ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 16 (2026) No. 1, pp. 115-132
DOI:10.33168/JSMS.2026.0107

Temporal Evolution and Driving Factor Identification of Carbon Emissions from Key Industrial Sectors in China

Yue Wang [1], Jinyu Duan [2]*

[1]College of Applied Arts and Science, Beijing Union University, Beijing 100020, China
[2]College of Business, Beijing Union University, Beijing 100020, China
1346572706@qq.com, 18175227357@163.com

Abstract. Driven by China's dual carbon strategic goals, exploring the temporal evolution patterns and differentiated driving mechanisms of carbon emissions across segmented industrial sectors is a fundamental scientific prerequisite for targeted refined low-carbon governance. This study takes 13 high-emission sectors covering the primary, secondary, and tertiary industries over 2001–2022 as research objects, and applies a residual-free weighted integrated decomposition model coupling the Logarithmic Mean Divisia Index (LMDI) and Shapley Value approaches. From five dimensions, including economic growth, population scale, industrial structure, energy intensity, and energy mix, this paper systematically identifies the driving factors of carbon emissions and reveals their temporal evolution rules and inter-sectoral heterogeneity.

Keywords: Industrial carbon emissions; temporal evolution; integrated LMDI-Shapley decomposition;

1. Introduction

Global climate warming and frequent extreme weather events have made greenhouse gas mitigation a universal consensus in international environmental governance. The Paris Agreement sets out global temperature control targets, and all countries have rolled out supporting policies for low-carbon transition. As the world's largest developing economy and top carbon emitter, China has proposed the medium-to-long-term strategies of carbon peaking by 2030 and carbon neutrality by 2060, and integrated the coordinated advancement of carbon reduction, pollution control, ecological expansion, and economic growth into the top-level design of ecological civilization construction(Guo et al.,2025). China's carbon emissions are predominantly generated from fossil fuel combustion (Shen et al.,2025), and significant disparities exist in energy consumption structures and production technologies across different industrial segments. Energy-intensive secondary industries such as power, steel, and building materials have long contributed the majority of national carbon emissions (Chen et al.,2025). Sustained urbanization has driven year-on-year growth in energy use within transportation, wholesale, and service sectors; agriculture, forestry, animal husbandry, and fishery (AFAF) produce relatively low total emissions and feature dual attributes of carbon release and ecological carbon sequestration, presenting great potential for agricultural low-carbon renovation (Huang et al.,2025).

The research window 2001–2022 fully spans five consecutive national Five-Year Plans (10th to the early stage of the 14th), each with tiered industrial regulation, energy consumption constraints, and renewable energy support policies, forming a natural quasi-experimental setting for policy impact evaluation (Yan et al.,2022). China's carbon governance framework is shifting from extensive aggregate emission control to sector-specific refined regulation. Ignoring the dual heterogeneity of industrial sectors and policy cycles will inevitably trigger practical conflicts, such as excessive compliance burdens on energy-intensive industries, insufficient incentives for service sectors, and poor regional policy adaptability. By constructing a 22-year long-term carbon emission panel dataset covering 13 full-spectrum industrial sectors and quantitatively decomposing multi-factor driving contributions, this paper can systematically review the real-world outcomes of energy conservation and emission reduction policies implemented over two decades and compare the effectiveness of different mitigation instruments. Meanwhile, it provides quantitative empirical evidence for drafting sector-specific low-carbon plans and differentiated regulatory schemes during the upcoming 15th Five-Year Plan, bearing both theoretical refinement value and practical implications for industrial and regional low-carbon governance.

2. Literature Review

2.1. Research on Carbon Emission Decomposition Methods

Index Decomposition Analysis (IDA) serves as the mainstream quantitative tool for identifying carbon emission drivers. Two residual-free decomposition models, namely the LMDI and Shapley Value, have gained the widest application. Relevant research can be divided into three distinct developmental phases.

The first phase covers 2000–2010, the era of international theoretical foundation construction. Ang (2005) refined the LMDI decomposition framework and verified its merits of zero residual error and compatibility with unbalanced time-series panel datasets, establishing it as a globally recognized benchmark model. Nevertheless, LMDI operates on the premise that all driving variables are independent, making it incapable of capturing interaction effects between factors. In the same period, the Shapley Value method was introduced into energy and carbon emission research. Derived from cooperative game theory, it quantifies the joint impacts of multiple factors. However, its estimation stability deteriorates sharply when positive and negative contributions coexist. Early studies adopted only a single model without any integrated optimization design (Qu,2019).

The second phase spans 2011–2020, marked by localized expansion of relevant research in China. Chinese scholars extensively applied the LMDI approach to carbon emission estimations at provincial and single-industry scales, generally selecting five core drivers: economic growth, population scale, industrial structure, energy intensity, and energy mix. However, existing literature is fragmented, with most studies focusing on isolated sectors such as agriculture, steel manufacturing, and transportation. A small body of research attempted weighted integration of the two models, yet weights were assigned subjectively without statistical verification of result consistency, resulting in insufficient estimation robustness (Qiu et al.,2019).

The third phase started from 2021 to the present, representing the frontier exploration of integrated decomposition methods. Song Jiekun et al. (2013) first adopted the Kendall coefficient to test the consistency between LMDI and Shapley outputs, though their empirical analysis merely relied on short-term urban samples. Yang Shunshun (2024)coupled LMDI with the Structural Decomposition Analysis (SDA) model, yet failed to incorporate the Shapley Value's unique strength in identifying factor interaction effects. Most multi-industry studies still employ LMDI alone. To date, no standardized integrated decomposition framework validated by objective statistical tests has been developed to fit the 22-year-long time series adopted in this research (Dong&Yang,2024).

2.2. Empirical Research on Temporal Differentiation of Industrial Carbon Emissions

Existing temporal carbon emission research adopts two primary perspectives: regional and sectoral, with three prominent limitations.

From the regional perspective, Li Hao et al. (2026) and Sun Li et al. (2024) applied the Theil Index and Spatial Durbin Model, respectively, to measure provincial carbon agglomeration characteristics, yet their analyses were confined to the macro provincial scale without disaggregating time-series emissions into segmented industrial sectors. Dong Zhichao et al. conducted industrial decomposition for the Yangtze River Basin with limited industrial coverage (Dong&Yang,2024).

Deficiencies are more prominent on the sectoral side: First, incomplete industrial coverage: most existing papers only examine individual sectors, lacking comprehensive estimations covering 13 sub-sectors across the primary, secondary, and tertiary industries that account for 49.7% of China's total carbon emissions. Second, crude time segmentation: research periods are not divided according to policy milestones of Five-Year Plans, making it impossible to capture abrupt shifts in driving mechanisms triggered by policy shocks. Third, superficial heterogeneity analysis: literature merely draws crude distinctions between manufacturing and service aggregates, without cycle-specific quantitative contribution data to support refined emission reduction policy formulation (Wang&Wu,2024).

