides traditional industrial bases such as Tangshan (average 0.75), Handan (0.68), and Xuzhou (0.67) maintaining high coordination levels through solid industrial accumulation, modern metropolises such as Tianjin and Suzhou have realized efficient synergy between economic development, society, and ecology via the in-depth integration of the service industry and high-tech industries,⁵⁴ with their CCD-SCPR values remaining at a high level for a long time, becoming benchmarks for coordinated development. Meanwhile, “latecomer catch-up” cities have demonstrated unique growth vitality: central and western cities such as Yinchuan (66% growth), Yulin (64%), and Hami (61%) have leveraged dividends from national strategies such as the Western Development and the “Belt and Road” Initiative, increased infrastructure investment, and promoted the transition of industrial structures from resource-dependent to diversified and synergistic, achieving rapid leaps in coupling coordination degree. This development path of “policy empowerment-infrastructure upgrading-industrial optimization” not only enables such cities to form a virtuous cycle of “high growth-medium-high level” but also serves as an important practical sample for central and western cities to narrow the development gap with eastern developed cities and optimize the national urban coordinated development pattern.⁵⁵ As a key echelon connecting high and low-level cities, medium-level cities are mostly regional sub-central cities. Facing pressures of slow traditional industrial upgrading and lacking advantages in high-end industrial agglomeration, their coordination evolution is highly consistent with the national overall trend. Some cities, such as Huanggang in the central region and Mianyang in the western region, are attempting to break through development bottlenecks by undertaking industrial transfer and fostering emerging industries,⁵⁶ but the effectiveness of transformation still awaits time due to factors such as brain drain and insufficient funds. Low-level cities are mainly concentrated in remote central and western regions and the northeastern region, predominantly relying on agriculture or

resource-based industries, with weak economic foundations and backward public services, resulting in long-term low CCD-SCPR. Some resource-exhausted cities and major agricultural cities also face multiple challenges, such as population outflow and ecological degradation. Their coordinated development not only requires sustained tilt of national policies but also depends on finding distinctive development paths aligned with their own endowments.

Cluster analysis of the coupling coordination degree of synergistic carbon and pollution reduction

The CCD-SCPR varies significantly among cities. Classifying cities with similar characteristics facilitates the development of targeted strategies and recommendations for synergistic carbon and pollution reduction.⁵⁷ A cluster analysis was conducted on 297 Chinese cities using historical averages of carbon emission intensity, $PM_{2.5}$, and CCD-SCPR. The optimal number of clusters is four (Figure 4). In terms of the overall spatial structure, the four clusters mainly exhibit a “core-periphery” clustering pattern, forming a circular expansion sequence of Cluster 3, Cluster 2, Cluster 4, and Cluster 1 from the inside out, which reveals the in-depth correlation between environmental governance effects and regional development stages (Figure 5).

Cluster 4 includes three cities in North China’s heavy industrial zones, characterized by high carbon emission intensity, high $PM_{2.5}$, and high CCD-SCPR. Elevated emissions and pollution arise from intensive heavy industries, while the high CCD-SCPR reflects a pollution control-industrial upgrading synergy developed through long-term environmental governance. This mechanism enables traditional industrial bases to achieve relative economic-ecological coordination under high environmental pressure via upgraded end-of-pipe treatment and circular economy models. Cluster 2 covers 40 cities with mid-to-high CCD-SCPR, corresponding to traditional industrial cities in the central and eastern regions; subjected to industrial transfer and resource dependence, these regions face significant pollution and emission pressures, but due to the pollution haven effect, their synergistic governance level is slightly lower than that of Cluster 4 despite the establishment of green thresholds in undertaking industrial transfer (e.g., some cities in Anhui and Hubei). As the most widely covered type (105 cities), Cluster 3 has medium-level indicators across the board, mainly including transitioning resource-based cities and small-to-medium industrial cities; its characteristics reflect the typical contradictions during industrial structure adjustment—narrowing emission reduction potential of traditional industries and immature emerging green industries, resulting in a “bottleneck period” for synergistic governance. Cluster 1 includes 149 cities, featuring “low carbon emission intensity-low $PM_{2.5}$ -low CCD-SCPR,” covering ecologically fragile areas in the western region and low-pollution small-to-medium cities in the eastern region; their low environmental pressure stems from low-intensity economic activities or constraints of ecological protection policies, yet the low CCD-SCPR indicates shortcomings in the synergy between ecological value conversion and economic development, leading to the coordination dilemma of prioritizing protection while facing insufficient development.⁵⁸ This spatial pattern of gradual expansion from the core to peripheral governance optimization

