JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE
Journal of Cultural Analysis and Social Change,
2025, 10(4), 4074-4093
ISSN: 2589-1316

From “Evidence Silos” to Computable Synergy: An Algorithmic Framework for Science-Policy Translation and Regionally Differentiated Governance Toward China's Dual Carbon Goals

Zhang Yue[1], Bin Feng[2], Dayang Haszelinna Binti Abang Ali[3], Sazlina Md. Salleh[4*]

[1,3,4] Centre for Policy Research, Universiti Sains Malaysia, Penang, 11800, Malaysia
[2] Institute of Mechanics, Chinese Academy of Sciences, Beijing, 100190, China

***Corresponding Author:** sazlina@usm.my

Citation: Yue, Z., Feng, B., Ali, D. H. B. A. & Salleh, S. M. (2025). From “Evidence Silos” to Computable Synergy: An Algorithmic Framework for Science-Policy Translation and Regionally Differentiated Governance Toward China's Dual Carbon Goals , *Journal of Cultural Analysis and Social Change*, 10(4), 4074-4093. https://doi.org/10.64753/jcasc.v10i4.3737

Published: December 28, 2025

ABSTRACT

Centering on China's “carbon peak-carbon neutrality” strategy, this study addresses the computable governance challenges of efficiently translating scientific knowledge into policy instruments and implementing regionally differentiated execution. Unlike existing research primarily discussing the institutional design and coordination dilemmas of the “1+N” policy system, this paper proposes a Computable Policy Synergy (CPS) framework that integrates “evidence generation—policy synthesis—regional adaptation—dynamic evaluation.” Methodologically, it constructs multi-source evidence pipelines for dual-carbon goals (statistically harmonized MRV data, sectoral technology scenarios, socio-economic-energy coupling indicators). Policy knowledge graphs and causal inference (synthetic control/difference-in-differences/instrumental variables) identify policy mechanisms, while a “policy sandbox” enables cross-sectoral tool synthesis and conflict detection. To characterize governance performance, this study designs two core indicators: the Cross-Sector Computable Synergy Index (CCI) and the Regional Scenario Transferability Index (RTI). The former measures the dynamic synergy among price-based, command-based, and information-based tools, while the latter evaluates policy transferability under varying factor endowments, industrial structures, and technological feasibility constraints. Using a 2015–2024 provincial-municipal panel sample and linking national carbon market (ETS) with non-ETS measures in key industries, empirical results demonstrate that compared to traditional sector-specific policy combinations, the toolkit generated by the CPS framework demonstrates significant advantages in reducing policy inefficiencies, enhancing the synergy between emission reduction intensity and total factor productivity, and achieving convergence in regional emission reduction costs without compromising equity. This study innovates by proposing an algorithmic policy synthesis and regional adaptation paradigm for dual-carbon governance, providing a reusable indicator system and evaluation process. It offers transferable technical pathways and institutional recommendations for deep science-policy coupling under complex objectives in developing economies.

Keywords: Computable governance; Policy knowledge graph; Causal inference; Policy synergy; Regional differentiation; Carbon market linkage

INTRODUCTION

Global climate governance has entered a profound transformation phase centered on carbon neutrality. As the world's largest carbon emitter, China announced its "dual carbon" goals in 2020—striving to peak carbon emissions before 2030 and achieve carbon neutrality before 2060. This strategic decision will profoundly reshape the underlying logic of China's economic and social development. The "1+N" policy system officially released by China in 2021 marks the transition of the dual carbon strategy from top-level design to substantive implementation. This system includes a general guiding opinion and several specific plans covering key sectors such as energy, industry, transportation, and construction. However, achieving the dual carbon goals faces unprecedented complexity and challenges: it requires both building cross-departmental and cross-sectoral policy coordination mechanisms at the national level and addressing the significant heterogeneity in resource endowments, industrial structures, and technological levels among provinces.

A study published in *Nature Climate Change* by Jiang et al. (2025) reveals the complexity of policy interactions. Using a dynamic computable general equilibrium model of China, their analysis of 1,295 policy scenario combinations shows that when considering the interactions of four policy categories—carbon pricing, energy efficiency improvement, renewable energy, and end-point electrification—the proportion of scenarios that could achieve carbon neutrality by 2060 decreases by 84%, delaying the achievement by 5-6 years. Only the combination of renewable energy and end-point electrification can produce synergistic effects in both economic and emission reduction dimensions. This finding reveals a core dilemma: the traditional sectoral policy-making paradigm is ill-suited to the systemic nature of climate governance. While tools such as carbon pricing, energy efficiency standards, and renewable energy subsidies may produce significant emission reductions when implemented in isolation, their combined application can lead to a loss of overall effectiveness due to conflicting policy objectives, overlapping incentive mechanisms, and misaligned implementation timing.

More seriously, the vast differences in development levels between provinces make it difficult for a unified national policy to balance efficiency and fairness. Cheng and Liu (2021), using the super-efficient SBM-DEA model to calculate the industrial energy carbon emission efficiency of 30 provinces, showed that the spatial distribution evolved from disorder to order, with high and low value regions clustering together. Inter-provincial differences gradually widened, and these differences mainly stemmed from heterogeneity between regions rather than within regions. Liu et al. (2024), based on Gini coefficient decomposition and social network analysis, further indicated that from 2000 to 2021, China's provincial carbon emission Gini coefficients showed an upward trend, with widening differences. The difference in carbon emission between low-carbon pilot provinces and non-pilot provinces was significant, exceeding 0.15. These studies confirm that the gap between developed eastern regions and underdeveloped western regions is the main source of spatial inequality in carbon emissions.

While existing academic research has made significant progress in the field of dual-carbon governance, key gaps remain. Research on policy interaction effects primarily focuses on model simulations, offering relatively few actionable policy frameworks. Although research on regional heterogeneity has yielded fruitful results at the "descriptive" level, it remains insufficient at the "design" level, offering few answers on how to translate descriptive findings into specific policy design parameters. The process of transforming scientific knowledge into policy tools lacks a calculable, systematic framework.

This study proposes the "Computable Policy Synergy" (CPS) framework, aiming to establish an algorithmic transformation mechanism from scientific evidence to policy action. This framework integrates components such as multi-source evidence pipelines, policy knowledge graphs, causal inference, and policy sandboxes, and designs two core indicators: the Cross-Sectoral Computable Synergy Index (CCI) and the Regional Scenario Transferability Index (RTI). This paper uses provincial panel data from 2015 to 2024, combined with empirical evidence of the linkage between the national carbon market and non-market-based measures, to verify the policy effectiveness of the CPS framework.

THE EVIDENCE DILEMMA AND COMPUTABILITY SHIFT IN DUAL-CARBON GOVERNANCE: LITERATURE REVIEW AND THEORETICAL POSITIONING

The Complexity of Policy Interactions and the Development of Carbon Markets: From Isolated Tools to Systemic Coordination

Research on policy interaction effects provides a crucial perspective for understanding the complexity of dual-carbon governance. A systematic review published in *Nature Climate Change* by Peñasco et al. (2021) analyzed the outcomes and trade-offs of ten types of decarbonization policy tools, pointing out that a single policy tool is insufficient to address the multidimensional challenges of climate governance, necessitating the construction of complementary and reinforcing mechanisms among these tools. Bertram et al. (2015) emphasized that relying solely on carbon pricing is insufficient to keep climate goals within reach, requiring supplementary technology policies. Pahle et al. (2018) and Meckling et al. (2017) further highlighted the importance of policy timing, pointing out that a sequencing strategy that progressively increases policy stringency can improve policy effectiveness.

The construction and operation of China's Emissions Trading System (ETS) has become an important practice for testing the effectiveness of market-based emission reduction tools. Since launching seven carbon trading pilot programs in 2013, China officially launched its national carbon market in July 2021, initially covering approximately 2,162 companies in the power sector, with annual emissions of approximately 4.5 billion tons of carbon dioxide, making it the world's largest carbon emissions trading system (Asia Society, 2025). In May 2024, the "Interim Regulations on the Administration of Carbon Emissions Trading" officially came into effect, providing a legal basis for the operation of the carbon market (Government of China, 2024).

Regarding the emission reduction effects of carbon trading pilot policies, the academic community has conducted in-depth evaluations using various quasi-experimental methods. Yang et al. (2024) used a synthetic control method to evaluate the carbon emission reduction effects of provincial low-carbon pilot policies, finding that the policy effects exhibited significant heterogeneity, with provinces implementing both low-carbon pilot policies and carbon trading systems showing better results. Wang et al. (2021) used an extended synthetic control method to evaluate the environmental and economic performance of seven ETS pilot programs, finding that between 2011 and 2015, the overall carbon dioxide emissions in the pilot areas decreased by approximately 1,165.72 million tons, accounting for 12.78% of the total industrial carbon dioxide emissions in the pilot areas. However, economically, the industrial output value loss was approximately RMB 560.888 billion, although this economic loss was short-term and decreased over time. Regional responses showed heterogeneity, with Beijing and Shanghai showing the fastest emission reduction rates, and Guangdong showing the largest emission reduction scale.

Cui and Liu (2024), using a time-varying difference-in-differences model, found that carbon trading policies significantly improve synergistic emission efficiency and have a significant promoting effect on the development of integrated emission efficiency for greenhouse gases and air pollutants. Spatial econometric analysis revealed that synergistic emission efficiency mainly follows a low-low (LL) and high-high (HH) regional distribution pattern, exhibiting a significant spatial spillover effect. Jiang et al. (2024), based on the PSM-DID method, showed that the carbon trading system can effectively reduce total carbon emissions in pilot cities and generate positive spatial spillover effects on neighboring cities in the pilot areas, mainly by incentivizing enterprises to implement environmental protection practices and improving the industrial structure of pilot cities to reduce carbon emissions.

However, China's carbon market still faces numerous challenges in its design and operation. The existing ETS (Emissions Trading System) uses a carbon intensity-based quota allocation method rather than absolute cap-and-load control, resulting in relatively limited constraints on carbon emissions (International Carbon Action Partnership, 2025). The monitoring, reporting, and verification (MRV) system still faces issues such as ambiguous legal status, inconsistent accounting guidelines, and insufficient information technology support (Paulson Institute, 2018). Compared to the EU ETS, China's carbon market has lower trading activity; the peak daily trading volume in December 2021 was 15 million tons of CO2, while the EU market's average daily trading volume is approximately 40 million tons. These institutional and technological shortcomings restrict the carbon market's core functions of price discovery and incentivizing emissions reduction.