2.3. Research Linking Carbon Emissions and Five-Year Plan Policies

Five-Year Plans serve as China's top coordination mechanism for industrial development, energy management, and emission reduction, with distinct regulatory stringency across cycles. Internationally, Song et al. (2025) constructed a provincial panel covering 36 sectors from 1997 to 2019 and confirmed that planned industrial policies improve industrial low-carbon transition indices, but only estimated average policy effects without disaggregating driving factor gaps by sector and cycle. Domestic literature has verified the emission reduction effects of dual energy consumption control and capacity regulation, yet three gaps persist: Policy evaluation relies predominantly on qualitative discussion without cycle-specific quantitative decomposition; empirical samples concentrate on provincial datasets, ignoring heterogeneous policy responses across sub-sectors; and time-series analysis is fragmented and fails to connect the full transition chain of industrialization, energy-saving retrofits, renewable energy expansion, and capacity phase-out, hindering clarification of coupling relationships between policy gradients and carbon emission evolution. Overall, current literature lacks a multi-factor quantitative decomposition framework segmented by sub-sectors and policy cycles, which restricts the design of refined carbon governance schemes.

This study draws on sectoral carbon emission panel data from the China Emission Accounts and Datasets (CEADs), constructs an equally weighted integrated LMDI-Shapley decomposition model validated via Kendall statistical tests, strictly segments research periods according to the five Five-Year Plans, systematically calculates the proportional shares of driving factors across 13 industrial sectors, and fully identifies the temporal patterns and sector-differentiated carbon emission drivers to address multiple deficiencies in existing research.

3. Methodology

3.1. Construction of Weighted Integrated LMDI-Shapley Decomposition Model

3.1.1. Additive LMDI Decomposition Baseline

This paper establishes a sectoral carbon emission accounting framework based on the Kaya Identity (Kaya,1990;Zhao et al.,2024) decomposing five core variables: population, economic output, industrial value added, energy consumption, and carbon emission factor. The baseline identity is specified as:

$$C = P \times \times \left(\frac{VA_i}{G}\right) \times \left(\frac{E_i}{VA_i}\right) \times \left(\frac{C_i}{E_i}\right) (1)$$

Where,

C = total carbon emissions of a sector

P = national total population

G = national gross domestic product (GDP)

VA_i = value added of sector i

E_i = total energy consumption of sector i

F_i/E_i = carbon emission factor of energy

The additive LMDI decomposition model is adopted to decompose total carbon emission changes from the base year to target year t, separating five independent effects: population scale (P), economic growth (G/P, measured as GDP per capita), industrial structure (VA_i/G, i.e.the share of sector i's value added in national GDP), energy intensity (E_i/VA_i), and energy mix (C_i/E_i, the carbon emission coefficient of the sector's energy consumption). These five factors correspond to the five multiplicative components in Eq. (1) and capture the full spectrum of drivers, from macroeconomic scale to sectoral technological and structural characteristics.

LMDI features zero residual error and compatibility with unbalanced long-term panel data. However, it assumes independence among driving factors and cannot quantify variable interaction effects, thus only acting as a standalone benchmark estimation tool.

3.1.2. Shapley Value Decomposition Model

To remedy LMDI's limitation in capturing factor interactions, this study introduces the Shapley Value decomposition derived from cooperative game theory (Shapley,1953;Zhang et al,2025). The model retains the same five driving factors as the LMDI framework: population scale, economic growth, industrial structure, energy intensity, and energy mix. The marginal contribution formula for a single factor i is defined as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} [v(S \cup \{i\}) - v(S)] \quad (2)$$

Where,

n = total number of driving factors (n = 5)

$|S|$ = number of factors contained in subset S
$v(S)$ = the value function (carbon emission change) of subset S
$v(S \cup \{i\}) - v(S)$ = marginal carbon emission change generated by adding factor i to subset S

The Shapley method quantifies both synergistic and antagonistic multi-factor interaction mechanisms, yet its estimation stability declines when positive and negative contributions coexist. Therefore, weighted integration with LMDI is implemented to improve overall reliability.

3.1.3. Weighted Integrated Emission Change Formula

Following the weighted combination framework proposed by Liang et al. (2018) , an integrated weighting framework is built based on Kendall compatibility test results. The comprehensive carbon emission change effect for each factor is calculated as:

$$\Delta C_{rt} = \sum_k w_k \cdot \Delta C_{rtk} \quad (3)$$

Where,

$$k = 1 for LMDI, k = 2 for Shapley$$
$$w_k = 0.5 for both models$$
$$\Delta C_{rt} = weighted average comprehensive emission change of the r-th driving factor in year t$$
$$\Delta C_{rtk} = carbon emission change of the r-th factor in year t estimated via model k$$

Model weights are objectively determined via the subsequent Kendall compatibility test (Section 3.2.1). The Kendall test verifies the consistency between LMDI and Shapley results, and equal weights are assigned when no systematic divergence is detected (see Section 3.2.1 for detailed test results and weight justification).

3.2. Model Consistency Test and Contribution Calculation

3.2.1. Kendall's W Coefficient Compatibility Test

The Kendall's W coordination coefficient is applied to test overall consistency between LMDI and Shapley outputs, avoiding bias from subjective weight assignment. Two test groups are constructed: annual single-year effects and cumulative multi-period effects, with a significance level $\alpha = 0.01$.

Test results show coordination coefficients $W = 0.9986$ for annual samples and $W = 0.9762$ for period samples, both statistically highly significant ($p < 0.01$). This confirms no systematic divergence in factor contribution rankings between the two models, providing a statistical basis for equal-weight integration in the Liang et al. (2018) framework. Equal weights are thus assigned: $w_1(LMDI) = W_2(Shapley) = 0.5$

3.2.2. Proportional Share Index of Driving Factors

A proportional share metric is constructed to eliminate bias from different total emission baselines and enable standardized cross-factor comparison:

$$\rho = \frac{\Delta C_k}{\sum_k |\Delta C_k|} \times 100\% \quad (4)$$

Where,

ΔC_k Weighted integrated emission effect of the k-th driving factor;

The proportional share index defined in Eq. (4) standardizes each factor's contribution by the sum of absolute factor effects within the same sector and period. This normalization ensures that all contributions are expressed on a comparable percentage basis within each individual sector's own emission change, making the metric independent of the sector's absolute emission scale or its share of national emissions. Consequently, the decomposition results for a small-emission sector and a large-emission sector are equally informative for understanding their respective driving mechanisms, supporting cross-sectoral comparisons without requiring the sample to cover a fixed percentage of national emissions.

The denominator equals the sum of absolute values of all factor effects in the same period to prevent offsetting between positive and negative values and ensure additive, comparable contribution ratios.

Economic interpretation of signs: $\rho > 0$ = emission-increasing driving effect; $\rho > 0$ = emission-reduction inhibitory effect; Larger absolute values indicate stronger factor influence. Heatmaps for each Five-Year Plan period are plotted based on this index to visualize cross-sector and cross-factor contribution disparities.