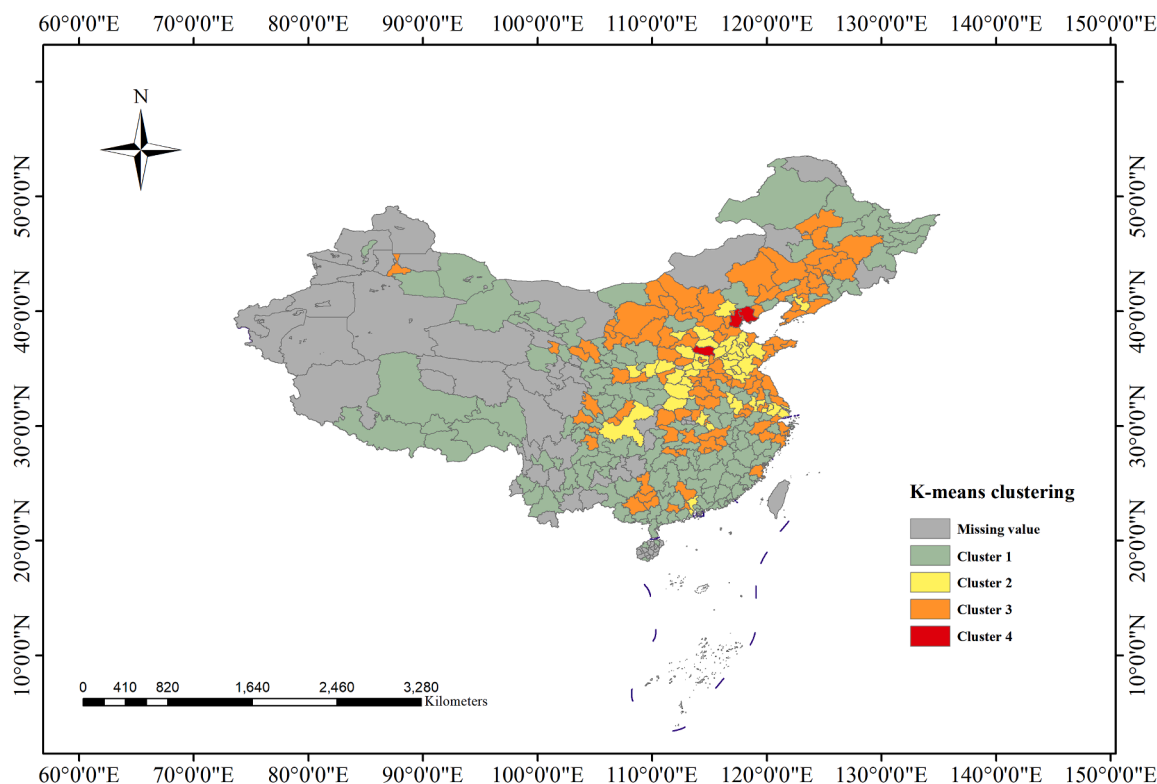


Figure 5. Spatial distribution of clusters

The figure shows the spatial distribution of four clusters across 297 Chinese cities. Map source: GS(2024)0650.

areas not only reflects the deep-seated contradictions of unbalanced regional development in China but also provides empirical basis for formulating differentiated synergistic governance strategies: high-pressure regions need to strengthen in-depth low-carbon industrial transformation, medium-pressure regions should break through transformation bottlenecks, and low-pressure regions need to explore synergistic paths for ecological economy.

Impact of data element marketization on the coupling coordination degree of synergistic carbon and pollution reduction

At the intersection of the global climate governance system's deep restructuring and China's green and low-carbon transformation, the DEM is emerging as a crucial breakthrough to address the dual constraints of "efficiency-equity" in synergistic pollution and carbon emission reduction. Existing studies indicate that traditional environmental governance paradigms are hindered by information silos and misallocation of resources, making it challenging to accurately identify the co-origin relationship between PM_{2.5} and CO₂ emissions. Data elements are reshaping environmental governance, yet regional development imbalances and digital divides exacerbate differentiation in collaborative governance.⁵⁹ This study employs the DID method to explore the impact of the DEM, represented by data trading platforms, on the CCD-SCPR. The DEM exerts a significant positive effect on promoting syn-