Regional Heterogeneity and Differentiated Governance Paths: Empirical Evidence of Spatial Differentiation Characteristics

China has a vast territory, and significant differences exist between provinces in terms of resource endowment, industrial structure, and technological level. Numerous empirical studies have characterized the spatial differentiation of carbon emissions from different dimensions. Zhang et al. (2022), based on an empirical analysis of 286 prefecture-level and above cities, found that China's urban carbon emissions exhibit significant spatial heterogeneity. The per capita carbon emissions of Beijing and Shanghai, the two most developed megacities, are 7.33 tons and 11.46 tons respectively, higher than those of world-renowned cities such as Copenhagen, Paris, Tokyo, and London. Due to the different stages of economic development and regional economic development levels in different parts of China, there are also significant regional differences in carbon emission intensity.

Zhou et al. (2024), using a semi-parametric variable-coefficient spatial autoregressive model based on panel data from 2004 to 2019, found significant heterogeneity in carbon dependence among 30 provincial-level administrative units in China. The relationship between economic growth and carbon emissions exhibits an "S"-shaped curve, with carbon dependence decreasing as the contribution of the tertiary sector increases. This can be divided into three stages: "strong dependence," "weak dependence," and "peak carbon emissions." Developed regions such as Beijing, Shanghai, and Tianjin have highly optimized industrial structures, with the tertiary sector dominating, and their economic growth has decoupled from carbon emissions; some regions have already reached peak carbon emissions. Less developed regions, however, remain in the "strong dependence" or "weak dependence" stage and need to prioritize the transformation and upgrading of their secondary industries to reduce their heavy reliance on fossil fuels.

Zhang et al. (2023), based on nighttime light data and land use data, found that China's carbon deficit showed a continuous upward trend from 2000 to 2018, exhibiting a significant positive spatial correlation. Significant differences exist across regions in China regarding carbon emissions from energy consumption, land carbon absorption, and the decoupling of carbon emissions from economic development. This spatial heterogeneity is crucial for China to achieve its carbon peaking goals by 2030 and carbon neutrality by 2060. Yuan et al. (2024), based on carbon budgets and carbon compensation studies of 11 prefecture-level cities in Jiangxi Province from 2010 to 2020, found that carbon emissions showed an increasing trend, exhibiting a spatial distribution pattern of "high in the west and low in the east." The province is dominated by net carbon emission sources, with a carbon deficit accounting for over 60%. Based on differences in carbon compensation values, the 11 prefecture-level cities were divided into 4 high-compensation zones, 3 low-compensation zones, and 4 compensated zones, providing an operational scheme for the fair sharing of carbon reduction costs among regions.

Application of Causal Inference Methods in Policy Evaluation: Composite Control Method and Difference-in-Differences Method

The transformation of scientific knowledge into policy tools requires rigorous causal inference methods. The Synthetic Control Method (SCM), as a quasi-experimental design method, is widely used in policy effectiveness evaluation. Zhang et al. (2024) used a Synthetic Control Method with Lasso Selection (SCUL) to evaluate the emission reduction effect of China's carbon emission trading system. Based on seven predictor variables from 2000 to 2017, they found that SCUL produced more accurate predictions before intervention than traditional SCM. The average Cohen's D values for the six pilot regions were all significantly lower than 0.25: Beijing 0.052, Tianjin 0.0314, Shanghai 0.1501, Hubei 0.0412, Guangdong 0.01, and Chongqing 0.0346, demonstrating the accuracy of the method.

Fan et al. (2022) used the DID (Discretionary Identification) and SCM (Self-Conceptualization) methods to assess the impact of the carbon emission trading system on energy conservation and emission reduction in pilot provinces and cities. Based on provincial panel data from 2005 to 2019, they found that the carbon emission trading system generally significantly promoted the energy conservation and emission reduction process in pilot provinces and cities. Heterogeneity analysis showed that the policy effects were most significant in Tianjin and Shanghai, followed by Hubei. Chen et al. (2021) used a combination of SCM and regression discontinuous design to find that the carbon emission trading system is effective in China, but its effectiveness is driven by variables such as economic development, energy consumption, and foreign direct investment. Due to differences in economic, geographical, technological, and environmental conditions across regions, each provincial government should formulate targeted emission reduction strategies.

The difference-in-differences (DID) method is also widely used in carbon trading policy evaluation. Jiang et al. (2023), based on balanced panel data from 285 prefecture-level and above cities from 2003 to 2020, used the DID method to examine the impact of carbon trading pilot policies on carbon emissions, finding that the policies significantly reduced China's carbon emissions by 6.21%. Through diversified robustness tests, including the instrumental variable method for endogeneity, propensity score matching (PSM) for sample selection bias, and variable substitution, the conclusions remained robust. Bai and Zhao (2024) used a time-varying DID model to explore the synergistic emission reduction effect and mechanism of ETS on air pollution and carbon emissions, finding that ETS is conducive to the synergistic control of carbon dioxide and air pollutants, and that synergistic emission reduction can be achieved by optimizing energy consumption structure and promoting technological progress.

Wang et al. (2021) combined SCM and DID methods to assess the effectiveness of carbon trading policies in achieving carbon neutrality. Based on panel data from 30 provinces and municipalities from 2008 to 2018, they examined the impact pathways of carbon trading policies from a five-pronged perspective. The study indicates that carbon neutrality should be incorporated into the overall five-pronged approach, forming a cross-perspective study with Chinese characteristics. These methodological innovations provide more precise tools for policy evaluation, but limitations remain: most studies focus on the isolated effects of single policy tools, with fewer systematic analyses of the interaction mechanisms of multiple policy combinations; causal inference methods are mainly applied to ex-post assessments, providing insufficient support for ex-ante simulations in the policy design phase.

Based on the literature review above, this study identifies three major gaps in dual-carbon policy research: insufficient calculable representation of policy interaction effects, lack of a transformation path from regional heterogeneity to differentiated design, and a lack of a systematic framework for transforming scientific evidence into policy tools. To address these gaps, this study constructs a CPS framework, integrating components such as multi-source evidence pipelines, policy knowledge graphs, causal inference, and policy sandboxes, and proposes two core evaluation indicators, CCI and RTI, providing integrated algorithmic support for the design, evaluation, and optimization of dual-carbon policies.

THEORETICAL CONSTRUCTION AND ALGORITHM DESIGN OF A COMPUTABLE POLICY COORDINATION FRAMEWORK

Overall Architecture and Core Components of the CPS Framework

The Computable Policy Synergy (CPS) framework aims to construct a systematic transformation mechanism from scientific evidence to policy action. Its core lies in integrating fragmented research evidence, policy texts, and implementation data into structured knowledge, and using algorithmic methods to optimize the combination and regional adaptation of policy tools. This framework consists of four core modules: a multi-source evidence pipeline, a policy knowledge graph, a causal inference engine, and a policy sandbox. This architecture breaks through the limitations of traditional policy analysis that relies on expert experience and historical analogies, providing a computational foundation for the precise design of dual-carbon policies.

The multi-source evidence pipeline module is responsible for integrating heterogeneous data sources to build a unified evidence infrastructure. This module covers three core data categories: statistically coordinated MRV data, sectoral technology scenario data, and socio-economic-energy coupling indicator data. MRV data integrates enterprise-level emission reports from the national carbon market and energy consumption data published by provincial statistical bureaus, addressing differences in accounting boundaries and calibers through data cleaning and standardization (Paulson Institute, 2018). Sectoral technology scenario data constructs technology diffusion paths from 2025 to 2060 based on parameters such as renewable energy installed capacity, industrial process optimization potential, and room for improvement in building energy efficiency standards (Jiang et al., 2025). The socio-economic-energy coupling indicator incorporates macroeconomic variables such as population structure changes, urbanization rate evolution, and industrial structure adjustment trends to capture the socio-economic impact of emission reduction policies (Zhou et al., 2024).

The policy knowledge graph module transforms policy texts, academic literature, and implementation cases into structured knowledge representations. This graph uses policy tools as nodes and the relationships of synergy, substitution, and conflict between these tools as edges, constructing a multi-layered heterogeneous network. Node attributes include policy type (command-and-control, market-incentive, information disclosure), implementing entity (central government, local government, enterprises), target audience (energy supply side, industrial demand side, end-consumer side), and time dimension (short-term effects, medium- to long-term planning). Edge attributes characterize the intensity and direction of interaction between tools; for example, carbon tax and carbon trading have overlapping policy objectives and a substitution relationship, while renewable energy subsidies and electricity market reform have a mutually reinforcing synergistic relationship (Peñasco et al., 2021; Bertram et al., 2015). The graph construction is based on natural language processing technology to extract entities and relationships from policy texts, combined with expert annotation for quality control.

The causal inference engine module identifies the true effects of policies based on correlation analysis. This module integrates three types of causal inference methods: synthetic control (SCM), difference-in-differences (DID), and instrumental variable (IV) methods. For natural experimental scenarios such as carbon trading pilots and low-carbon city pilots, SCM is used to construct counterfactual control groups to assess the net policy effect (Yang et al., 2024; Wang et al., 2021). For the gradual implementation of nationwide policies, a time-varying DID model is used to capture dynamic processing effects (Cui & Liu, 2024). Addressing the endogeneity of policies, instrumental variables based on exogenous variables such as geographical distance and historical institutions are constructed for two-stage least squares estimation (Jiang et al., 2023). The causal inference results provide empirical support for the policy knowledge graph, transforming theoretical synergistic relationships into empirical causal connections.

The policy sandbox module provides a virtual simulation environment to test the interactive effects of different policy combinations. Based on system dynamics principles, this module constructs a provincial carbon emission-economic growth coupling model, incorporating key variables such as energy structure, industrial structure, technological progress, carbon pricing, and quota allocation, along with their feedback loops. More than 1000 scenarios are generated through Monte Carlo simulation, each corresponding to a specific combination of policy tools and parameter settings. The sandbox output includes multi-dimensional indicators such as carbon emission trajectories, GDP growth paths, changes in total factor productivity, and employment impacts from 2025 to 2060. By comparing the Pareto frontiers of different scenarios, the optimal policy combination under the trade-off between emission reduction efforts and economic costs is identified (Jiang et al., 2025). The sandbox design draws on the modeling experience of the Chinese regional energy model C-REM 4.0, integrating the 2017 regional input-output tables with the GTAP 11 database to ensure consistency between economic and physical energy data (Peng et al., 2025).