4. Data Sources

Data are sourced from the CEADs Carbon Emission Database, China Energy Statistical Yearbook, China Statistical Yearbook, and China Industrial Statistical Yearbook across all years. Sectoral value added is uniformly converted to constant 2000 prices to eliminate price fluctuation interference. Core indicators include sectoral energy consumption, sectoral value added, national total population, national GDP, and carbon emission factors for all energy varieties. National population and GDP data are obtained from the China Statistical Yearbook to maintain consistency with the Kaya identity specification in Eq. (1).

Following the Industrial Classification for National Economic Activities and CEADs statistical standards, 13 sub-sectors are selected to represent the full spectrum of emission sources across the primary, secondary, and tertiary industries. The selection criteria are threefold: (1) inclusion of the primary industry's representative sectors (Agriculture, Forestry, Animal Husbandry, and Fishery); (2) coverage of all energy-intensive manufacturing sectors as defined by China's statistical authorities, including electric power, ferrous and non-ferrous metals, non-metallic minerals, chemicals, petroleum processing, paper, textiles, and construction; and (3) representation of tertiary industry emissions through transportation, wholesale/retail, and other services. These 13 sectors are used as a representative sample for decomposition analysis; their internal emission structure is reported in Table 1. For context, China's aggregate carbon emissions reached 10,051.2 Mt CO_2 in 2022, with the secondary industry contributing 82.8% (the dominant emission source), the tertiary industry 15.7%, and AFAF only 1.50%.

5. Results and Analysis

5.1. Static Industrial Carbon Emission Patterns in 2022

5.1.1. Static Sectoral Emission Composition

Based on the 13 core industrial sectors screened in Section 2.2.1, this section decomposes the static carbon emission structure of segmented industries in 2022. The carbon emission share and standard abbreviation of each sector are displayed in Table 1.

Table 1. Carbon Emission Composition and Abbreviations of 13 Selected High-Emission Sectors in 2022

Industrial Category	Key Sector	Share within Selected Sectors (%)	Abbreviation
Primary Industry	Agriculture, Forestry, Animal Husbandry, and Fishery (AFAF)	3.01	FF
Secondary Industry	Production and Supply of Electric Power, Heat, and Gas	22.57	PE
	Smelting and Pressing of Ferrous Metals	13.46	SF
	Manufacture of Non-metallic Mineral Products	9.09	NP
	Manufacture of Raw Chemical Materials and Chemical Products	8.44	RC
	Processing of Petroleum, Coal, and Other Fuels	6.71	PC
	Smelting and Pressing of Non-ferrous Metals	5.42	SN
	Construction	5.94	CI
	Manufacture of Paper and Paper Products	2.61	PP
	Manufacture of Textiles	2.88	TI
Tertiary Industry	Transport, Storage, and Postal Services	6.47	TT
	Wholesale, Retail, Accommodation, and Catering Services	3.22	WS
	Other Tertiary Sectors	10.20	OS

Note: The percentages reported in the "Share within Selected Sectors (%)" column represent each sector's proportion of total emissions within the 13-sector sample. These 13 selected sectors collectively account for 49.7% of China's national energy-related CO_2 emissions in 2022. The sample was designed to cover all major emission sources across the primary, secondary, and tertiary industries. Sector abbreviations are used throughout the subsequent analysis.

5.2. Overall Temporal Evolution Characteristics of Carbon Emissions (2001–2022)

The study period 2001–2022 covers five consecutive Five-Year Plans (from the 10th to the early 14th). Iterative policy updates lead to distinct phased shifts in carbon emission driving mechanisms in China . Figure 1 presents the annual trajectory of China's total carbon emissions and the corresponding growth rates from 2000 to 2022, with dashed vertical lines marking the boundaries of the five Five-Year Plans. The emission trajectory clearly validates the five-stage division: rapid growth during the 10th FYP, accelerated expansion during the 11th FYP, peak and moderation during the 12th FYP, stagnation during the 13th FYP, and divergent patterns in the early 14th FYP. Based on this observed trajectory and the underlying policy shifts documented in the literature (Guo et al.2025;Chen et al,2025), the 22-year evolution is divided into the following five progressive stages:

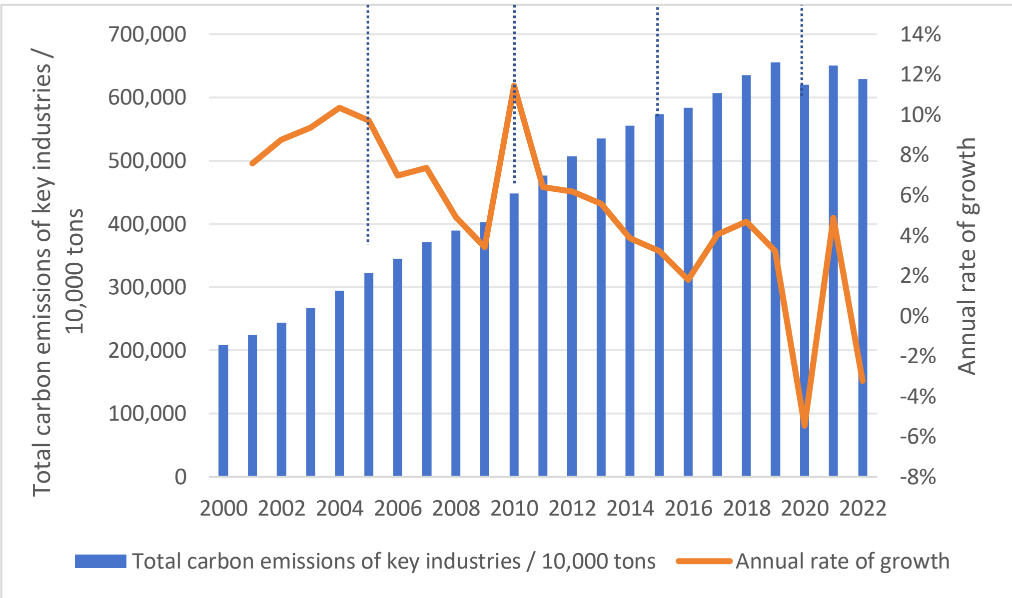

Fig.1: Total carbon emissions of the 13 selected sectors, 2000–2022 (10,000 tons CO_2)

Data source: CEADs Carbon Emission Database (aggregated national total).

Stage 1 (2001–2005, 10th Five-Year Plan): Extensive Expansion Phase. Industrialization and urbanization advanced rapidly without systematic top-down emission reduction regulations. Economic scale expansion served as the sole dominant driver of carbon emissions, while mitigation effects were negligible, leading to sustained growth in emission rates.

Stage 2 (2006–2010, 11th Five-Year Plan): Mandatory Energy Efficiency Constraints Implemented For the first time, binding reduction targets for energy consumption per unit GDP were formulated. Policies, including small thermal power shutdowns and industrial energy-saving retrofits, were rolled out to form stable emission reduction forces driven by energy efficiency improvement. Nevertheless, economic growth remained the primary factor boosting carbon emissions.