ergy in pollution and carbon reduction, maintaining robustness across different control variable combinations, thereby confirming Hypothesis 2 (Table 2). Data elements improve resource allocation by reducing information asymmetry, creating a positive feedback loop between pollution control and carbon reduction. Cross-departmental data-sharing platforms and standardized exchanges eliminate barriers between pollutant monitoring and carbon accounting. For example, big data from electricity consumption aids emission correlation identification. Blockchain, machine learning, and digital twins improve the precision and responsiveness of in synergistic pollution and carbon emission reduction.⁶⁰ Furthermore, labor density has a significant negative impact on CCD-SCPR, due to labor-intensive industries concentrating in traditional manufacturing and low-end services, and excessive population agglomeration exacerbating resource-environmental pressure.⁶¹ Urbanization and economic development exert significant positive effects, reflecting the scale effect and improved governance efficiency of centralized environmental facilities in urbanization, and the synergy of increased environmental investment and green industrial restructuring in advanced economic stages, consistent with the Environmental Kuznets Curve's phased characteristics. Accordingly, optimize the green alignment of labor allocation and industrial structure, anchor green transformation in urbanization and economic quality improvement; deepen institutional supply for the reform of DEM, establish inter-regional environmental data mutual recognition and sharing

Table 2. Regression results								
Variables	DID (1)	DID (2)	DID (3)	DID (4)	SmartCity (5)	PSM-DID (6)	PSM-DID (7)	Moderating (8)
DEM	0.092*** (7.06)	0.008*** (2.73)	0.065*** (5.05)	0.015*** (4.95)	0.015*** (4.75)	0.0184*** (4.5211)	0.0163*** (4.0416)	−0.001 (−0.15)
lnpgdp			0.079*** (18.78)	0.018*** (6.62)	0.018*** (6.41)		0.0215** (2.4499)	0.018*** (6.49)
ur			−0.009 (−0.99)	0.016*** (4.38)	0.016*** (4.38)		0.0114 (1.0530)	0.016*** (4.40)
tr			−0.168*** (−16.97)	−0.003 (−0.97)	−0.003 (−1.02)		0.0193** (2.0372)	−0.003 (−1.01)
labor			0.420*** (3.80)	−0.331*** (−7.19)	−0.324*** (−7.04)		−0.4052*** (−3.3351)	−0.330*** (−7.18)
tec			0.171*** (7.98)	0.004 (0.88)	0.005 (0.93)		0.0129 (0.6010)	0.004 (0.83)
SmartCity					0.002** (2.42)			
eri* DEM								5.207** (2.32)
eri								−0.040* (−1.79)
_cons	0.386*** (299.04)	0.386*** (1,546.74)	0.092*** (5.88)	0.300*** (24.31)	0.302*** (24.43)	0.4197*** (620.8640)	0.3100*** (7.9414)	0.302*** (24.43)
N	6,784	6,784	6,784	6,784	6,783	900	900	6,784
R-squared	0.007	0.965	0.123	0.965	0.965	0.9701	0.9711	0.965
City FE	NO	YES	NO	YES	YES	YES	YES	YES
Year FE	NO	YES	NO	YES	YES	YES	YES	YES
This table reports the estimated impact of DEM on CCD-SCPR using DID, PSM-DID, and moderation models. Columns (1)-(4) present baseline DID estimates with the progressive inclusion of control variables and two-way fixed effects (Tables S1 and S2). Column (5) uses a SmartCity policy indicator as an alternative treatment. Columns (6)-(7) provide PSM-DID robustness checks. Column (8) tests the moderating effect of environmental regulation via the interaction term. City and year fixed effects are included where indicated. t-statistics in parentheses. Note: ***p < 0.01, **p < 0.05, and *p < 0.1.								

Table 3. Regression results of two-stage least squares (2SLS) estimates

First stage	Coef.	t	St.Err.	Second stage	Coef.	z	St.Err.
IV	0.032***	6.40	0.005	DEM	0.679***	5.46	0.124
lnpgdp	−0.024***	−4.93	0.005	lnpgdp	0.078***	17.14	0.005
ur	−0.004	−0.46	0.009	ur	−0.013	−1.01	0.013
tr	0.012	1.03	0.012	tr	−0.214***	−9.53	0.022
labor	1.500***	3.81	0.394	labor	−0.918*	−1.83	0.501
tec	0.025*	1.76	0.014	tec	0.176***	5.39	0.033
Constant	0.078***	4.44	0.018	Constant	0.119***	7.24	0.016
R-squared			0.168				
F			15.88				
Prob > F			0.000				

This table presents first-stage and second-stage results of the instrumental variable (IV) approach addressing endogeneity. Control variables and constant are included in both stages (Tables S1 and S2). Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

mechanisms, pilot integrated digital supervision platforms for carbon-pollution reduction in key urban agglomerations, and strengthen the integration of digital technologies with traditional environmental governance tools to comprehensively enhance synergistic governance efficiency.