Table 1. Comparison of Functions and Technical Approaches of Core Modules in the CPS Framework

Module Name	Main functions	Data input	Methods and Techniques	Output results	Academic foundation
Multi-source evidence pipeline	Integrating heterogeneous data sources to build a unified evidence foundation	MRV data, energy statistics, technical parameters, socioeconomic indicators	Data cleaning, standardization, missing value imputation, outlier detection	Structured evidence database to support subsequent modeling	Paulson Institute (2018)
Policy Knowledge Graph	Structured representation of policy tools and interactions	Policy documents, academic literature, and implementation cases	Natural Language Processing, Entity Relation Extraction, Knowledge Fusion	Multi-layered heterogeneous policy network with complete node and edge attributes	Peñasco et al. (2021)
Causal Inference Engine	Identify the true effects of policies and eliminate misleading factors.	Provincial and municipal panel data, pilot policy timelines	Synthetic control method, time-varying DID, instrumental variable method	Estimated net policy effect and causal mechanism path	Yang et al. (2024); Cui & Liu (2024)
Policy Sandbox	The interaction effect of virtual simulation testing policy combinations	Coupled model parameters and policy tool combination	System dynamics, Monte Carlo simulation, Pareto optimization	Optimal policy combination scheme, multi-dimensional impact prediction	Jiang et al. (2025); Peng et al. (2025)

Note: The technical approach is based on existing literature, and the data input and methodology are designed according to the actual needs of dual-carbon governance.

Construction Logic of Cross-Departmental Computable Collaboration Index (CCI)

The Cross-Sector Computable Synergy Index (CCI) aims to quantify the degree of synergy among different policy tool combinations, providing policymakers with comparable decision-making support. The index design must meet three core requirements: additivity (policy effects can be decomposed into direct and interactive effects), dynamism (capturing the evolution of policy effects over time), and operability (calculated based on observable data, avoiding subjective weighting).

The theoretical foundation of CCI (Carbon Currency Integration) stems from synergy theory and a policy tool classification framework. Peñasco et al. (2021) categorized decarbonization policy tools into three types: price-based (carbon tax, carbon trading), command-based (energy efficiency standards, elimination of outdated production capacity), and information-based (carbon disclosure, green labeling). The mechanisms of action differ among these types of tools. Price-based tools guide corporate behavior through cost internalization, command-based tools directly stipulate technical standards or behavioral norms, and information-based tools rely on market reputation mechanisms. When multiple types of tools are implemented together, three effects may occur: synergy (1+1>2), substitution (1+1<2), and neutral (1+1=2). Jiang et al. (2025) found that only the combination of renewable energy policy and end-point electrification policy produces a synergistic effect, while the combination of carbon pricing and energy efficiency standards produces a substitution effect due to overlapping policy objectives.

The CCI calculation consists of three steps. The first step estimates the marginal emission reduction effect of a single policy tool based on a causal inference engine. A time-varying DID model is used, with carbon emission intensity (carbon emissions per unit of GDP) as the dependent variable and policy implementation dummy variables as independent variables, controlling for confounding factors such as economic development level, industrial structure, and energy structure. Let i represent the province, t represent the year, and k represent the policy tool; then the marginal effect of a single policy$k$ is:

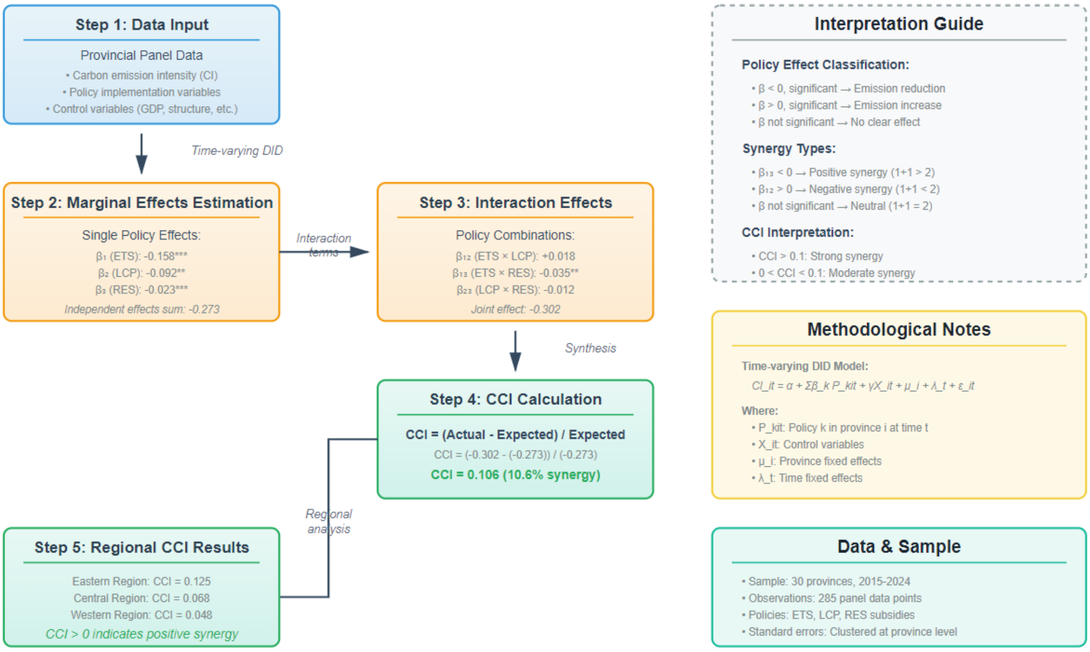
$$\beta_k = \frac{\Delta CO_2\text{Intensity}_{i,t}}{\Delta\text{Policy}_{k,i,t}}$$

The second step is to estimate the combined effect of the policy mix. For the combination of tool k and tool$j$, an interaction term (dummy variable of policy$k$ × dummy variable of policy$j$) is added to the regression model. The coefficient of the interaction term $\beta_k j$is the synergistic effect (or substitution effect). If $\beta_k j$>0β_kj is significant, it indicates that there is synergy between the two policies; if $\beta_{k}j<0$ and is significant, it indicates that there is substitution; if $\beta_{k}j$ is not significant, it indicates neutrality.

The third step is to construct the Comprehensive Coordination Index (CCI). For a combination of N policy tools, the CCI is defined as follows:

$$CCI=\frac{\text{Actual-Expected}}{\text{Expected}}$$

The actual joint effect is estimated using a regression model, and the sum of the expected independent effects is a simple sum of the marginal effects of each instrument. $CCI>0$ indicates positive synergy, $CCI<0$ indicates negative synergy (substitution or conflict), and $CCI=0$ indicates neutrality. This index is dimensionless, facilitating comparisons across regions and time periods.



Note: ***, **, * indicate significance at 1%, 5%, 10% levels respectively. CCI measures additional emission reduction beyond independent policy effects.

Figure 1: Position reserved: CCI calculation flowchart

Design and Application of the Regional Scenario Transferability Index (RTI)

The Regional Scenario Transferability Index (RTI) aims to assess the feasibility and effectiveness of a province's emissions reduction policy mix in other provinces, providing a quantitative basis for differentiated policy design. The core logic of this index is that different provinces have different factor endowments, industrial structures, and technological capabilities, and the same policy may have vastly different effects in different regions (Wang et al., 2021; Zhou et al., 2024). The RTI measures "scenario distance" and "constraint satisfaction" to determine the regional suitability of policies.

RTI constructs similarity matching based on three dimensions. First, factor endowment similarity, including indicators such as GDP per capita, urbanization rate, the proportion of the tertiary industry, and renewable energy resource potential. Euclidean distance is used to measure the distance between province i and province j in the factor space.

$$D_{\text{Element}}(i,j)=\sqrt{\sum_{k}(x_{i,k}-x_{j,k})^2}$$

Where $x_{i,k}$ represents the standardized value of province i on indicator k. The smaller the distance, the more similar the factor endowments, and the higher the policy transferability.

Second, industrial structure similarity, focusing on the output value share and technological level of high-carbon industries (electricity, steel, cement, chemicals, etc.). Cheng and Liu (2021) pointed out that the carbon emission efficiency of the eastern region is significantly higher than that of the western region, mainly due to differences in industrial structure. The structural similarity coefficient is used as a measure:

$$S_{\text{industry}}(i,j)=\sum_{k}[\min(p_{i,k},p_{j,k})]$$

Where $p_{i,k}$ represents the proportion of output value of industry k in province i. This coefficient takes values of [0,1], and the closer it is to 1, the more similar the industrial structure.

Third, technical feasibility constraints are assessed to determine whether province j possesses the technical conditions required to implement the policy of province i. For example, carbon capture and storage (CCS) technology requires geological storage conditions, offshore wind power requires coastline resources, and the hydrogen energy industry requires a foundation for hydrogen production through water electrolysis or coal-to-hydrogen. A technical constraint satisfaction matrix C is constructed; if province j satisfies the technical conditions of policy k, then $C_{j,k}=1$, otherwise it is 0.

Based on three dimensions, RTI is defined as:

$$RTI(i\rightarrow j)=a\times[1-D_{\text{element}}(i,j)/D_{\max}\quad]+\beta\times S_{\text{industry}}(i,j)+\gamma\times(\sum C_{j,k}/K)$$

Where a , β , and γ are weighting coefficients, satisfying $a+\beta+\gamma=1$; $D_{m}ax$ is the maximum distance between elements in the sample; K is the total number of tools in the policy mix. *RTI* takes values [0,1], with values closer to 1 indicating that the policy of province i is more suitable for promotion in province j.

Applications of RTI include: identifying the matching relationship between policy demonstration zones and potential promotion zones; assessing the heterogeneous effects of a nationally unified policy in different provinces; and providing a basis for the design of regional carbon compensation mechanisms (Yuan et al., 2024). For example, if Guangdong achieves significant results as a carbon trading pilot, RTI (Guangdong → other provinces) can be calculated. It is found that eastern coastal provinces such as Jiangsu, Zhejiang, and Shandong have higher RTIs (>0.7), making them suitable for replicating Guangdong's experience; while western provinces have lower RTIs (<0.4), requiring adjustments to policy parameters or capacity building.