Stage 3 (2011–2015, 12th Five-Year Plan): Large-Scale Deployment of Wind and Solar Power The policy of replacing small coal-fired power units with large high-efficiency units was fully implemented, and renewable energy entered mass commercialization. Energy intensity optimization and clean energy substitution jointly formed dual emission reduction pathways, yet the emission control capacity of industrial restructuring remained limited.

Stage 4 (2016–2020, 13th Five-Year Plan): Supply-Side Reform and Emission Growth Moderation. Supply-side structural reform and mandatory carbon intensity assessment were carried out simultaneously. Phasing out excess high-energy capacity became the core governance measure, and industrial restructuring emerged as the most powerful emission reduction factor. While total emissions continued to grow during this period, the growth rate decelerated from 4.5 to 3.0, with some heavy industries experiencing temporary emission reductions. This phase marked the transition from absolute emission growth to a period of growth moderation, laying the foundation for subsequent decoupling.

Stage 5 (2021–2022, Early 14th Five-Year Plan): Polarized Industrial Low-Carbon Transition The top-level Dual Carbon strategy was fully rolled out, prompting in-depth low-carbon retrofits in heavy industries. However, post-pandemic economic recovery pushed up fossil fuel demand in transportation and service sectors, resulting in prominent divergence in transition progress across industries.

Overall, China’s industrial carbon emissions follow a progressive evolutionary path:

Scale-driven emission growth → Mild offset via energy efficiency → Coordinated emission control by energy and industrial restructuring → Deep decoupling through industrial adjustment → Polarized industrial transition

This trajectory aligns perfectly with tiered policy intensities of successive Five-Year Plans, providing macro-temporal support for subsequent interpretation of stage-specific driving contributions and differentiated policy design.

5.3. Estimation Results and Visualization

5.3.1. Description of Industry and Stage Division

Based on the equal-weight integrated model (weight = 0.5), the proportional share index defined in Eq. (4) is calculated for each driving factor, sector, and Five-Year Plan period. These proportional shares are calculated from the weighted integrated factor effects (ΔC_rt) defined in Eq. (3), combining LMDI and Shapley results with equal weights as justified by the Kendall compatibility test.This index normalizes each factor's contribution by the sum of absolute factor effects within the same sector and period, ensuring that all contributions are expressed as comparable percentages and that positive and negative effects do not offset each other. The results are visualized as heatmaps in Figures 2–6, where red cells indicate emission-increasing (positive) effects, blue cells indicate emission-reducing (negative) effects, and color intensity reflects the relative magnitude of each factor's contribution. This visualization approach enables intuitive cross-sectoral and cross-factor comparisons, revealing both the dominant drivers of carbon emissions and the heterogeneous mitigation performance across industrial sectors over the five policy cycles. The following subsections provide detailed interpretations of each Five-Year Plan period based on these heatmaps.

5.4. In-Depth Analysis of Driving Contributions by Five-Year Plan Cycle

The heatmaps (Figures 2–6) are plotted based on the absolute-value-based relative contribution index defined in Eq. (4). In these heatmaps, red cells denote emission-boosting effects and blue cells denote emission-reduction effects, with color intensity reflecting the magnitude of each factor's relative contribution.

5.4.1.The 10th Five-Year Plan (2001 －2005): Dominance of Extensive Expansion and Absence of Systematic Mitigation Regulations

During the 10th Five-Year Plan period, China experienced rapid industrialization and urbanization in the absence of nationwide systematic low-carbon regulatory frameworks. Industrial development prioritized scale expansion, while energy-saving retrofits and renewable energy deployment remained in their initial stages. As shown in Figure 2, the heatmap for this period reveals a distinct pattern: the Economic Growth and Population Scale rows are uniformly red across all 13 sectors, confirming that scale expansion served as the universal driver of rising carbon emissions. The Energy Intensity and Energy Mix rows are predominantly light blue, indicating weak and insufficient inhibitory effects that failed to offset the emission increments generated by scale expansion. The Industrial Structure row shows a notable exception: the agriculture, forestry, animal husbandry, and fishery (FF) sector appears in dark blue, reflecting significant emission reduction through the shrinking share of primary industry in the national economy. In contrast, all other sectors exhibit red or pale red cells in this row, indicating that industrial restructuring had not yet become a meaningful mitigation channel. Overall, the 10th Five-Year Plan period was characterized by scale-dominated emission growth with minimal technological or structural offset.

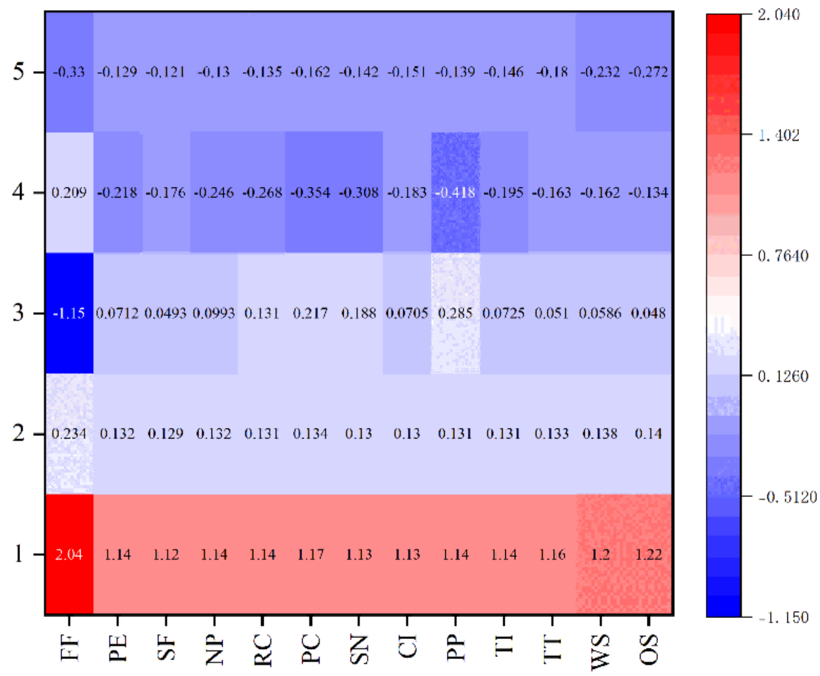

Fig.2: Heatmap of proportional share of Carbon Emission Drivers for Thirteen Key Industrial Sectors in the 10th Five-Year Plan Period

5.4.2.The 11th Five-Year Plan (2006 – 2010): Binding Energy Intensity Targets and Initial Mitigation Effects

The 11th Five-Year Plan incorporated GDP energy intensity reduction as a binding assessment indicator for the first time. Policies including the decommissioning of small thermal power units and industrial energy-saving retrofits established formal technological mitigation channels. However, sustained industrialization and urbanization kept economic growth as the primary driver of emission increases. As illustrated in Figure 3, the Economic Growth row remains predominantly red across all sectors, with particularly deep red cells in Construction (CI) and Textiles (TI), indicating that scale-driven emission growth remained dominant. The Population Scale row shows slightly deeper red compared with the previous period, reflecting the emission pressure from rural-to-urban labor migration into secondary and tertiary industries. The Energy Intensity row exhibits extensive blue cells across most sectors, with the deepest blue appearing in Textiles (TI) and Construction (CI), demonstrating that energy-saving technological renovations delivered substantial emission reductions per unit of output. The Energy Mix row remains predominantly light blue, indicating that clean energy substitution was still limited in scale and effectiveness. The Industrial Structure row displays divergent patterns: Power (PE) and Non-metallic Mineral Products (NP) shifted to blue (inhibitory) cells due to the phase-out of backward production capacity, while Non-ferrous Metals (SN) and service sectors remained red (emission-boosting), indicating that structural mitigation had not yet covered all industrial categories. This period marks the transition from pure scale-driven growth to a pattern where energy efficiency improvements began to partially offset emission increases.