The moderating effect of environmental regulation

Previous findings show DEM significantly improves CCD-SCPR. Unlike European and American countries, which typically rely on market-driven mechanisms and decentralized governance with mature market economies, China's model combines top-down policy guidance with bottom-up market empowerment, suited to its dual tasks of industrialization, urbanization, and ecological protection. Its large-scale gradient regional governance and integration of digital technology with traditional policies offer unique insights and universal value for other developing countries with similar constraints. Synergistic carbon-pollution reduction governance, a complex multi-agent system, is shaped by interactions between formal environmental regulation and DEM, directly influencing governance efficiency boundaries. This study uses a moderating effect model to test its synergistic mechanism. The main effect coefficient of environmental regulation is significantly positive, confirming that strict formal government environmental regulation itself can force enterprises to fulfill their carbon reduction and pollution abatement responsibilities by setting emission reduction standards and strengthening supervision and law enforcement, directly promoting the improvement of CCD-SCPR (Table 2). More critically, the interaction term coefficient between DEM and environmental regulation is also significantly positive, which shows that government environmental regulation does not function in isolation. Instead, it significantly enhances the governance efficiency of DEM through institutional guarantees and guiding roles, verifying Hypothesis 3. From the perspective of operational logic, environmental regulation provides a clear institutional framework for the circulation and application of data elements, such as unified environmental data statistical standards and administrative impetus for cross-departmental data sharing, effectively addressing practical obstacles such as "data silos" and "ambiguous property rights" in the process of DEM. In turn, data el-

ements drive the transformation of environmental regulation from an "extensive" to a "precision-oriented" model by improving information transparency and optimizing regulatory precision. Examples include dynamic supervision based on real-time monitoring data and differentiated emission reduction quota allocation, which significantly reduce regulatory implementation costs and enterprise compliance costs, forming a synergistic closed loop of institutional guarantee and technological empowerment.

Endogeneity test

Exclude other policy impacts

During the sample period, the Chinese government implemented several important data element-related reforms, such as smart city construction, which directly affect urban synergistic carbon and pollution reduction effects and may impact the sustainability of DEM. To avoid the interference of such policies on the baseline conclusions, this study further controlled for the impact of smart city construction policies in the regression. It indicates that the coefficient of DEM shows no significant difference from the baseline results, confirming that the conclusions are not disturbed by other policies (Table 2).

Instrumental variable method

Since the number of selected instrumental variables equals the number of endogenous explanatory variables, no over-identification issue exists. The F-statistic from the first stage indicates that the instrumental variable is valid and can address potential endogeneity concerns. In the first stage of the 2SLS estimation, the coefficient of the instrumental variable is significantly positive, reflecting a strong correlation between the instrument and DEM. After introducing the instrumental variable in the second-stage regression, the coefficient of DEM on CCD-SCPR remains significantly positive, which is consistent with the core findings and further confirms the robustness of the hypothesis (Table 3).

Additionally, on the basis of addressing endogeneity via the instrumental variable method, this study further eliminates endogeneity impacts using the DID method, dynamic panel model, and propensity score matching (PSM) method. The regression results further verify the validity of the baseline conclusions.

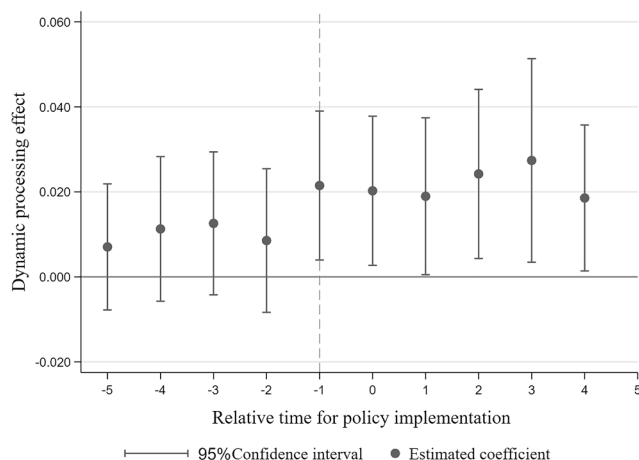


Figure 6. Parallel trend test

The figure shows the results of a parallel trend test of the difference-in-differences estimation. Data are represented as estimated coefficients and 95% confidence intervals for the difference between treatment and control groups before and after DEM implementation. The vertical dashed line denotes the timing of DEM implementation.