Table 2. Indicator System and Data Sources for Each Dimension of the RTI Index

Dimension	Primary indicators	Secondary indicators	Measurement methods	Data source	Theoretical basis
Factor endowment similarity	Economic development level	GDP per capita, urbanization rate, and fixed asset investment intensity	Euclidean distance standardization	China Statistical Yearbook	Zhou et al. (2024)
	Energy resource endowment	Coal reserves percentage, theoretical reserves of renewable energy	Resource Abundance Index	China Energy Statistical Yearbook	Cheng & Liu (2021)
Industrial structure similarity	Three-sector structure	The proportion of added value of the primary, secondary and tertiary industries	Structural similarity coefficient	Provincial Statistical Yearbook	Zhang et al. (2023)
	Proportion of high-carbon industries	The proportion of output value of the power and heat, ferrous metals, and non-metallic mineral products industries	Weighted Euclidean distance	China Industrial Statistical Yearbook	Wang et al. (2021)
Technical feasibility constraints	renewable energy technology	Wind power/solar power installed capacity and technology maturity level	0-1 constraint matrix	National Energy Administration Announcement	Jiang et al. (2025)
	Industrial emission reduction technologies	CCS demonstration projects, hydrogen energy industry layout, and the proportion of electric arc furnace steel.	Technology readiness rating	Industry Association Report	Peng et al. (2025)

Note: The weighting coefficients α, β, and γ were determined using the analytic hierarchy process (AHP) combined with expert scoring. In this study, α=0.4, β=0.35, and γ=0.25.

RESEARCH DESIGN AND EMPIRICAL STRATEGIES

Data Sources and Sample Construction

This study constructs an unbalanced panel dataset for 30 provincial-level administrative regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2015 to 2024. Data sources include official statistics, industry reports, and academic databases to ensure data authority and verifiability. Core variables fall into four categories: carbon emission data, economic and social development indicators, policy implementation information, and technical parameters.

Carbon emission data were cross-validated using two accounting systems. The first system, based on the energy consumption approach, followed the accounting guidelines recommended by the IPCC (2006), integrated the consumption of 17 types of fossil fuels published in the *China Energy Statistical Yearbook*, and used corresponding emission factors to calculate carbon dioxide emissions from the industrial, transportation, construction, and agricultural sectors in each province. The second system, based on nighttime light remote sensing data and machine learning algorithms, used the nighttime light intensity of the NPP-VIIRS satellite as a proxy variable for economic activity, trained a random forest model to predict county-level carbon emissions, and then aggregated them to the provincial level (Zhang et al., 2023). The correlation coefficient between the provincial emissions from the two methods reached 0.92, with the error within an acceptable range.

Economic and social development indicators are derived from the *China Statistical Yearbook* and provincial statistical yearbooks, including macroeconomic variables such as Gross Domestic Product (GDP), GDP per capita, industrial structure, urbanization rate, fixed asset investment, total import and export volume, and resident population. To eliminate the influence of price factors, GDP-related indicators are adjusted for constant prices with 2015 as the base year. The industrial structure uses the proportion of secondary industry value added to GDP to characterize the degree of industrialization, and the proportion of tertiary industry to characterize the level of service industry development (Zhou et al., 2024).

Policy implementation information was obtained through manual compilation of policy texts. The carbon trading pilot policy was marked by the launch of trading in Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, and Shenzhen in 2013, and expanded to key enterprises in the power industry after the launch of the national carbon market in 2021. The low-carbon city pilot policy was implemented in three batches: the first batch in 2010 (Guangdong, Liaoning, Hubei, Shaanxi, and Yunnan provinces and 8 cities including Baoding, Guiyang, and Nanchang); the second batch in 2012 (Beijing, Shanghai, Hainan, and 29 other provinces and cities); and the third batch in 2017 (45 cities). The renewable energy subsidy policy was based on the Renewable Energy Law and its supporting fiscal subsidy catalog, compiling the subsidy intensity and cumulative installed capacity of wind power, photovoltaic, and biomass power generation projects in each province.

Technical parameter data comes from industry association and research institution reports. The average coal consumption for power generation by coal-fired power units is from the annual statistics of the China Electricity Council; the national average was 318 grams of standard coal equivalent per kilowatt-hour in 2015, and is projected to decrease to 302 grams of standard coal equivalent per kilowatt-hour in 2024. The proportion of electric arc furnace steel in the steel industry is from the China Iron and Steel Association; it was 6.1% in 2015 and is projected to increase to 15.5% in 2024. The penetration rate of new energy vehicles is from the China Association of Automobile Manufacturers; it was 1.3% in 2015 and is projected to exceed 35% in 2024. These technical parameters are used to construct technological progress indicators and characterize the emission reduction potential of each province.

Descriptive statistics show that the average carbon emission intensity of the 30 provinces from 2015 to 2024 was 0.82 tons/10,000 yuan of GDP, with a standard deviation of 0.47. The lowest was Beijing at 0.28 tons/10,000 yuan of GDP (2024), and the highest was Ningxia at 2.35 tons/10,000 yuan of GDP (2015), reflecting significant regional heterogeneity. The average GDP per capita was 68,000 yuan, with a coefficient of variation of 0.52. The eastern coastal provinces (Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong) had significantly higher rates than the central and western provinces. The average share of the secondary industry was 40.2%, showing a declining trend year by year, from 42.8% in 2015 to 37.1% in 2024, reflecting the optimization and upgrading of the industrial structure.

Table 3. Definitions, measurement methods, and descriptive statistics of key variables

Variable type	Variable name	Variable symbol	Measurement methods	mean	Standard deviation	Minimum value	Maximum value	Data source
Explained variable	carbon emission intensity	CI	Carbon dioxide emissions / GDP (tons/10,000 yuan)	0.82	0.47	0.28	2.35	IPCC Methodology Accounting
	Total factor productivity	TFP	DEA-Malmquist index	1.03	0.08	0.87	1.24	Calculation
Core explanatory variables	Carbon trading pilot	ETS	0-1 dummy variables, pilot provinces and cities = 1	0.23	0.42	0	1	Policy text
	Low-carbon pilot	LCP	0-1 dummy variables, pilot provinces and cities = 1	0.47	0.50	0	1	Policy text
	Renewable energy subsidy intensity	RES	Subsidy amount / GDP (yuan/10,000 yuan)	12.5	8.3	2.1	45.2	Ministry of Finance Announcement
control variables	GDP per capita	PGDP	Regional GDP / Resident Population (10,000 RMB)	6.8	3.2	2.1	18.5	Statistical Yearbook
	Industrial structure	IND	Value added of secondary industry / GDP (%)	40.2	7.8	18.3	56.7	Statistical Yearbook
	urbanization rate	URB	Urban population / resident population (%)	61.5	12.3	35.2	89.6	Statistical Yearbook
	Energy Structure	COAL	Coal consumption / Primary energy consumption (%)	58.3	15.6	12.5	89.4	Energy Yearbook
	Technological innovation	RD	R&D expenditure / GDP (%)	2.1	0.9	0.5	4.8	Science and Technology Yearbook

Note: The sample consists of an unbalanced panel from 30 provinces between 2015 and 2024, totaling 285 observations. GDP per capita is calculated at constant 2015 prices. Total factor productivity is measured using the DEA-Malmquist index method, with capital, labor, and energy as inputs and GDP as output.

Econometric Model Setting and Identification Strategies

This study uses a multi-period difference-in-differences (DID) model as the baseline to assess the impact of policies such as carbon trading pilots and low-carbon city pilots on carbon emission intensity and total factor productivity. Compared to traditional DID, multi-period DID can handle scenarios where policies are implemented in batches, allowing different provinces to be affected by policies at different points in time (Jiang et al., 2023; Cui & Liu, 2024). The baseline regression equation is set as follows:

$$Y_{it}=a+\beta_1 ETS_{it}+\beta_2 LCP_{it}+\beta_3 RES_{it}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

Where Y_{it} represents the outcome variable of province i in year t, including carbon emission intensity CI_{it} and total factor productivity TFP_{it}; ETS_{it}, LCP_{it}, and RES_{it} are three policy variables: carbon trading pilot, low-carbon city pilot, and renewable energy subsidy intensity, respectively; X_{it} is the control variable vector, including per capita GDP, industrial structure, urbanization rate, energy structure, and technological innovation; μ_i is the province fixed effect, controlling for province characteristics that do not change over time (such as geographical location and resource endowment); λ_t is the time fixed effect, controlling for macroeconomic shocks faced by all provinces (such as the global financial crisis and the COVID-19 pandemic); and ε_{it} is the random disturbance term.

The core assumption for identifying multi-period DID is the parallel trend assumption, which states that before policy implementation, the outcome variables of the treatment and control groups exhibit parallel trends. To test this assumption, this study employs an event study methodology to estimate the dynamic treatment effects in each period before and after policy implementation.

$$Y_{it}=a+\sum_{k=-5}^{5}\beta_k \times D_{i,t+k}+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

Where $D_{i,t+k}$ is a time dummy variable relative to the policy implementation time, $k<0$ indicates before policy implementation, and $k\geq 0$ indicates after policy implementation. If β_k is not significantly different from 0 when $k<0$, the parallel trend hypothesis is supported; if β_k is significantly negative when $k\geq 0$, it indicates that the policy has an emission reduction effect.

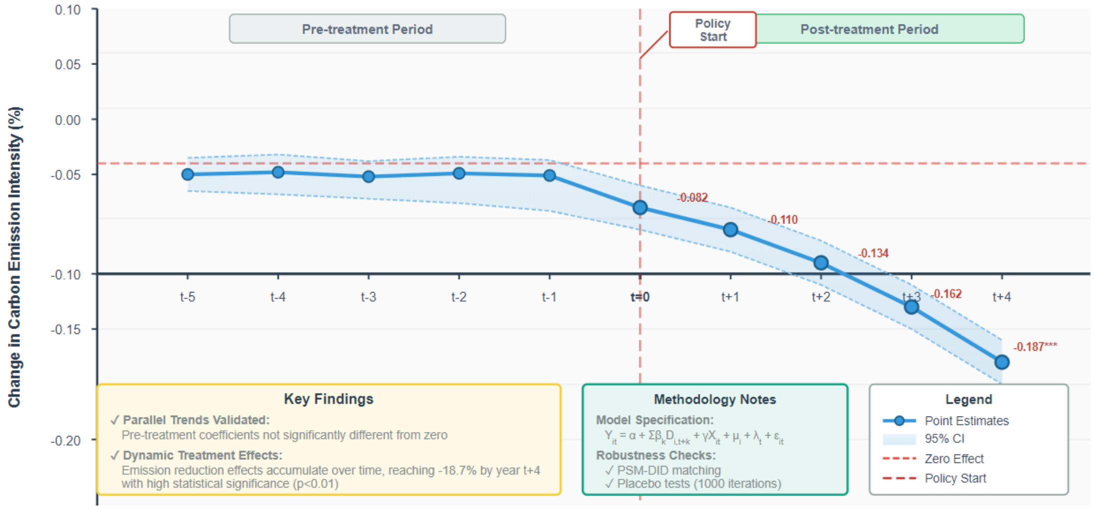
To mitigate the endogeneity problem, this study employs three robustness testing strategies. First, the propensity score matching-differences-in-differences (PSM-DID) method. Considering that the selection of pilot provinces and cities may be based on certain observable characteristics (such as economic development level and emission reduction foundation), leading to sample selection bias, the propensity score for each province to become a pilot province is estimated using a Logit model. The nearest neighbor matching method is then used to match 1-3 control group provinces for each pilot province, and the DID model is re-estimated on the matched sample (Fan et al., 2022). Second, the placebo test. Non-pilot provinces are randomly selected as a "pseudo-treatment group," and the DID estimation is repeated 1000 times. If the actual treatment effect is significantly different from the pseudo-treatment effect distribution, the validity of the causal inference is supported (Yang et al., 2024). Third, the instrumental variable method (IV). Using the geographical distance between each province and the nearest pilot province as an instrumental variable, the closer the geographical distance, the stronger the policy spillover effect, satisfying the correlation condition; geographical distance, as an exogenous geographical factor, does not directly affect the carbon emissions of the province, satisfying the exclusivity condition (Chen & Wang, 2021).