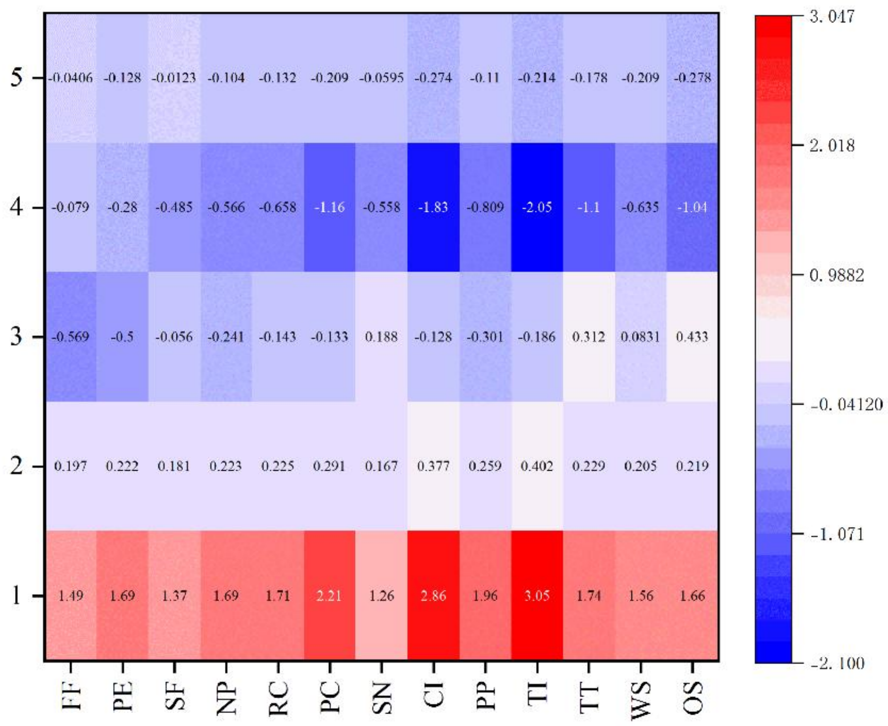

Fig.3: Heatmap of proportional share of Carbon Emission Drivers for Thirteen Key Industrial Sectors in the 11th Five-Year Plan Period

5.4.3.The 12th Five-Year Plan (2011－2015): Large-Scale Renewable Deployment and Coordinated Mitigation Pathways

During the 12th Five-Year Plan period, the policy of replacing small coal-fired power units with large high-efficiency generators was fully implemented, and wind and photovoltaic power entered mass commercialization. Energy intensity optimization and clean energy substitution formed dual mitigation pathways. As shown in Figure 4, the Economic Growth row remains generally red but with lighter shades compared with the 11th Five-Year Plan, indicating that the emission-boosting effect of scale expansion was gradually moderating. The Agriculture, Forestry, Animal Husbandry, and Fishery (FF) sector shows the deepest red in this row, reflecting emission growth associated with agricultural modernization. The Energy Intensity row displays evenly distributed light blue inhibitory cells, indicating that energy-saving retrofits had become a stable and broad-based mitigation force. The Energy Mix row shows a notable expansion of dark blue cells, particularly in service sectors (WS, OS), reflecting the accelerated clean energy substitution through coal-to-electricity and coal-to-gas projects in the tertiary industry. The Industrial Structure row exhibits reversed differentiation compared with the previous period: Power (PE) and Non-metallic Mineral Products (NP) shifted from blue to red, indicating a temporary shrinkage of structural mitigation potential after earlier capacity phase-outs, while Non-ferrous Metals (SN) show deep red cells driven by infrastructure and high-end manufacturing demand. This period marks the emergence of coordinated emission reduction through energy efficiency improvements and clean energy substitution, alongside heterogeneous structural adjustment outcomes across sectors.

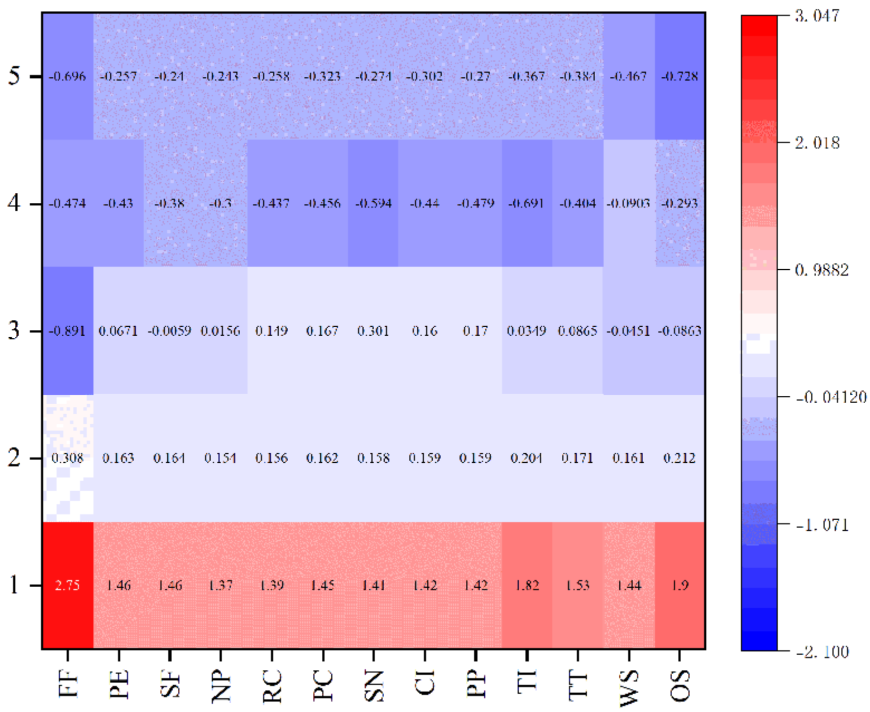

Fig.4: Heatmap of proportional shares of Carbon Emission Drivers for Thirteen Key Industrial Sectors in the 12th Five-Year Plan Period

5.4.4.The 13th Five-Year Plan (2016 – 2020): Supply-Side Reform and Multi-Factor Synergistic Suppression