Robustness test

Parallel trend test

It shows that all regression coefficients are insignificant, indicating no systematic differences between the treatment group and the control group before the implementation of DEM (Figure 6). Whereas after policy implementation, the regression coefficients are significantly positive. Thus, the treatment and control groups selected in this study are comparable and satisfy the parallel trend assumption, making it feasible to use the DID model to evaluate the impact of DEM on the CCD-SCPR.

Propensity score matching-difference-in-differences

The selection of data trading platforms is typically non-random, which may lead to sample selection bias and result in biased estimates. Therefore, following the approach of Shi et al.,⁶² PSM is

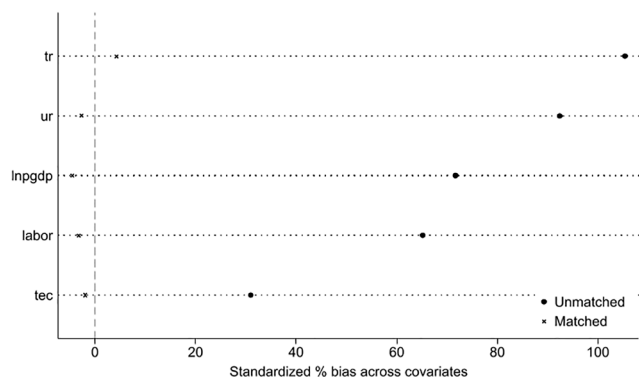


Figure 7. Covariate balance

The figure shows covariate balance before and after propensity score matching. Data are represented as absolute standardized percentage bias of covariates before (○) and after (●) matching. Vertical dashed line indicates zero bias.

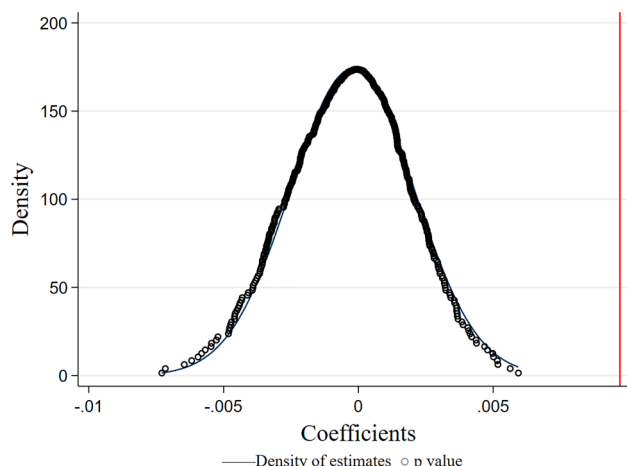


Figure 8. Placebo test

The figure shows the results of a placebo test with random treatment assignments. Data are represented as the distribution of estimated coefficients from 500 random placebo assignments. The dashed vertical line denotes the mean coefficient. The solid vertical line indicates the baseline DID estimate for comparison.

applied to reconstruct the control and treatment groups and reduce the self-selection bias associated with DEM. PSM first calculates the propensity score based on factors influencing the construction of data trading platforms, matches each treated sample with the closest control sample in terms of propensity score, forming pairs with similar influencing factors on CCD-SCPR, and finally obtains the average treatment effect between groups. Comparing differences in variables before and after matching, a standard deviation absolute value less than 0.2 is considered a good matching effect.⁶³ It indicates that the absolute values of the matched standard deviations are all less than 0.1, and none passed the *t* test, indicating a strong matching effect (Figure 7).

Placebo test

To exclude the potential bias caused by unobservable random factors during the sample period in the estimation of the multi-period DID model, this study tested the exogeneity of the DEM implementation time by randomly selecting an intervention time point for each sample subject. A placebo test was conducted for the dummy treatment group.⁶⁴ Due to space constraints, only the placebo test for 500 random samples is shown. The estimated coefficients for the placebo treatments are clustered around zero, in clear contrast to the positive and significant coefficients obtained in the baseline model (Figure 8 and Table 2). Therefore, it can be concluded that unobserved random factors do not affect the results of the multi-period DID estimation, confirming the robustness of the above empirical findings.