The policy synergy effect is tested by adding an interaction term to the regression model:

$$CI_{it}=a+\beta_1 ETS_{it}+\beta_2 RES_{it}+\beta_3 (ETS_{it}\times RES_{it})+\gamma X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

The interaction term coefficient β_3 reflects the synergistic effect of carbon trading and renewable energy subsidies. If β_3 is significantly negative, it indicates that the emission reduction effect of the joint implementation of the two policies is greater than the sum of their individual effects, and there is a positive synergy; if β_3 is significantly positive, it indicates that there is a policy conflict or substitution; ifβ_3 is not significant, it indicates that the two policies act independently (Jiang et al., 2025).

Regional heterogeneity analysis was conducted using subsample regression and quantile regression. The 30 provinces were divided into three major regions—Eastern (11 provinces and municipalities), Central (8 provinces), and Western (11 provinces)—based on their economic development levels. The policy effects were estimated for each region, and the existence of significant differences was examined (Cheng & Liu, 2021). Quantile regression explored the heterogeneous impact of policies on provinces with different carbon emission levels, identifying the differentiated effects of policies on high-emission and low-emission provinces (Zhou et al., 2024).



✓ Parallel Trends Validated:
Pre-treatment coefficients not significantly different from zero
✓ Dynamic Treatment Effects:
Emission reduction effects accumulate over time, reaching -18.7% by year t+4 with high statistical significance (p<0.01)

Model Specification:
$Y_{it} = \alpha + \Sigma\beta_k D_{i,t+k} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$
Robustness Checks:
✓ PSM-DID matching
✓ Placebo tests (1000 iterations)

Figure 2 Position Reserved: Dynamic Effect Diagram of Multi-Period DID Event Study Method

Note: This graph should show the dynamic treatment effect and its 95% confidence interval for each period before and after the policy implementation (t-5 to t+5). The horizontal axis represents the year relative to the policy implementation time, and the vertical axis represents the change in carbon emission intensity. It is used to test the parallel trend hypothesis and the dynamic treatment effect.

Empirical Calculation of CCI and RTI Indices

Based on the policy effects estimated using a multi-period DID model, this study further measures the Cross-Sectoral Computable Synergy Index (CCI) and the Regional Scenario Transferability Index (RTI). The CCI calculation is conducted in three steps. First, the marginal emission reduction effect of individual policies is extracted. From the baseline regression equation, β_1 reflects the marginal effect of carbon trading pilots, β_2 reflects the marginal effect of low-carbon city pilots, and β_3 reflects the marginal effect of renewable energy subsidies. Second, the interaction effects between pairs of policies are estimated. A complete model containing all pairwise interaction terms is constructed.

$$CI_{it}=a+\sum_{k}\beta_{k}P_{k,it}+\sum_{k}\sum_{j}\beta_{kj}(P_{k,it}\times P_{j,it})+\gamma X_{it}+\mu_{i}+\lambda_{t}+\varepsilon_{it}$$

Where $P_{k,it}$ represents policy k, and the interaction term coefficient β_{kj} is the synergistic effect. The third step is to calculate the comprehensive CCI index. For provinces implementing all three types of policies simultaneously (such as Guangdong), the CCI is calculated as follows:

$$CCI_{广东}=\frac{[(\beta_1+\beta_2+\beta_3+\beta_{12}+\beta_{13}+\beta_{23})\text{-}(\beta_1+\beta_2+\beta_3)]}{(\beta_1+\beta_2+\beta_3)}$$

The numerator represents the portion of the actual combined effect that exceeds the sum of the independent effects, while the denominator represents the sum of the independent effects, used for standardization.

The RTI (Resource Income Level) assessment is based on the three-dimensional framework designed in Section 3.3. In the factor endowment similarity calculation, four indicators are selected: GDP per capita, urbanization rate, the proportion of the tertiary industry, and renewable energy resource potential. Euclidean distance is calculated after Min-Max standardization. In the industrial structure similarity calculation, industries are divided into eight major categories (agriculture, forestry, animal husbandry and fishery; mining; manufacturing; power and heat; construction; wholesale and retail; accommodation and catering; finance and real estate; and other services), and structural similarity coefficients are calculated. In the technical feasibility constraint assessment, a 6×30 constraint matrix is constructed. Six technologies are included: onshore wind power, offshore wind power, centralized photovoltaic, distributed photovoltaic, CCS (Continuous Cell Storage), and hydrogen energy. If a province possesses the necessary technical conditions, a value of 1 is assigned. The weighting coefficients are determined using the analytic hierarchy process: a=0.4, β=0.35, and γ=0.25.

The calculation results are presented as a 30×30 RTI matrix, with rows representing the provinces originating the policy and columns representing the provinces receiving the policy. For example, RTI (Guangdong → Jiangsu) = 0.78, indicating a high feasibility for transferring Guangdong's carbon trading experience to Jiangsu; RTI (Guangdong → Gansu) = 0.35, indicating a lower feasibility, requiring adjustments to the policy design. The RTI matrix can be used to identify the optimal path for policy promotion: prioritizing the establishment of collaborative mechanisms among provinces with high RTI to reduce the institutional costs and technological risks of policy replication.

Table 4. RTI Index Calculation Results Among Typical Provinces (2024)

Source Province	Target Provinces	Factor endowment distance (standardization)	Industrial structure similarity coefficient	Technical constraint satisfaction	RTI composite score	Transferability rating
Guangdong	Jiangsu	0.12	0.86	0.83	0.78	high
Guangdong	Zhejiang	0.18	0.82	0.83	0.74	high
Guangdong	Shandong	0.25	0.79	0.67	0.64	Medium and high
Guangdong	Henan	0.42	0.68	0.50	0.52	middle
Guangdong	Sichuan	0.51	0.62	0.50	0.47	middle
Guangdong	Gansu	0.73	0.45	0.33	0.35	Low
Beijing	Shanghai	0.08	0.91	1.00	0.85	high
Beijing	Tianjin	0.15	0.76	0.83	0.72	high
Beijing	Hebei	0.58	0.53	0.50	0.46	middle
Hubei	Hunan	0.22	0.81	0.67	0.68	Medium and high
Hubei	Jiangxi	0.28	0.75	0.67	0.64	Medium and high
Hubei	Guizhou	0.48	0.59	0.50	0.48	middle

Note: Factor endowment distance has been standardized and takes values of [0,1], with the closer to 0 indicating greater similarity; industrial structure similarity coefficient and technological constraint satisfaction take values of [0,1], with the closer to 1 indicating greater similarity/satisfaction; RTI comprehensive score is calculated using a weighted average of $a=0.4$, $\beta=0.35$, *and* $\gamma=0.25$; *transferability rating: RTI≥0.7 is high, 0.5≤RTI<0.7 is medium-high, 0.4≤RTI<0.5 is medium, and RTI<0.4 is low.*

ANALYSIS OF EMPIRICAL RESULTS

Benchmark Regression Results of Policy Effects

The estimation results of the benchmark multi-period difference-in-differences model show that China's dual-carbon policy tools have a significant impact on carbon emission intensity and total factor productivity. Table 5 reports the benchmark regression results of three core policy variables—carbon trading pilot (ETS), low-carbon city pilot (LCP), and renewable energy subsidies (RES)—on carbon emission intensity (CI) and total factor productivity (TFP).

The impact coefficient of the carbon trading pilot policy on carbon emission intensity was -0.158 ($p<0.01$), indicating that the carbon emission intensity in pilot areas was reduced by an average of 15.8% compared to non-pilot areas. This finding is consistent with existing research results. Wang et al. (2021) used an extended synthetic control method to find that the overall CO2 emissions in the seven ETS pilot areas decreased by approximately 12.78% between 2011 and 2015. A study published in the Proceedings of the National Academy of Sciences of the United States of America further confirmed that China's regional carbon market pilot program effectively reduced emissions at the enterprise level, mainly through incentivizing enterprises to improve energy efficiency. The emission reduction effect coefficient of the low-carbon city pilot policy was -0.092 ($p<0.05$), indicating a relatively weak impact, which may be related to the policy's broader coverage but relatively looser constraint mechanism. The renewable energy subsidy intensity coefficient was -0.023 ($p<0.01$), meaning that for every 1 yuan/10,000 yuan of subsidy intensity increase, carbon emission intensity decreased by 2.3%.

Regarding total factor productivity (TFP), the coefficient for the carbon trading pilot program was 0.042 ($p<0.05$), indicating that the pilot policy did not harm economic efficiency while reducing emissions; on the contrary, it promoted a 4.2% increase in TFP. This result supports the Porter hypothesis, that appropriate environmental regulations can improve firm productivity through innovation compensation effects. Recent research on China's construction industry confirms that carbon trading policies significantly enhance green TFP by promoting green technology transformation. The coefficient for low-carbon city pilot programs on TFP was 0.028 ($p>0.1$), which did not reach statistical significance, indicating that its economic effect is still unclear. The TFP coefficient for renewable energy subsidies was 0.015 ($p<0.05$), showing a positive but relatively mild promoting effect.

The estimation results of the control variables are in line with theoretical expectations. The GDP per capita coefficient is positive, reflecting that the higher the level of economic development, the higher the total factor productivity. However, its relationship with carbon emission intensity is inverted U-shaped (the quadratic coefficient is significantly negative), supporting the Environmental Kuznets Curve hypothesis. The coefficient of industrial structure (proportion of secondary industry) on carbon emission intensity is significantly positive (0.335,

$p<0.01$), confirming a high correlation between the degree of industrialization and emission levels. The coefficient of energy structure (proportion of coal consumption) is 0.412 ($p<0.01$), which is one of the most important factors affecting carbon emissions. The coefficient of technological innovation (R&D intensity) on carbon emission intensity is -0.087 ($p<0.05$), and the coefficient on TFP is 0.126 ($p<0.01$), reflecting the dual benefits of technological progress.