Supply-side structural reform and mandatory carbon intensity assessment were implemented simultaneously during the 13th Five-Year Plan period. Eliminating excess high-energy capacity became the core governance instrument, fundamentally transforming the carbon emission driving mechanism. As shown in Figure 5, the heatmap for this period reveals a dramatic shift. The Economic Growth row exhibits extreme color contrast: Power (PE) shows a deep red cell, reflecting sustained emission pressure from expanding economy-wide electricity demand, while most energy-intensive heavy industries (SF, NP, RC, SN, CI, PP) display blue cells, indicating that the emission-suppressing effect of capacity reduction policies outweighed the emission-increasing effect of scale expansion. The Industrial Structure row features extensive dark blue inhibitory zones for Power (PE) and Non-metallic Mineral Products (NP), confirming that industrial restructuring emerged as the most powerful mitigation lever in this phase. The Energy Intensity row shows mixed patterns: several heavy industries display red cells (e.g., SF, NP, SN), reflecting improved efficiency of residual capacity after production contraction rather than emission increases. The Energy Mix row shows the deepest blue in the Power (PE) column, highlighting remarkable progress in clean energy transition through explosive growth in non-fossil energy installed capacity. Notably, the service sectors (TT, WS, OS) and light manufacturing (TI) retain red cells in the Economic Growth row, indicating that emission reduction policies had not yet achieved the same decoupling effects in these sectors. Overall, the 13th Five-Year Plan period marks the first phase in which multi-factor synergistic suppression—combining industrial restructuring, energy intensity improvement, and energy mix optimization—achieved absolute emission reductions in most energy-intensive heavy industries, while service and light manufacturing sectors continued to experience emission growth.

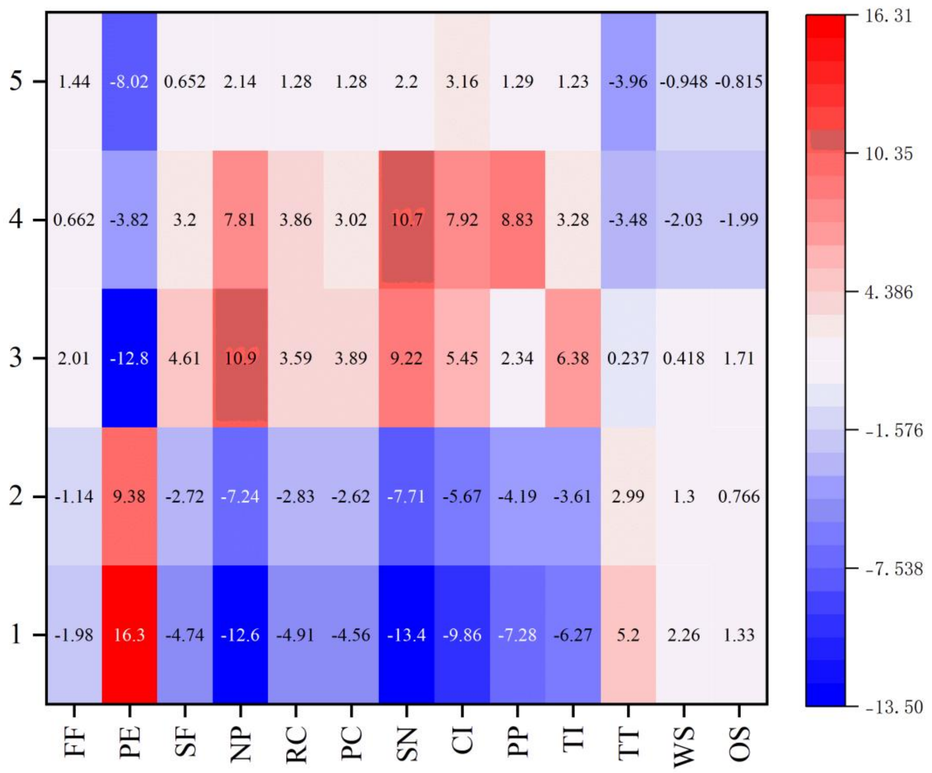

Fig.5: Heatmap of proportional share of Carbon Emission Drivers for Thirteen Key Industrial Sectors in the 13th Five-Year Plan Period

5.4.5.Early 14th Five-Year Plan (2021 –2022): Post-Pandemic Divergence and Mitigation Challenges

The period 2021–2022 represents the early stage of the 14th Five-Year Plan, heavily influenced by post-COVID-19 economic recovery. As shown in Figure 6, sectoral emission trajectories became highly divergent. Energy-intensive heavy industries, including Ferrous Metal Smelting (SF), Non-metallic Mineral Products (NP), and Raw Chemical Materials (RC), continue to display blue cells in the Economic Growth row, indicating that capacity regulation and energy efficiency improvements sustained the emission reduction trajectory established during the 13th Five-Year Plan. In these sectors, the Industrial Structure, Energy Intensity, and Energy Mix rows are predominantly blue, confirming that multi-factor synergistic suppression remained effective. In stark contrast, the Transportation sector (TT) shows deep red cells in the Energy Mix and Energy Intensity rows, reflecting a post-pandemic rebound in fossil fuel consumption and stalled efficiency improvements. The Textile sector (TI) exhibits a similar pattern, with a deep red cell in the Energy Mix row indicating a severe lag in clean energy substitution. The service sectors (WS, OS) show mixed patterns, with some mitigation factors remaining effective while others face renewed emission pressure from economic recovery. Overall, the early 14th Five-Year Plan period is characterized by intensified divergence in sectoral decarbonization progress. While heavy industries continued to achieve absolute emission reductions under policy constraints, transportation and light manufacturing faced emission rebound pressures amid demand recovery, highlighting the necessity for differentiated policy design that accounts for sector-specific transition characteristics.