Policy implications

Based on the conclusions above, the following recommendations are proposed. First, implement differentiated regional strategies. The eastern region should prioritize the low-carbon transformation of traditional industries and their integration with digital technologies. The central region ought to strengthen green thresholds for industrial transfers and

support the transformation of resource-based cities. The western region is advised to further develop projects such as “West-to-East Power Transmission” and promote the conversion of ecological value. Cities should advance industrial upgrading, cultivate green industries, or enhance ecological-economic synergy according to their specific conditions. Second, explore innovative governance pathways for megacities. Technologies can be utilized to reduce energy consumption in transportation and building sectors, thereby addressing the emission stacking effect in densely populated areas. It is recommended to establish carbon emission tracking and accounting systems, with forward-looking pilot mechanisms explored to account for emissions from relocated industries within the responsibility assessments of their original locations, to prevent the paradox of “local optimization versus global deterioration.” Third, promote the widespread adoption of data elements. Prioritize pilot projects for integrated digital supervision platforms for carbon and pollution reduction in urban agglomerations such as central and western urban agglomerations. Utilize blockchain and AI technologies to achieve the interconnection of cross-provincial environmental rights trading markets, tackling the challenge of fragmented regional governance. Embed industrial internet technologies into high-carbon industry processes to overcome techno-economic bottlenecks in low-carbon transformation for non-electric industries. Fourth, optimize the policy synergy framework. Data applications should be incorporated into environmental regulation assessments, with regulatory tools allocated in a differentiated manner and dynamic evaluation mechanisms established. Concurrently, labor allocation should be reasonably guided, urbanization-related environmental protection facilities should be planned synchronously, and investment in green technology research and development should be increased. Fifth, deepen reforms in the marketization of data elements. This requires promoting legislation on environmental data property rights and cross-departmental sharing standards, with the long-term goal of creating a unified national platform for carbon and pollution reduction information disclosure. Research should also explore AI-driven algorithms for the collaborative control of multi-medium pollution. Enterprises can be encouraged to contribute to environmental data resource development through incentive mechanisms for data openness, ultimately fostering a new governance ecosystem characterized by “data-driven incentives, market-based mechanisms, and institutional safeguards.”

Limitations of the study

This study has three main limitations. First, the chosen proxy for DEM, based on the establishment of data trading platforms, may not fully capture the multifaceted depth or transaction efficiency of marketization. Second, the aggregate coupling coordination degree (CCD-SCPR) metric, while effective for comparison, potentially obscures non-linear trade-offs between specific pollutants and carbon emissions across sectors. Third, the findings, derived from China’s unique top-down regulatory and rapid digitalization context, may have limited generalizability to nations with differing institutional and market structures.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Ping Jiang. (jiangping@fudan.edu.cn).

Materials availability

This study did not generate new unique reagents.

Data and code availability

- This article analyzes existing, publicly available data, accessible at [key resources table](#).
- This study does not report the original code.
- Any additional information required to reanalyze the data reported in this article is available from the [lead contact](#) upon request.

ACKNOWLEDGMENTS

This work is supported by the Shanghai Science and Technology Commission (grant no. 23ZR1404100), the Sino-German Center (grant no. M-0049), the National Natural Science Foundation of China (grant no: 72204099), and the Fudan Tyndall Centre of Fudan University (grant no. IDH6286315).

AUTHOR CONTRIBUTIONS

Conceptualization, Z.C. and X.D.; data curation, Z.C., X.C., and X.J.; investigation, Z.C., X.Y., and P.J.; methodology, Z.C., X.D., and X.Y.; software, Z.C., X.Y., and X.D.; writing – original draft, Z.C., X.D., and P.J.; validation, X.D., X.Y., and P.J.; visualization, Z.C. and X.J.; writing – review and editing, Z.C. and X.D.; funding acquisition, P.J. and X.D.; supervision, P.J. and X.D. All authors commented on the final article.

DECLARATION OF INTERESTS

The authors declare no competing interests.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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- [METHOD DETAILS](#)
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 - K-means clustering
 - Difference-in-differences model
 - Moderating effect model
 - Instrumental variable method
 - Parallel trend test
- [QUANTIFICATION AND STATISTICAL ANALYSIS](#)

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.isci.2026.115084>.