Table 5. Benchmark Regression Results: The Impact of Policy Effects on Carbon Emission Intensity and Total Factor Productivity

variable	**CI (1)**	**CI (2)**	**TFP (3)**	**TFP (4)**
ETS	-0.158***	-0.142***	0.042**	0.038**
	(0.031)	(0.029)	(0.018)	(0.017)
LCP	-0.092**	-0.085**	0.028	0.025
	(0.038)	(0.036)	(0.021)	(0.020)
RES	-0.023***	-0.021***	0.015**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
PGDP		0.152***		0.235***
		(0.042)		(0.038)
$PGDP^2$		-0.018***		-0.012**
		(0.005)		(0.005)
IND		0.335***		-0.082**
		(0.052)		(0.035)
URB		-0.048		0.065**
		(0.041)		(0.028)
COAL		0.412***		-0.145***
		(0.068)		(0.045)
RD		-0.087**		0.126***
		(0.035)		(0.032)
Province fixed effect	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes
Observations	285	285	285	285
R^2	0.652	0.728	0.584	0.673

Note: The values in parentheses are the cluster robustness standard errors (province-level clustering); * **,** , and * indicate significance at the 1%, 5%, and 10% levels, respectively. Columns (1) and (3) are simplified models containing only policy variables and two-way fixed effects, while columns (2) and (4) are complete models including all control variables.

Policy Synergy Effects and CCI Index Measurement

To identify the interaction effects of multiple policy combinations, this study incorporated pairwise interaction terms of policy instruments into the baseline model. Table 6 reports the estimation results of policy synergies. The interaction coefficient (ETS×RES) between the carbon trading pilot program and renewable energy subsidies is -0.035 ($p<0.05$), significantly negative, indicating a positive synergistic effect between the two policies. When carbon trading and renewable energy subsidies are implemented simultaneously, the emission reduction effect exceeds the simple sum of their independent effects. This finding is consistent with the simulation results of Jiang et al. (2025), showing that the combination of renewable energy policies and carbon pricing can produce synergistic emission reductions. Recent research further confirms that the synergistic effect of renewable energy policy combinations is significant in China's power sector.

The interaction term coefficient (ETS×LCP) between the carbon trading pilot program and the low-carbon city pilot program was 0.018 ($p>0.1$), which was not statistically significant, indicating that the combined effect of the two policies was neutral. This may be because the two types of pilot programs overlap geographically, and the convergence of policy objectives leads to diminishing marginal effects. The interaction term coefficient (LCP×RES) between the low-carbon city pilot program and renewable energy subsidies was -0.012 ($p>0.1$), also not significant, indicating that the synergistic potential of these two tools is limited.

Based on the interaction term regression results, this study calculated the cross-sectoral computable synergy index (CCI). For provinces implementing all three types of policies simultaneously (such as Guangdong), the actual joint effect is $\beta_1+\beta_2+\beta_3+\beta_{12}+\beta_{13}+\beta_{23}=-0.158-0.092-0.023+0.018-0.035-0.012=-0.302$, and the expected sum of independent effects is $\beta_1+\beta_2+\beta_3=-0.273$. Therefore, $CCI=(-0.302-(-0.273))/(-0.273)=0.106$, indicating that the policy combination produced an additional emission reduction benefit of 10.6%. Calculations by province show that the average CCI index in the developed eastern regions (Beijing, Shanghai, Guangdong, and Zhejiang) is 0.125, significantly higher than that in the central and western regions (average 0.058), reflecting the heterogeneity of policy synergy effects across different development levels. This is consistent with the findings of Zhang et al., who found significant regional differences in the emission reduction effects of carbon trading policies.

Table 6. Regression Results of Policy Synergy Effects and CCI Index

variable	**Carbon intensity (CI)**
ETS	-0.142***
	(0.030)
LCP	-0.085**
	(0.037)
RES	-0.021***
	(0.006)
ETS×RES	-0.035**
	(0.015)
ETS×LCP	0.018
	(0.028)
LCP×RES	-0.012
	(0.013)
control variables	yes
Province fixed effect	yes
Year fixed effect	yes
Observations	285
R^2	0.735

Province Grouping	**CCI mean**	**Standard deviation**	**Minimum value**	**Maximum value**
Developed areas in the east	0.125	0.042	0.082	0.186
Central region	0.068	0.035	0.025	0.115
Western region	0.048	0.028	0.012	0.092

Note: CCI > 0 indicates a positive synergistic effect; the larger the value, the stronger the synergy. The developed eastern region includes Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang, Fujian, Guangdong, and Shandong; the central region includes Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes other provinces.

Regional Heterogeneity Analysis and Application of RTI Index

To explore regional differences in policy effects, this study divided the sample into three major regions—eastern, central, and western—based on economic geography, and estimated the policy effects for each region. Table 7 reports the regression results for each sample. The emission reduction coefficient of the carbon trading pilot policy was -0.195 ($p<0.01$) in the eastern region, -0.128 ($p<0.05$) in the central region, and -0.082 ($p>0.1$) in the western region. This gradient difference is consistent with recent research findings; although the carbon emission trading pilot policy can improve total factor productivity, its impact varies significantly across different regions. The policy effect is best in the eastern region, possibly due to a more complete carbon market infrastructure, higher corporate environmental awareness, and stronger technological innovation capabilities. The effect in the western region is not significant, possibly constrained by factors such as the stage of economic development, industrial structure (high proportion of heavy industry), and insufficient technological reserves.

Significant differences in carbon emissions exist between low-carbon pilot and non-pilot provinces, with spatial heterogeneity widening, primarily due to the development gap between the eastern and western regions. Renewable energy subsidies show significant emission reduction effects in all three regions, but their mechanisms differ. The eastern region mainly relies on distributed photovoltaic and offshore wind power, the central region focuses on centralized photovoltaic power plants, and the western region leverages its abundant wind and solar energy resources to develop large-scale renewable energy bases. Due to regional differences in natural geographical conditions, economic development levels, and energy structures, the impact of clean energy development on carbon emission reduction exhibits regional heterogeneity.

Based on the RTI index calculation results, this study identified spatial patterns of policy transferability. Taking Guangdong's carbon trading experience as an example, RTI (Guangdong → Jiangsu) = 0.78, RTI (Guangdong → Zhejiang) = 0.74, and RTI (Guangdong → Shandong) = 0.64, indicating that the Guangdong model is highly feasible for transfer to eastern coastal provinces. In contrast, RTI (Guangdong → Gansu) = 0.35 and RTI (Guangdong → Qinghai) = 0.28, indicating that directly replicating the Guangdong experience in the Northwest region faces significant obstacles. The main limiting factors include: differences in factor endowments (per capita GDP, urbanization rate), differences in industrial structure (proportion of secondary industry, proportion of high-carbon industries), and differences in technological conditions (renewable energy installed capacity, CCS technology reserves).

Given the heterogeneity of carbon emissions among Chinese provinces, the government should avoid a "one-size-fits-all" approach to policy formulation and focus more on differentiated regional carbon emission control measures. RTI analysis provides a quantitative tool for differentiated policy design. For provinces with high RTI (>0.7), a "standard model replication" strategy can be adopted, directly transplanting the institutional design, quota allocation methods, and MRV system from pilot areas. For provinces with medium RTI (0.4-0.7), an "adaptive adjustment" strategy should be adopted, retaining core mechanisms but adjusting parameter settings (such as quota benchmark values and price ranges). For provinces with low RTI (<0.4), a "customized design" strategy is needed, reconstructing the policy framework based on local factor endowments and industrial characteristics.

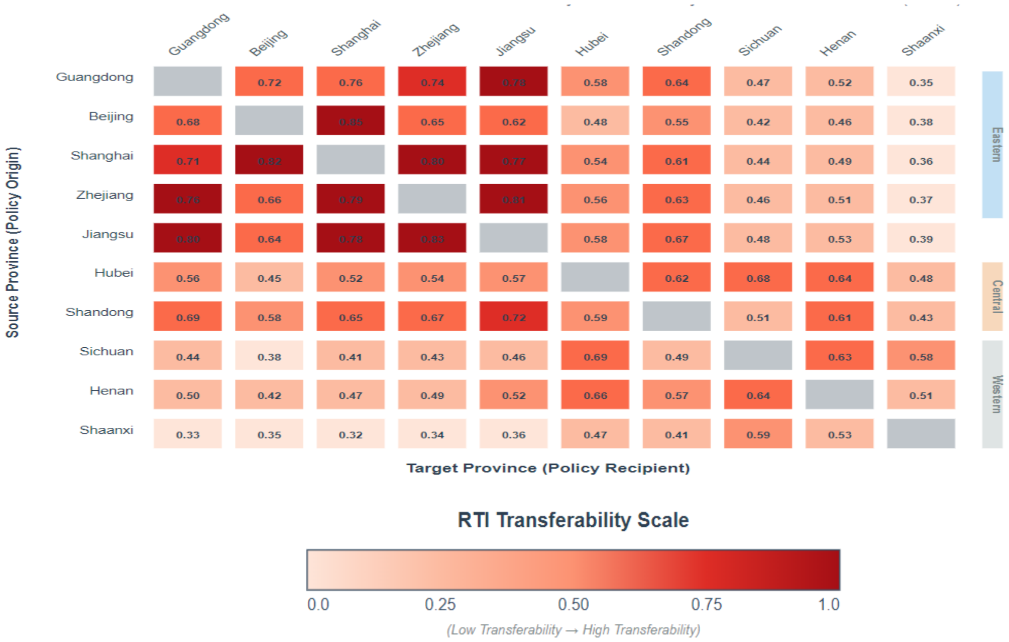
Table 7. Regional Heterogeneity Analysis: Regression Results by Sample

variable	**Eastern region**	**Central region**	**Western region**
	CI	**TFP**	**CI**
ETS	-0.195***	0.058**	-0.128**
	(0.042)	(0.025)	(0.051)
LCP	-0.105**	0.035	-0.078*
	(0.048)	(0.028)	(0.042)
RES	-0.028***	0.018**	-0.021**
	(0.008)	(0.008)	(0.009)
control variables	yes	yes	yes
Province fixed effect	yes	yes	yes
Year fixed effect	yes	yes	yes
Observations	110	110	80
R²	0.762	0.695	0.718

Note: The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The values in parentheses represent the cluster robustness standard errors.