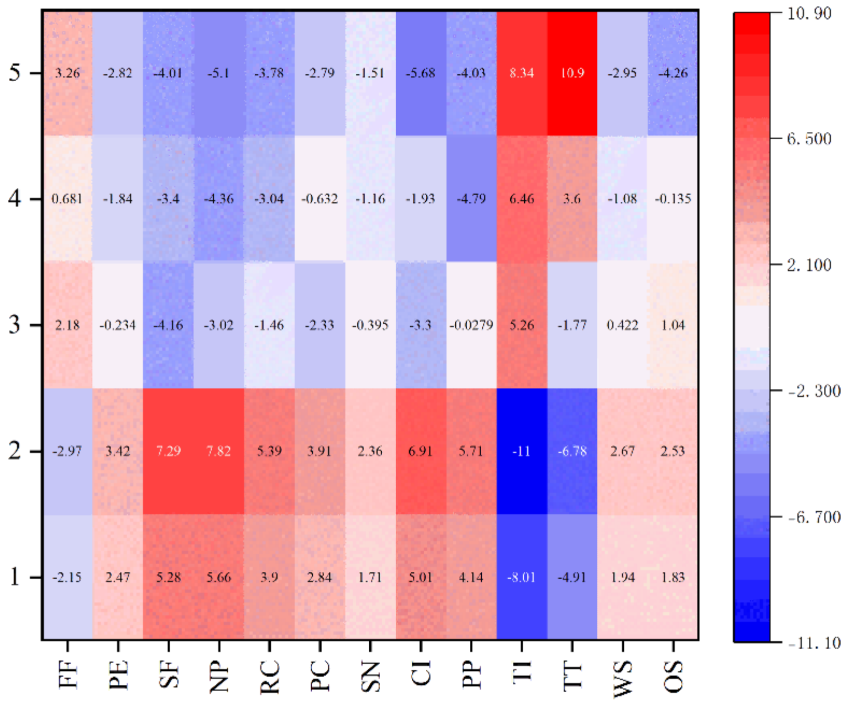

Fig.6: Heatmap of proportional share of Carbon Emission Drivers for Thirteen

5.5. Evolution Rules of Driving Factors and Industrial Echelon Heterogeneity

5.5.1. Cross-Cycle Evolution Patterns of Driving Factors

The heatmaps across the five policy cycles (Figures 2–6) reveal distinct evolutionary patterns for each driving factor. Economic Growth has consistently served as the fundamental driver of rising carbon emissions. From the 10th to the 12th Five-Year Plan periods, this factor appears uniformly red across all sectors, acting as the primary engine of sustained emission growth. During the 13th Five-Year Plan, however, the pattern fundamentally shifted: the Economic Growth row shows blue cells for most energy-intensive heavy industries, indicating that the emission-suppressing effect of capacity reduction policies exceeded the emission-increasing effect of scale expansion, yielding net emission reductions in these sectors. In the early 14th Five-Year Plan, this factor exhibits polarized patterns—continued blue for heavy industries but red for transportation and some service sectors, reflecting divergent post-pandemic recovery trajectories.

Population Scale exhibits similar patterns to Economic Growth. From the 10th to the 12th Five-Year Plan periods, this factor appears red across all sectors, reflecting the emission pressure from rural-to-urban labor migration into secondary and tertiary industries. During the 13th Five-Year Plan, the pattern diverges: blue cells appear in heavy industrial sectors where employment contraction accompanied capacity reduction, while red cells remain in sectors with continued labor inflows. In the early 14th Five-Year Plan, inter-sectoral labor mobility differentials further amplify the divergence of this factor across industries.

Energy Intensity demonstrates the most consistent mitigation performance across all periods. From the 11th Five-Year Plan onward, this factor appears predominantly blue across most sectors, with color intensity deepening over time as energy-saving technologies diffused throughout the industrial economy. The consistent blue pattern confirms that energy intensity improvement has been the most stable and broadly based emission reduction lever across all five policy cycles.

Energy Mix shows progressive strengthening of mitigation effects over time. In the 10th and 11th Five-Year Plan periods, this factor appears mostly light blue, indicating limited clean energy substitution. From the 12th Five-Year Plan onward, darker blue cells appear, particularly in the power sector and service industries, reflecting the accelerating deployment of renewable energy and coal-to-electricity conversions. The power sector shows the deepest blue in the 13th Five-Year Plan, highlighting the transformative impact of non-fossil energy expansion.

Industrial Structure exhibits the most heterogeneous and stage-dependent patterns. In the 10th Five-Year Plan, only the agriculture sector shows blue (structural emission reduction), while all other sectors appear red. During the 11th and 12th Five-Year Plans, the pattern becomes mixed: some heavy industries show blue due to capacity phase-outs, while others remain red. The 13th Five-Year Plan marks the peak of structural mitigation, with extensive dark blue cells in energy-intensive heavy industries. In the early 14th Five-Year Plan, the pattern becomes more nuanced, reflecting the diminishing marginal returns of capacity reduction in some sectors and the emergence of structural emission pressures in others.

5.5.2. Summary of Heterogeneity Across Four Industrial Echelons

Based on driving factor contributions and decarbonization progress, the 13 segmented industries are categorized into four echelons with distinct transition characteristics:

Energy-intensive heavy industries: Subject to the strictest policy constraints, they achieved coordinated triple mitigation from industrial, energy, and efficiency dimensions in the 13th Five-Year Plan and took the lead in absolute emission reduction. Untapped mitigation potential still exists in stock industrial retrofits.

Light manufacturing sectors: Moderate transition speed with preliminary energy-saving achievements. Output expansion in the 14th Five-Year Plan triggered emission rebounds, accompanied by huge gaps in renewable energy substitution.

Commercial and service sectors: Highly dependent on fossil fuels with far slower clean energy popularization than manufacturing, representing the core medium- and long-term bottleneck of carbon governance.

Agriculture, forestry, animal husbandry, and fishery: Low baseline emissions, realizing structural mitigation via shrinking industrial share, with integrated potential for emission reduction and ecological carbon sink development.

The conclusions on stage-wise evolution and industrial heterogeneity proposed in this paper are highly consistent with mainstream domestic research on industrial carbon emissions (Ang,2005; Chen et al,2025; Song,2025). Furthermore, the intensity changes of driving factors in each cycle fully match the gradient policy stringency of the five Five-Year Plans, which verifies the rationality of period segmentation based on national planning cycles and proves the adequate theoretical and practical reliability of our estimation results.

6. Conclusions and Policy Recommendations

6.1. Conclusions

6.1.1. Highly Concentrated Industrial Emissions and Distinct Industrial Heterogeneity

The secondary industry constitutes the primary carrier of energy-related carbon emissions in China. Within our representative sample of 13 sectors, three energy-intensive sectors—power and heat supply (22.57%), ferrous metal smelting (13.46%), and non-metallic mineral manufacturing (9.09%)—dominate the sample's emission structure, which aligns with their known dominance in national emissions. Although service industries, light manufacturing, and agriculture show relatively lower shares within the sample (10.20%, 5.49%, and 3.01%, respectively), they differ drastically in transition bottlenecks and emission reduction potential, making a unified regulatory framework inapplicable. Regional industrial endowments directly shape the distribution of carbon emission sources across provinces.

6.1.2. Phased Transformation of Carbon Emission Driving Mechanisms Aligned with Five-Year Plan Cycles

Over the past two decades, the driving forces behind carbon emissions have undergone fundamental shifts, following an evolutionary trajectory: scale-driven expansion → energy efficiency retrofits offsetting emission increments → coordinated mitigation via clean energy → in-depth decarbonization through industrial restructuring → polarized industrial low-carbon transition. Economic growth has consistently served as the fundamental driver of rising emissions, while energy intensity acts as a sustained mitigation lever across all cycles. The emission reduction capacity of industrial and energy structures has strengthened progressively with policy implementation, and the impact of population scale has shifted from unidirectional emission growth to bidirectional differentiation.

6.1.3. Widening Decarbonization Gaps across Industrial Echelons

Backed by dual energy consumption control and supply-side capacity cut policies, traditional energy-intensive heavy industries took the lead in realizing periodic decoupling between economic growth and carbon emissions through synergistic effects of multiple mitigation factors. Light manufacturing sectors have weak foundations for energy-saving renovation and face prominent risks of emission rebounds amid economic recovery. Commercial and service sectors lag significantly in fossil fuel substitution, representing the core bottleneck for medium- and long-term low-carbon transition. The agricultural sector achieves mild emission reduction as its industrial share shrinks, and it holds great potential for integrated development of ecological carbon sinks.