Received: August 27, 2025
Revised: December 15, 2025
Accepted: February 16, 2026
Published: February 19, 2026

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Carbon emissions	Emissions Database for Global Atmospheric Research (EDGAR)	https://www.destatis.de/EN/Themes/Countries-Regions/International-Statistics/DataSources/04_01_EDGAR_Data.html
PM _{2.5}	National Qinghai-Tibet Plateau Science Data Center	https://data.tpd.cn/en/data/bf0f4f8b-8d7e-4682-9041-53324d5e4d45
Green patent	National Intellectual Property Administration	https://english.cnipa.gov.cn
Other data used in this paper	China Urban Statistical Yearbook, the official website of the National Bureau of Statistics, local statistics bureau websites, statistical yearbooks, and the Wind Database.	Tables S1 and S2
Software and algorithms		
ArcGIS	ESRI	https://www.arcgis.com/index.html
MATLAB 2024b	Mathworks	https://www.mathworks.com/products/matlab.html
Origin 2024b	OriginLab	https://www.originlab.com/OriginProLearning.aspx
StataMP 18	StataCorp	https://www.stata.com

METHOD DETAILS

Coupling coordination degree

Since both CO₂ and air pollutants largely result from fossil fuel combustion, they share a common origin, leading to significant synergistic effects. End-of-pipe air pollution treatments often increase CO₂ emissions, highlighting their inherent coupling.⁶⁵ The coupling coordination degree model elucidates the interactions among multiple subsystems and the overall development of the system. This study uses the modified model proposed by Wang et al.⁶⁶ to assess the synergistic effects of carbon and pollution reduction across 297 Chinese cities, analyzing the variations in coordination degrees. The model is represented by Equation 1. In Equation 1, U_1 represents the minimum value between pollutant and carbon emissions in a city, and U_2 is the maximum. Data underwent range normalization to eliminate magnitude and direction differences. C is the coupling degree between the two systems, ranging from 0 and 1. T is the comprehensive coordination index. Coefficients a and b are both set to 0.5, reflecting the equal importance of air pollutant and carbon emission reduction systems. D , the degree of coordinated development, also ranges from 0 to 1. The larger the value of D , the stronger the synergistic effect of carbon and pollution reduction. According to the classification method of Liang et al.,⁶⁷ the coupling coordination degree was divided into stages and levels.

$$D = \sqrt{C * T}$$

$$C = \frac{2\sqrt{U_1 U_2}}{U_1 + U_2} = \sqrt{[1 - (U_2 - U_1)] \frac{U_1}{U_2}} \quad (\text{Equation 1})$$

$$T = aU_1 + bU_2$$

K-means clustering

Traditional econometric models often struggle with spatial dependence and capturing nonlinear spatiotemporal interactions. This study uses the k-means clustering to investigate the spatial clustering relationship between CO₂, PM_{2.5}, and the CCD-SCPR. K-Means is an unsupervised clustering algorithm that iteratively updates centroids in a multidimensional feature space. By setting a predefined number of clusters (K) and initial centroids, it assigns data to clusters that maximize intra-class similarity and minimize inter-class differences, effectively revealing the intrinsic group structures within multidimensional data.⁶⁸ Standardizing data is crucial in clustering to prevent features with larger scales from dominating the analysis. Research has shown that the Z-Score Standardization method performs better than normalization in clustering, as shown in Equation 2.⁶⁹ The K-Means algorithm begins by randomly initializing K centroids and assigning each sample to the nearest centroid based on Euclidean distance, as defined in

Equation 3. Centroids are then updated iteratively until convergence, maximizing intra-cluster similarity and minimizing inter-cluster similarity. To determine the optimal number of clusters (K), we apply the elbow method alongside the Calinski-Harabasz index.⁷⁰ This involves calculating the sum of squared errors (SSE) for various K values, and selecting the K at the “elbow” point where the SSE reduction rate slows significantly (Figure 4). In Equation 4, C_i denotes the cluster i , and μ_i represents its centroid.

$$Z = \frac{x - \mu}{\sigma} \quad (\text{Equation 2})$$

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (\text{Equation 3})$$

$$SSE(K) = \sum_{i=1}^K \sum_{x \in C_i} \|x - \mu_i\|^2 \quad (\text{Equation 4})$$

The Calinski-Harabasz index, known as the Variance Ratio Criterion (VRC), evaluates clustering quality by comparing Sum of Squared Between-Cluster (SSB) to Sum of Squared Within-Cluster (SSW),⁷¹ as illustrated in Equation 5. SSB measures the deviation of cluster centroids from the overall mean, while SSW measures the dispersion of samples within each cluster. In Equation 5, k represents the number of clusters, N denotes the total number of samples, m_i is the centroid of cluster i , m is the overall mean, n_i is the number of samples in cluster i , and $\|m_i - m\|$ represents the Euclidean distance. A higher VRC value indicates superior clustering quality. The optimal number of clusters is determined as the K that maximizes the index, balancing separation and cohesion among clusters.