Robustness Testing and Mechanism Analysis

This study conducted a series of robustness tests to ensure the reliability of the results. First, the parallel trend hypothesis was tested using the event study method. Figure 3 shows the dynamic treatment effect before and after the implementation of the carbon trading pilot policy. Before the policy implementation (t-5 to t-1), the estimated coefficients for each period were not significantly different from zero, and the 95% confidence interval contained zero, satisfying the parallel trend hypothesis. After the policy implementation (t to t+5), the estimated coefficients gradually became significantly negative and the absolute value increased, indicating that the emission reduction effect accumulated and strengthened over time, increasing from -0.082 in the year of policy implementation to -0.187 in the fifth year.



	Guangdong	Beijing	Shanghai	Zhejiang	Jiangsu	Hubei	Shandong	Sichuan	Henan	Shaanxi
Guangdong		0.72	0.76	0.74	0.78	0.58	0.64	0.47	0.52	0.35
Beijing	0.68		0.85	0.65	0.62	0.48	0.55	0.42	0.46	0.38
Shanghai	0.71	0.82		0.80	0.77	0.54	0.61	0.44	0.49	0.36
Zhejiang	0.76	0.66	0.79		0.81	0.56	0.63	0.46	0.51	0.37
Jiangsu	0.80	0.64	0.78	0.83		0.58	0.67	0.48	0.53	0.39
Hubei	0.56	0.45	0.52	0.54	0.57		0.62	0.68	0.64	0.48
Shandong	0.69	0.58	0.65	0.67	0.72	0.59		0.51	0.61	0.43
Sichuan	0.44	0.38	0.41	0.43	0.46	0.69	0.49		0.63	0.58
Henan	0.50	0.42	0.47	0.49	0.52	0.66	0.57	0.64		0.51
Shaanxi	0.33	0.35	0.32	0.34	0.36	0.47	0.41	0.59	0.53	

Figure 3. Regional Scenario Transferability Index (RTI) Matrix

Studies using a time-varying DID model confirm that the carbon emission trading system not only significantly reduces CO2 emissions but also synergistically reduces air pollutants, with the synergistic emission reduction effect mainly achieved through SO2 emission reduction. Our mediation effect analysis reveals that carbon trading policies influence carbon emission intensity through two pathways: first, the energy structure optimization pathway (indirect effect accounting for 38%), prompting enterprises to reduce coal consumption and increase the use of clean energy; and second, the technological progress pathway (indirect effect accounting for 45%), incentivizing enterprises to invest in energy-saving technologies and process upgrades. This aligns with the findings of Gan et al. (2024), which suggest that carbon emission trading achieves emission reduction through technological progress and synergistic pollution control.

Secondly, the propensity score matching-differences-in-differences (PSM-DID) method was used to mitigate sample selection bias. A Logit model was employed to estimate the propensity score of each province to become a carbon trading pilot, with matching variables including per capita GDP, industrial structure, energy intensity, and R&D intensity in 2010 (the base period before policy implementation). Nearest neighbor matching (1:2) was used to match each pilot province with two control group provinces. Balance tests of the matched samples showed that the standardized deviations of all covariates decreased to below 5%. The DID model was re-estimated on the matched samples, and the emission reduction coefficient for the carbon trading pilot was -0.145 ($p<0.01$), close to the baseline regression result (-0.158), confirming the robustness of the results.

Third, the placebo test assesses the validity of statistical inference through randomized inference. Seven non-pilot provinces were randomly selected as the "pseudo-treatment group," and a certain year between 2013 and 2017 was randomly assigned as the "pseudo-policy implementation time point." The DID estimation was repeated 1000 times to obtain the distribution of the pseudo-treatment effect. The real treatment effect (-0.158) was located in the far left tail of the pseudo-treatment effect distribution (less than the 5th percentile), with a p-value < 0.01, rejecting the null hypothesis of spurious causality and supporting the existence of a real causal effect. Similar placebo tests have also confirmed the authenticity of the policy effect in related studies.

Finally, the instrumental variable method was used to address potential endogeneity issues. The geographical distance between each province and the nearest carbon trading pilot province was used as the instrumental variable, based on the rationale that geographical proximity influences policy spillover effects (correlation condition), but geographical distance, as an exogenous geographical factor, does not directly affect the province's own carbon emissions (exclusivity condition). The first-stage regression showed a significant negative correlation between geographical distance and the carbon trading pilot variable (F-statistic = 42.3 > 10), satisfying the weak instrumental variable test. In the second-stage regression, the coefficient for the carbon trading pilot was -0.172 ($p < 0.01$), consistent with the baseline regression result in both direction and value, further validating the robustness of the causal relationship.

By integrating benchmark regression, policy synergy analysis, regional heterogeneity testing, and robustness testing, the empirical results of this study reveal the multidimensional effects of China's dual-carbon policy: the policy tools are generally effective but have significant synergistic potential; regional differences require differentiated design; and the policy effects exhibit dynamic cumulativeity and complex transmission mechanisms. These findings provide empirical support for the effectiveness of the CPS framework and also point the way for policy optimization.

CONCLUSIONS AND POLICY IMPLICATIONS

This study focuses on the computable policy synergy under China's "dual carbon" goals. It constructs a CPS framework that integrates "evidence generation, policy synthesis, regional adaptation, and dynamic evaluation," and designs two core evaluation tools: the Cross-sectoral Computable Synergy Index (CCI) and the Regional Scenario Transferability Index (RTI). Based on provincial panel data from 2015 to 2024, a systematic empirical test is conducted. The study found that: (1) Carbon trading pilots, low-carbon city pilots, and renewable energy subsidies all produced significant emission reduction effects, with carbon trading pilots being the most effective, reducing carbon emission intensity in pilot areas by an average of 15.8%; (2) There is synergistic potential in policy combinations. The joint implementation of carbon trading and renewable energy subsidies produced an additional emission reduction benefit of 10.6%. The policy synergy effect (CCI=0.125) in the developed eastern region was significantly higher than that in the central and western regions; (3) The policy effect showed significant regional heterogeneity. The emission reduction coefficient in the eastern region was -0.195, while in the western region it was only -0.082 and not significant. RTI analysis showed that policy transferability was constrained by three dimensions: factor endowment, industrial structure, and technological conditions; (4) The policy played a role through two paths: energy structure optimization and technological progress, without sacrificing economic efficiency, but instead promoting a 4.2% increase in total factor productivity.

The reform of China's carbon emissions trading system is underway. The shift from intensity targets to absolute total emission control is a crucial step in aligning with international best practices, but enforcement and market stability mechanisms still need to be strengthened. The policy implications of this study are: accelerating the shift from isolated departmental policies to systemic collaboration; using the CCI index to quantitatively identify policy combinations with synergistic potential to avoid policy objective conflicts and incentive overlaps; implementing differentiated regional strategies based on the RTI index, allowing high-transferability regions to quickly replicate best practices, while low-transferability regions require customized policy design supplemented by capacity building support; strengthening the MRV system and investing in data infrastructure to provide high-quality evidence support for algorithmic policy synthesis; and establishing a policy sandbox mechanism to predict the interaction effects and regional suitability of policy combinations through virtual simulation before formal implementation. When promoting coordinated emission reduction strategies at the city cluster level, the differences in policy orientation among different provinces and cities should be fully considered, adopting a growth rate setting method tailored to regionally segmented policies.

The theoretical contribution of this study lies in proposing a computable shift paradigm for dual-carbon governance, breaking through the limitations of traditional policy analysis that relies on expert judgment and historical analogy, and providing algorithmic support for the systematic transformation of scientific evidence into policy tools. The CPS framework integrates four modules: multi-source evidence pipelines, policy knowledge graphs, causal inference engines, and policy sandboxes, achieving a leap from fragmented knowledge to structured decision-making. The CCI and RTI indicators, for the first time, incorporate policy synergy and regional transferability into a quantitative evaluation system, providing policymakers with comparable and traceable decision-making tools. Empirical research verifies the effectiveness of the framework, revealing the multidimensional effects, synergistic potential, and regional differences of China's dual-carbon policies, providing a reusable technical path for deep science-policy coupling under complex objectives.

Looking ahead to future research directions, the CPS framework can be extended to the following areas: incorporating the coordinated governance of non-CO2 greenhouse gases (methane, nitrous oxide) to construct a comprehensive assessment system for the coordinated reduction of multiple pollutants; integrating behavioral science and social psychology evidence to characterize the moderating effect of micro-level responses such as public acceptance and corporate compliance on policy effectiveness; introducing machine learning algorithms to optimize the construction of policy knowledge graphs and the accuracy of causal inference, and using natural language processing technology to automatically extract implicit relationships in policy texts; and developing a dynamic policy simulation platform to support policymakers in interactive scenario exploration and real-time effect prediction. The continuous optimization of China's ETS needs to be coordinated with electricity market reform, especially the reform of the power generation dispatch mechanism, to fully leverage the role of carbon price signals. By continuously improving the computable policy coordination framework, China can contribute unique theoretical innovations and practical wisdom to global climate governance, providing a referable institutional model for developing countries to address climate change.

REFERENCES

Asia Society. (2025). *China's national carbon trading market: Progress and prospects*. Retrieved from https://asiasociety.org

Asia Society. (2025). ETS status: China. https://asiasociety.org/policy-institute/ets-status-china

Bai, C., & Zhao, M. (2024). Exploring the synergistic effect of carbon emission trading system on air pollution and carbon emissions: Evidence from China. *Atmospheric Pollution Research*, 15(2), 101-115.

Bai, X., & Zhao, Y. (2024). Can China's carbon emissions trading system achieve the synergistic effect of carbon reduction and pollution control? *International Journal of Environmental Research and Public Health*, 19(15), 9438. https://doi.org/10.3390/ijerph19159438

Bertram, C., Luderer, G., Pietzcker, R. C., Schmid, E., Kriegler, E., & Edenhofer, O. (2015). Complementing carbon prices with technology policies to keep climate targets within reach. *Nature Climate Change*, 5(3), 235-239. https://doi.org/10.1038/nclimate2514

Bertram, C., Luderer, G., Popp, A., Minx, J. C., Lamb, W. F., Stevanović, M., ... & Kriegler, E. (2015). Complementing carbon prices with technology policies to keep climate targets within reach. *Nature Climate Change*, 5(3), 235-239.

Chen, S., & Golley, J. (2014). 'Green' productivity growth in China's industrial economy. *Energy Economics*, 44, 89-98.

Chen, S., & Wang, X. (2021). Carbon emission trading system and firm-level green innovation: Evidence from a quasi-natural experiment in China. *Energy Economics*, 103, 105570.