6.2. Policy Recommendations

6.2.1. Prioritize High-Emission Heavy Industries to Consolidate Structural Decarbonization and Tap Clean Energy Mitigation Potential

Power supply, ferrous metal smelting, and non-metallic mineral manufacturing are the dominant sources of carbon emissions, where industrial restructuring, energy intensity improvement, and energy mix optimization have formed synergistic inhibitory effects. Follow-up measures should sustain such governance outcomes:

Strictly enforce capacity management and dual energy consumption constraints for energy-intensive industries, and regularly phase out outdated coal-fired power units, backward smelting, and cement production capacity; Increase investment in wind, photovoltaic, and supporting energy storage projects to raise the proportion of non-fossil power generation and optimize the power sector's energy mix; Popularize energy-saving technologies such as waste heat and pressure recovery and low-carbon smelting in steel and cement production links, establishing long-term stable emission reduction support via energy intensity optimization.

6.2.2. Establish a Dynamic Long-Term Low-Carbon Policy Framework Matching the Temporal Evolution of Driving Mechanisms

The driving forces of industrial carbon emissions have kept evolving over two decades, so fixed, uniform policy standards are inappropriate. Regulatory priorities should be dynamically adjusted according to industrial development stages:

Maintain long-term fiscal subsidies for industrial energy-saving retrofits to sustain the stable mitigation effects of energy intensity improvement; Improve supporting policies for renewable energy industries to steadily expand the coverage of clean energy substitution; Implement differentiated energy consumption assessments for individual industries to address the polarized transition characteristics of the early 14th Five-Year Plan, abandoning one-size-fits-all total emission control; Launch supporting policies, including green vocational training and employment support for labor transfers, to counteract emission increments caused by population expansion.

6.2.3. Remediate Transition Bottlenecks of Light and Service Sectors via Tiered Classified

Low-Carbon Renovation

Industries vary greatly in low-carbon foundations and emission growth logic, requiring tiered coordinated governance:

For light manufacturing sectors (construction, papermaking, textiles): Prioritize substituting coal and heavy oil with biomass fuels and electricity, improve circular industrial chains, and set strict clean production access thresholds to ease emission rebounds during economic recovery; For transportation, wholesale, and retail service sectors: Accelerate the popularization of new energy freight vehicles and public transport, and carry out electrification energy-saving renovations for commercial buildings to resolve fossil fuel reliance in the transport sector; For agriculture, forestry, animal husbandry, and fishery: Capitalize on shrinking industrial share to realize natural structural emission reduction, promote electric agricultural machinery, and develop forest and farmland carbon sink projects to achieve synergistic emission cuts and carbon sequestration.

References

Ang, B.W. (2005). LMDI decomposition approach: A guide for implementation. Energy Policy, 33(7), 867-871.

Chen, P.Y., & Tian, L.X. (2025). Research on accounting, modeling and forecasting of carbon emissions in China's industrial sectors. Energy and Climate Change, 1(2), 174-207.

Dong, Z.C., & Yang, M. (2024). Analysis of carbon emissions in the middle and lower reaches of the Yangtze River based on LMDI under the Dual Carbon Goals. Environment and Sustainable Development, 49(5), 57-65.

Guo, W.Q., Yu, Z.P., Lei, M., et al. (2025). Research on decomposition of carbon emission driving factors and decoupling effort effects. Research of Environmental Sciences, 38(2), 209-219.

Huang, Z.J., Song, M.Y., Fan, Z.D., et al. (2025). Spatiotemporal evolution and influencing mechanisms of industrial carbon emissions in China at the city-industry scale: From the perspective of industrial linkages. Environmental Science, 46(2), 647-659.

Kaya, Y. (1990). Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios. IPCC Energy and Industry Subgroup, Response Strategies Working Group, Paris.

Li, H., Gao, L., Zhang, Z.R., et al. (2026). Spatiotemporal evolution and driving factor analysis of carbon emissions in regions along China's Belt and Road Initiative. Journal of Environmental Economics, (in press).

Liang, Y., Niu, D., Zhou, W., & Fan, Y. (2018). Decomposition analysis of carbon emissions from energy consumption in Beijing-Tianjin-Hebei, China: A weighted-combination model based on logarithmic mean Divisia index and Shapley value. Sustainability, 10, 2535.

Qiu, Y.H., Wang, P., & Su, S.P. (2019). Spatiotemporal evolution and driving factors of carbon emissions from agricultural land use based on IPCC and LMDI models. Resource Development & Market, 35(5), 625-631.

Qu, S.N. (2019). Carbon emission decomposition: Theoretical basis, path analysis and method evaluation. Urban and Environmental Studies, (3), 98-112.

Shapley, L.S. (1953). A value for n-person games. In Kuhn, H.W., & Tucker, A.W. (Eds.), Contributions to the Theory of Games II (pp. 307-317). Princeton University Press.

Shen, M., Hou, Y., Liang, K., et al. (2025). Energy-system characteristic shifts and their quantitative impacts on China's CO_2 trajectory: Evidence from a high-resolution energy allocation analysis–LMDI sectoral decomposition. Energy, 335, 137905.

Song, J.K., & Dou, J.F. (2013). Research on zero-residual factor decomposition model for energy consumption carbon emissions. Journal of China University of Petroleum (Natural Science Edition), 37(1), 183-189.

Song L, Yuan J, Li T and Zhang J (2025) Can targeted industrial policy drive low-carbon transformation? evidence from China’s Five-Year Plans. Front. Environ. Sci,13,1564489.

Sun, L., Liu, W., & He, Y. (2024). Influencing factors and spatial distribution of carbon emission efficiency in the Beijing-Tianjin-Hebei region. Land and Resources Science and Technology Management, 41(3), 28-38.

Wang, M., & Wu, Y.M. (2024). Dynamic changes and network structure evolution of industrial carbon emissions in China. Environmental Science, 45(10), 5591-5600.

Yan, G., Zheng, Y.X., Wang, X.S., et al. (2022). Research on carbon peaking pathways of key industries and sectors in China. Research of Environmental Sciences, 35(2), 309-319.

Yang, S.S. (2024). Structural drivers of carbon emission growth in China's industrial sectors based on coupled SDA-LMDI decomposition. Resources Science, 46(5), 881-894.

Zhang, X., Chai, Y.F., & Han, X.Y. (2025). Quantitative calculation method for carbon emission reduction contribution of power grids. Chinese Journal of Electric Power, 58(9), 175-182.

Zhao S, Li Z, Deng H, You X, Tong J, Yuan B and Zeng Z (2024) Spatial-temporal evolution characteristics and driving factors of carbon emission prediction in China-research on ARIMA-BP neural network algorithm. Front. Environ. Sci, 12,1497941.