$$VRC_k = \frac{SS_B}{SS_W} \times \frac{(N - k)}{(k - 1)}$$

$$SS_B = \sum_{i=1}^k n_i \|m_i - m\|^2 \quad (\text{Equation 5})$$

$$SS_W = \sum_{i=1}^k \sum_{x \in C_i} \|m_i - m\|^2$$

Difference-in-differences model

Difference-in-differences (DID) models have been employed as an efficient tool for evaluating policy implementation effects.⁷² In this study, the DEM was treated as a quasi-natural experiment, designating cities with data trading platforms as the treatment group and those without as the control group. Given the phased implementation of this policy, a multi-period DID model was employed.⁷³ The DID model is specified as in Equation 6, where i represents the city, t denotes time, and CCD-SCPR is the dependent variable. DEM is the key explanatory variable. $Control_{it}$ represents a series of control variables, θ_i and λ_t denote city fixed effects and time fixed effects, respectively. ε_{it} is the random error term. The model parameters are provided in Tables S1 and S2.

$$CCD-SCPR_{it} = \alpha_0 + \alpha_1 DEM_{it} + \delta Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (\text{Equation 6})$$

Moderating effect model

Whether DEM and government environmental regulation can complement each other to produce synergistic effects on CCD-SCPR is analyzed using a moderating effect model. Drawing on the research of Ji et al.,⁷⁴ environmental regulation (eri) is measured by the ratio of the frequency of environmental vocabulary to the total word count in prefecture-level city government work reports. An interaction term between DEM and environmental regulation is added to construct a moderating effect model, as shown in Equation 7. Here, α_2 denotes the coefficient of the interaction term, reflecting the moderating role of environmental regulation in the synergistic effect of DEM on CCD-SCPR.

$$CCD-SCPR_{it} = \alpha_0 + \alpha_1 DEM_{it} + \alpha_2 DEM_{it} * eri + \delta Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (\text{Equation 7})$$

Instrumental variable method

To mitigate potential endogeneity concerns, an instrumental variable is constructed following the research approach of Bai and Yu,⁷⁵ and a two-stage least squares (2SLS) estimation is employed. Specifically, the number of internet broadband subscribers in each city is adopted as the instrumental variable. On the one hand, the market-oriented development of data factors relies on the large-scale generation, aggregation, circulation, and utilization of data. The number of internet broadband subscribers reflects the coverage breadth and usage depth of urban data infrastructure, thereby satisfying the relevance condition. On the other hand, broadband

network construction is primarily driven by historical and industry-specific factors such as communication technology iteration cycles, investment strategies of telecommunication operators, and early-stage infrastructure planning. These factors are not directly causally linked to the current policies or corporate behaviors related to pollution and carbon reduction in each city. Moreover, a city's current performance in pollution and carbon reduction is unlikely to significantly affect its past broadband subscriber scale, thus satisfying the exogeneity condition. The 2SLS method was applied for instrumental variable regression.

$$DEM_{it} = \alpha_0 + \alpha_1 IV_{it} + \delta Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (\text{Equation 8})$$

$$CCD-SCPR_{it} = \alpha_0 + \alpha_1 DEM_{it} + \alpha_2 IV_{it} + \delta Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (\text{Equation 9})$$

In the first stage represented by Equation 8, the instrumental variable (IV) is used to explain DEM, and the predicted values are obtained using the regression coefficients. In the second stage shown in Equation 9, regression is performed by replacing the actual statistical measure of DEM with its predicted value as the core explanatory variable.

Parallel trend test

The DID model requires a fundamental assumption: prior to policy implementation, the treatment and control groups should exhibit similar time effects or data trends, meaning no systematic differences exist. This assumption is consistent with the parallel trend assumption. This study conducted a parallel trends test to explore the dynamic effects of DEM. The specific model is shown in Equation 10, where k represents the implementation time of the DEM. Considering the potential lagged impact of the DEM on CCD-SCPR, a policy window period of five years before and after implementation was selected, with the first period before implementation serving as the reference group. Therefore, k took values in the range $[-5, 5]$, including $k \neq -1$.

$$CCD-SCPR_{it} = \alpha_0 + \sum_{k \geq -5, k \neq -1}^5 \alpha_k DEM_{it}^k + \delta Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (\text{Equation 10})$$

QUANTIFICATION AND STATISTICAL ANALYSIS

The figures were plotted using ArcGIS, MATLAB 2024b, Origin 2024b and StataMP 18.