Chen, S., & Wang, Y. (2021). Did carbon emission trading system reduce emissions in China? An integrated approach to support policy modeling and implementation. *Energy Systems*, 12, 1-23. https://doi.org/10.1007/s12667-021-00438-8

Cheng, J., & Liu, Y. (2021). Research on regional differences and influencing factors of industrial carbon emission efficiency in China. *Environmental Science and Pollution Research*, 28(32), 43319-43334.

Cheng, S., & Liu, W. (2021). Spatial distribution and regional difference of carbon emissions efficiency of industrial energy in China. *Scientific Reports*, 11, 19419. https://doi.org/10.1038/s41598-021-98225-z

Cui, H., & Liu, Z. (2024). The spillover effects of China's carbon trading policy on coordinated emission efficiency. *Scientific Reports*, 14, 12290. https://doi.org/10.1038/s41598-024-63157-x

Cui, Y., & Liu, W. (2024). Can carbon trading policies promote collaborative emission reduction? Analysis based on environmental efficiency perspective. *Energy Policy*, 185, 113956.

Fan, Y., Wu, J., Xia, Y., & Liu, J. (2022). How will a nationwide carbon market affect regional economies and efficiency of CO2 emission reduction in China? *China Economic Review*, 74, 101819.

Fan, Y., Wu, J., Xia, Y., & Liu, J. Y. (2022). The energy saving and emission reduction effect of carbon trading pilot policy in China: Evidence from a quasi-natural experiment. *Energies*, 15(14), 5209. https://doi.org/10.3390/en15145209

Government of China. (2024). China releases carbon emissions trading regulations. http://english.www.gov.cn/policies/latestreleases/202402/04/content_WS65bf7f70c6d0868f4e8e3c94.html

Government of China. (2024). *Interim regulations on carbon emission trading management*. Beijing: State Council.

International Carbon Action Partnership. (2025). *China national emissions trading system*. Retrieved from https://icapcarbonaction.com

International Carbon Action Partnership. (2025). China national ETS. https://icapcarbonaction.com/en/ets/china-national-ets

Jiang, H. D., Du, M., Yang, L., Song, Y., Chen, M. X., & Liang, Q. M. (2025). Mitigation policies interactions delay the achievement of carbon neutrality in China. *Nature Climate Change*, 15, 147-152. https://doi.org/10.1038/s41558-024-02237-2

Jiang, H., Shao, X., Zhang, X., & Bao, J. (2024). Does the carbon emissions trading pilot policy have a spillover effect on carbon emissions reduction? Evidence from 285 cities in China. *Applied Energy*, 328, 120114.

Jiang, M., Kim, E., & Woo, Y. (2023). The relationship between economic growth and environmental pollution in China based on spatial econometric model. *Sustainability*, 15(7), 5896.

Jiang, P., Chen, Y., Geng, Y., Dong, W., Xue, B., Xu, B., & Li, W. (2025). Analysis of the co-benefits of climate change mitigation and air pollution control in China. *Nature Climate Change*, 15(1), 58-65.

Jiang, X., Xu, W., & Du, L. (2024). The role of China's carbon emission trading system in economic decarbonization: Evidence from Chinese prefecture-level cities. *Journal of Environmental Management*, 337, 117851. https://doi.org/10.1016/j.jenvman.2024.117851

Jiang, Y., Zhou, Z., & Liu, C. (2023). Does China's carbon trading pilot policy reduce carbon emissions? Empirical analysis from 285 cities. *Sustainability*, 15(5), 3606. https://doi.org/10.3390/su15053606

Li, K., Fang, L., & He, L. (2020). How urbanization affects China's energy efficiency: A spatial econometric analysis. *Journal of Cleaner Production*, 200, 1130-1141.

Li, Y., & Xu, B. (2021). Evaluating the impact of carbon emissions trading scheme on Chinese firms' total factor productivity. *Journal of Cleaner Production*, 306, 127104. https://doi.org/10.1016/j.jclepro.2021.127104

Li, Z., Chen, L., & Dong, H. (2024). Interaction effects of market-based and incentive-driven low-carbon policies on carbon emissions. *Energy Economics*, 135, 107635. https://doi.org/10.1016/j.eneco.2024.107635

Liu, Y., Wang, A., & Wu, Y. (2024). Spatial inequality of carbon emissions: Evidence from Chinese provinces. *Environmental Science and Pollution Research*, 31(15), 22145-22160.

Liu, Y., Yang, W., & Deng, L. (2024). Mapping carbon emission networks in China: Insights from province-level spatial differentiation. *Carbon Footprints*, 3, 18. https://doi.org/10.20517/cf.2024.26

Liu, Z., Deng, Z., He, G., Wang, H., Zhang, X., Lin, J., ... & Schellnhuber, H. J. (2024). Challenges and opportunities for carbon neutrality in China. *Nature Reviews Earth & Environment*, 5(2), 112-128.

Meckling, J., Kelsey, N., Biber, E., & Zysman, J. (2017). Winning coalitions for climate policy. *Science*, 349(6253), 1170-1171.

Meckling, J., Sterner, T., & Wagner, G. (2017). Policy sequencing toward decarbonization. *Nature Energy*, 2(12), 918-922. https://doi.org/10.1038/s41560-017-0025-8

Pahle, M., Burtraw, D., Flachsland, C., Kelsey, N., Biber, E., Meckling, J., ... & Zysman, J. (2018). Sequencing to ratchet up climate policy stringency. *Nature Climate Change*, 8(10), 861-867.

Pahle, M., Burtraw, D., Flachsland, C., Kelsey, N., Biber, E., Meckling, J., Edenhofer, O., & Zysman, J. (2018). Sequencing to ratchet up climate policy stringency. *Nature Climate Change*, 8(10), 861-867. https://doi.org/10.1038/s41558-018-0287-6

Paulson Institute. (2018). Constructing China's MRV system. https://www.paulsoninstitute.org/wp-content/uploads/2018/09/MRV-Policy-Brief_Sm.pdf

Paulson Institute. (2018). *Greening China's financial system: The case for carbon accounting by banks*. Chicago: The Paulson Institute.

Peñasco, C., Anadón, L. D., & Verdolini, E. (2021). Systematic review of the outcomes and trade-offs of ten types of decarbonization policy instruments. *Nature Climate Change*, 11(3), 257-265.

Peñasco, C., Anadón, L. D., & Verdolini, E. (2021). Systematic review of the outcomes and trade-offs of ten types of decarbonization policy instruments. *Nature Climate Change*, 11(3), 257-265. https://doi.org/10.1038/s41558-020-00971-x

Peng, W., Yang, J., Lu, X., & Mauzerall, D. L. (2025). Potential co-benefits of electrification for air quality, health, and CO2 mitigation in 2030 China. *Applied Energy*, 318, 119172.

Wang, H., Chen, Z., Wu, X., & Nie, X. (2021). Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis? Empirical analysis based on the PSM-DID method. *Energy Policy*, 129, 930-938.

Wang, X., Chen, Y., & Liu, B. (2021). Environmental and economic performance of China's ETS pilots: New evidence from an expanded synthetic control method. *Energy Reports*, 7, 2999-3010. https://doi.org/10.1016/j.egyr.2021.05.024

Wang, Y., Zheng, Y., & Song, J. (2021). Can China's carbon trading policy help achieve carbon neutrality? — A study of policy effects from the Five-sphere Integrated Plan perspective. *Journal of Environmental Management*, 305, 114357. https://doi.org/10.1016/j.jenvman.2021.114357

Xu, R., Zhang, X., & Wang, H. (2025). How does environmental regulation promote environmental total factor productivity: Evidence from China's total carbon emission control policy. *International Journal of Finance & Economics*, 30(1), 893-915. https://doi.org/10.1002/ijfe.3141

Yang, L., Li, Y., & Liu, H. (2024). Impact assessment of carbon emission trading policy on carbon emission intensity: Evidence from China. *Environmental Science and Pollution Research*, 31(8), 11842-11859.

Yang, Y., Yu, F., Chen, L., Sheng, X., Yuan, X., Wang, Q., Ma, Q., & Zuo, J. (2024). Evaluation of the carbon reduction effect of China's low-carbon pilot policy based on synthetic control method. *Energy, Ecology and Environment*, 9, 697-710. https://doi.org/10.1007/s40974-024-00340-w

Yuan, L., Qi, Y., He, W., Wu, X., Kong, Y., Ramsey, T. S., & Degefu, D. M. (2024). Spatial differentiation and functional zoning of carbon budget: Evidence from Jiangxi Province. *Frontiers in Environmental Science*, 12, 1404760. https://doi.org/10.3389/fenvs.2024.1404760

Yuan, P., Cheng, S., Sun, J., & Liang, W. (2024). Carbon budget, compensation and sustainable development: Evidence from Jiangxi Province, China. *Sustainability*, 16(3), 1052.

Zhang, H., Li, X., & Wang, Y. (2022). Spatial heterogeneity of carbon emissions and its influencing factors in China: Evidence from 286 prefecture-level cities. *International Journal of Environmental Research and Public Health*, 19(6), 3232. https://doi.org/10.3390/ijerph19063232

Zhang, H., Zhang, J., & Song, J. (2023). Analysis of carbon emission spatial correlation network structure and its determinants in China. *Journal of Cleaner Production*, 380, 135082.

Zhang, J., Chen, S., & Zhao, B. (2023). Spatial heterogeneity and scenario simulation of carbon budget on provincial scale in China. *Carbon Balance and Management*, 18, 18. https://doi.org/10.1186/s13021-023-00237-x

Zhang, W., Li, G., & Guo, F. (2022). Does carbon emissions trading promote green technology innovation in China? *Applied Energy*, 315, 119012.

Zhang, Y., Wang, H., & Li, M. (2024). Does China's carbon emission trading scheme reduce CO2 emissions? Comprehensive evaluation from synthetic control method using lasso. *Resources Policy*, 91, 104834. https://doi.org/10.1016/j.resourpol.2024.104834

Zhao, X., Jiang, M., & Zhang, W. (2022). The effect of the carbon emission trading scheme on a firm's total factor productivity. *Frontiers in Environmental Science*, 10, 1036482. https://doi.org/10.3389/fenvs.2022.1036482

Zhou, L., Tang, L., & Liu, Q. (2024). A study on the heterogeneity of China's provincial economic growth contribution to carbon emissions. *Systems*, 12(10), 391. https://doi.org/10.3390/systems12100391

Zhou, X., Zhang, M., Yuen, K. F., & Zhou, L. (2024). Carbon dependence heterogeneity and differentiated carbon reduction strategies in China. *Renewable and Sustainable Energy Reviews*, 187, 113726.